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Productivity and flexibility improvement of assembly lines for high-mix low-volume production. A white goods industry case

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PRODUCTIVITY AND FLEXIBILITY IMPROVEMENT OF ASSEMBLY LINES FOR HIGH-MIX LOW-VOLUME PRODUCTION. A WHITE GOODS INDUSTRY CASE

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Productivity and flexibility improvement of assembly lines for high-mix low-volume production. A white goods industry case.

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Universidad de Zaragoza

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Abstract

The global trends of mass customisation and mass personalisation drive high-mix low-volume industrial production, characterised by high variety of products in low quantities each. Thus, mass customisation requires that assembly systems are simultaneously highly productive and flexible, contrary to the traditional dichotomy between them. The so called 4th industrial revolution brings several key enabling technologies which could help to address this. However, implementation methodologies for assembly 4.0 are still an open issue. In fact, to benefit from all the potential advantages brought by Industry 4.0, a previous level of operational excellence is required along with a holistic analysis of the system. In consequence, this thesis aims to understand and define how to improve the productivity and flexibility of assembly operations under high-mix low-volume demand.

The overarching aim is divided into three objectives. First, understanding the relationship between Industry 4.0 and assembly operations, as well as its implications for the human operators. Second, developing a methodology and the tools to evaluate the performance of different flexible assembly line configurations. Finally, to design assembly systems that improve their productivity by at least +25% under high-mix low-volume demand by introducing a combination of automated and manual workstations.

To address the understanding stage, a systematic literature review was carried out and a conceptual framework for Assembly 4.0 was developed. Two assembly systems performance evaluation tools—an analytical mathematical model and several discrete events simulation models—were developed, validated and verified. A real industry study case from a global white goods manufacturer was employed for verification and as starting point for further analysis. Design of experiments and multiple simulation scenarios were used to investigate three key issues.

First of all, the most critical factors affecting the performance of manual multi-model assembly lines were identified. Secondly, the performance of semiautomatic parallel walking-worker lines was compared to semiautomated and manual fixed-

worker lines. Finally, the use of milkrun trains for in-plant logistics of multi-model assembly lines under severe disturbances was investigated.

The simulation results showed that parallel walking-worker lines can outperform fixed-worker lines in all demand scenarios, achieving at least the +25% productivity goal. They also allow to seamlessly reduce the number of operators without compromising the line balancing, therefore enabling efficient low-volume production. In-plant logistics simulation results indicate that milkruns can be a great way to protect assembly lines from disturbances originated in upstream processes.

Further research following the results obtained in this thesis may include expanding and integrating the current simulation models to analyse parallel walking-worker lines incorporating logistics, breakdowns and maintenance, and quality control problems and rework policies. Another avenue for research would be the use of other performance evaluation tools, such as scheduling techniques, to assess the operational performance of different semiautomated walking-worker line configurations both in terms of automation and layout. Incorporating Industry 4.0 technologies—such as cobots for assembly or material handling tasks, augmented reality for operator cognitive support, or AGVs for driving the milkrun trains—to the simulation models to evaluate their global impact. Finally, the work presented in this thesis encourages the actual implementation of semiautomated parallel walking-worker assembly lines in an industrial context.

Universidad de Zaragoza

Mejora de productividad y flexibilidad de líneas de montaje para producción en serie corta y variada. Un caso de estudio de la industria de los electrodomésticos.

Adrián Miqueo Delgado

Resumen

Las tendencias globales de la personalización e individualización en masa impulsan la producción industrial en serie corta y variada; y por tanto una gran variedad de productos en pequeñas cantidades. Por ello, la customización en masa precisa de sistemas de ensamblaje que sean a la vez altamente productivos y flexibles, a diferencia de la tradicional oposición entre ambas características. La llamada cuarta revolución industrial trae diversas tecnologías habilitadoras que podrían ser útiles para abordar este problema. Sin embargo, las metodologías para implementar el ensamblaje 4.0 todavía no han sido resueltas. De hecho, para aprovechar todas las ventajas potenciales de la Industria 4.0, es necesario contar con un nivel previo de excelencia operacional y un análisis holístico de los sistemas productivos. Esta tesis tiene como objetivo entender y definir cómo mejorar la productividad y la flexibilidad de las operaciones de montaje en serie corta y variada.

Esta meta se ha dividido en tres objetivos. El primer objetivo consiste en comprender las relaciones entre la Industria 4.0 y las operaciones de ensamblaje, así como sus implicaciones para los operarios. El segundo objetivo consiste en desarrollar una metodología y las herramientas necesarias para evaluar el rendimiento de diferentes configuraciones de cadenas de ensamblaje. El último objetivo consiste en el diseño de sistemas de ensamblaje que permitan incrementar su productividad al menos un 25 %, produciendo en serie corta y variada, mediante la combinación de puestos de montaje manual y estaciones automatizadas.

Para abordar la fase de comprensión y definición del problema, se llevó a cabo una revisión bibliográfica sistemática y se desarrolló un marco conceptual para el Ensamblaje 4.0. Se desarrollaron, verificaron y validaron dos herramientas de evaluación del rendimiento: un modelo matemático analítico y varios modelos de simulación por eventos discretos. Para la verificación, y como punto de partida para los análisis, se ha utilizado un caso de estudio industrial de un fabricante global de electrodomésticos. Se han empleado múltiples escenarios de simulación y técnicas

de diseño de experimentos para investigar tres cuestiones clave.

En primer lugar, se identificaron los factores más críticos para el rendimiento de líneas de montaje manuales multi-modelo. En segundo lugar, se analizó el rendimiento de líneas de montaje semiautomáticas paralelas con operarios móviles en comparación con líneas semiautomáticas o manuales con operarios fijos, empleando diversos escenarios de demanda en serie corta y variada. Por último, se investigó el uso de trenes milkrun para la logística interna de líneas de ensamblaje multi-modelo bajo la influencia de perturbaciones.

Los resultados de las simulaciones muestran que las líneas paralelas con operarios móviles pueden superar a las de operarios fijos en cualquier escenario de demanda, alcanzando como mínimo el objetivo de mejorar la productividad en un 25 % o más. También permiten reducir cómodamente el número de operarios trabajando en la línea sin afectar negativamente al equilibrado de la misma, posibilitando la producción eficiente de bajo volumen. Los resultados de las simulaciones de logística interna indican que los milkrun pueden proteger las líneas de ensamblaje de las perturbaciones originadas en procesos aguas arriba.

Futuras líneas de investigación en base a los resultados obtenidos en esta tesis podrían incluir la expansión e integración de los modelos de simulación actuales para analizar las cadenas de montaje paralelas con operarios móviles incorporando logística, averías y mantenimiento, problemas de control de calidad y políticas de gestión de los retrabajos. Otra línea podría ser el uso de diferentes herramientas para el análisis del desempeño como, por ejemplo, técnicas de programación de la producción que permitan evaluar el desempeño operacional de diferentes configuraciones de cadenas de montaje con operarios móviles, tanto en términos de automatización como de organización en planta. Podrían incorporarse tecnologías de la Industria 4.0 a los modelos de simulación para evaluar su impacto operacional global –como cobots para ensamblaje o para la manipulación de materiales, realidad aumentada para el apoyo cognitivo a los operarios, o AGVs para la conducción de los trenes milkrun. Por último, el trabajo presentado en esta tesis acerca las líneas de ensamblaje semiautomáticas con operarios móviles a su implementación industrial.

Dedication

A Consuelo y Manolo

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Nomenclature

Input Parameters

μ	Mean of a distribution
σ	Standard deviation of a distribution
B_{CO}	Number of batches of the same product family before changeover
BC	Buffer capacity
CT	Cycle time
CT_{MR}	Milkrun cycle time
d	Expected component consumption over a milkrun cycle
J	Number of automated workstations
K	Number of manual workstations
L	Number of assembly lines
LB	Assembly line balance
M	Number of product models
N	Number of containers of a component in the milkrun train
n	Number of pieces of a component in the product
Q	Batch size
q	Number of pieces of a component per container
T_h	Milkrun operator handling time
T_h^e	Milkrun operator handling time, empty container

T_h^f	Milkrun operator handling time, full container
T_p	Processing time
T_s	Setup time
T_t	Milkrun transportation time
T_t	Milkrun transportation time
W	Number of workers
WC	Work Content
WC_R	Work Content ratio

Disturbances

CV_c	Conforming pieces per container coefficient of variability
CV_p	Processing time coefficient of variability
CV_q	Batch size coefficient of variability
CV_s	Setup time coefficient of variability
FTY	First Time Yield

Key Performance Indicators

LT_B	Batch lead time
LT_U	Unit lead time
P_S	Surface productivity
P_{Labour}	Labour productivity
P_{Line}	Line productivity
S	Stock at assembly line
Th	Throughput
U	Milkrun utilisation

Indices

i	All-purpose index
j	Index of automated stations
k	Index of manual workstations
l	Index of assembly lines
m	Index of product models
w	Index of workers

Acronyms / Abbreviations

AGV	Autonomous Guided Vehicle
AL	Assembly Line
AR	Augmented Reality
AS	Assembly
AS40	Assembly Systems 4.0
BC	Buffer Capacity
BOM	Bill of Materials
CIM	Computer Integrated Manufacturing
CM	Communication
CO	Changeover
CPS	Cyber-Physical System
DES	Discrete Events Simulation
DMS	Dedicated Manufacturing System
DoE	Design of Experiments
FIFO	First In, First Out
FMS	Flexible Manufacturing Systems
FTY	First Time Yield
FWAL	Fixed-Worker Assembly Line
HmLv	High-mix Low-volume
HRC	Human-Robot Collaboration
I4.0	Industry 4.0
IoT	Internet of Things
JIT	Just in Time
KET	Key Enabling Technologies
KPI	Key Performance Indicator
LP	Lean Production
LPS	Lean Production System
MIP	Mixed-Integer Programming
MR	Mixed Reality
MRP	Material Requirements Planning
MTM	Methods-Time Measurement

OEE	Overall Equipment Effectiveness
POU	Point of Use
PWWAL	Parallel Walking-Worker Assembly Line
QC	Quality Control
SD	Standard Deviation
SME	Small and Medium Enterprises
SMED	Single-Minute Exchange of Die
SOP	Standard Operations Procedure
SPC	Statistical Process Control
SW	Standardised Work
TPS	Toyota Production System
VR	Virtual Reality
VRP	Vehicle Routing Problem
VSM	Value Stream Map
WIP	Work in Progress
WWAL	Walking-Worker Assembly Line

CHAPTER 1

Introduction

Assembly operations face a traditional dichotomy between the high productivity brought by automation and the superior flexibility of manual assembly lines. The white goods production global context is characterised by high product customisation demand trends and the new possibilities brought by the new *smart* technologies.

Despite the near-unlimited potential benefits of introducing disruptive digital technologies to assembly lines, the actual implementation methodologies and the operational maturity required for successfully digitalising the assembly operations remain an open issue.

This thesis aims to understand and define assembly lines capable of flexibly dealing with highly customised products while achieving high productivity, and therefore are ready for the so-called fourth industrial revolution: Industry 4.0.

This chapter presents the thesis background and motivation, followed by the research problem, the research aims and questions, the scope, and finally outlines the structure of the document.

1.1 Background and motivation

The first industrial revolution took place during the 18th to 19th centuries in Western countries. It was enabled by steam engines and the mechanisation of labour, and it allowed a steep increase in the production of crafted goods. In a *simple market* paradigm where demand for industrial products vastly outweighed supply, there was a stable driving force for production volume growth [1, p.17–20].

The second industrial revolution took place at the end of the 19th century or early 20th century, depending on the geographical region. It was brought by technological advances—interchangeable parts, electricity, Bessemer process for steel, among others—as well as organisation and management innovations, such as scientific management and production lines. It enabled mass production, which became the dominant production system paradigm until the 1980s. Mass production allowed manufacturing in large volumes at low cost, by standardising products (i.e., reducing product variety) to benefit from economies of scale and labour specialisation. This led to more and more people being able to afford industrially crafted products, which fuelled the cycle of increasing production volume and further reduction of costs [1, p.21–32].

In the second half of the 20th century, the development of electronics and computers brought automation and robotic production as well as much faster information flows. Low-cost standard products were not sufficient anymore, resulting in product variety and delivery time becoming the new major goals of production systems, which defined the *volatile market* conditions [2]. Developed in Japan in the 1950s and 1960s, the Toyota Production System (TPS, [3]) emerged as the best way to achieve the aforementioned goals. Its global expansion (named *Lean* production [4, 5]) in the 1980s was concurrent with the appearance of another key development: *Flexible Manufacturing Systems* (FMS), which integrate computers, numerically controlled machines and automated material handling devices [6, p.158]. Both Lean and FMS, which are not mutually exclusive, aim at processing medium-sized volumes of products featuring a certain degree of variety. This production paradigm, covering approximately from the 1980s until the present, is characterised by the volatile market, widespread information technologies, Lean production and FSM. It has been named Industry 3.0 [2, 7], to signify the expected next production paradigm: the 4th industrial revolution or Industry 4.0, enabled by several digital technologies [8].

To better understand the potential impact of this so-called 4th industrial revolution on assembly systems, several basic concepts need to be introduced: industrial assembly, automation, productivity and flexibility and the mass customisation and mass personalisation demand trends.

Assembly is the part of a production process where various components and sub-assemblies are joined together so that the product acquires its final form, becoming finished. *Industrial assembly* is, following the definition by Nof et al., "the aggregation of all processes by which various parts and sub-assemblies are built together to form a complete, geometrically designed assembly or product (such as a machine or an electronic circuit) either by an individual, batch or a continuous process" [9, p.2]. The assembly system utilised is of critical importance since it greatly affects productivity, product quality and cost.

The assembly line introduced by Henry Ford is considered the first modern assembly system and proved very effective for producing large quantities of a single, standard product. *Assembly lines* can be defined as "an arrangement of workers, machines and equipment in which the product being assembled passes consecutively from one specialised operation to the next until completed. It is also called a production line" [9, p.2].

Regarding the agent implementing the assembly action, "the manipulative operations may be performed by robots, people, or combinations of both" [6, p.148]. Depending on the degree of automation, the basic types of assembly are three:

> Assembly systems are utilized in virtually all types of durable goods manufacturing. There are three basic types of assembly systems: (1) manual assembly, which is carried out by human assemblers, usually with the aid of simple power tools . . . (2) Assembly systems that combine human assemblers and automated mechanisms . . . (3) Fully automated assembly systems for mass-produced parts, and particularly in hazardous environments [6, p.167].

Automated and hybrid systems employ industrial robots to carry out parts or all the assembly steps, which rises productivity and reduces labour costs. One of the key enabling technologies for the 4th industrial revolution is collaborative robotics, which present significant advantages over conventional assembly robots in terms of safety, cost and ease of implementation and reconfiguration [10, 11]. This focus on automated systems reconfigurability is closely related to the traditional dichotomy between productivity and flexibility.

Productivity—i.e. efficiency, the quantity of input resources necessary to produce a certain output—cannot alone express the actual capability of a production system to address market demand and to adapt to its successive changes [12]. Increasing focus on product variety and customisation requires that assembly systems are designed and operated with flexibility in mind [13]. However, this approach may make it difficult to benefit from the productivity advantages resulting from economies of scale and process specialisation. Traditional dedicated assembly systems leverage computers and automated machinery to achieve very low production costs for standard, non-customised products. Nonetheless, they require very high investments and therefore high production volumes to become profitable. Opposed to dedicated automated systems, fully manual assembly continues to exist despite its low productivity because of its extremely high flexibility. This makes it viable for addressing niche markets and specialist products (Figure 1.1).

Occupying the middle ground between both, flexible assembly systems are capable of integrating automated and manual assembly stations so that a certain variety of products can be produced efficiently, even in medium-size production volumes.

Assembly systems *flexibility* "can be viewed as the capacity of a system to

Figure 1.1: Traditional dichotomy between highly productive but inflexible automated systems, and manual assembly lines which are very flexible but are less productive.

change and assume different positions or states in response to changing requirements with little penalty in time, effort, cost, or performance" [14, p.262] (based on [15]). Out of the ten types of flexibility identified by ElMaraghy et al. [14, p.263] (based on Browne et al. [16] and Sethi and Sethi [17]), this thesis focuses on the following four:

- *Product* Flexibility: "Ease (time and cost) of introducing products into an existing product mix. It contributes to agility."
- *Volume* Flexibility: "The ability to vary production volume profitably within production capacity."
- *Expansion* Flexibility: "Ease (effort and cost) of augmenting capacity and/or capability, when needed, through physical changes to the system."
- *Production* Flexibility: "Number of all part types that can be produced without adding major capital equipment."

The increasing consideration for flexibility is closely related to the evolution of global demand trends. Although traditionally there existed a clear segmentation between mass-produced goods and made-to-order products, the markets have been shifting towards the customisation of mass-produced items. Although this was not economically viable in the past; technological advances have made it possible. In the near future, mass customisation could not only become desirable but expected of any manufacturing company wanting to remain competitive [2].

Mass customisation is trending since the 1980s, characterised by the change in demand variety and volume per product reference: "Compared to mass production (that peaked in 1955), the variety of each product in mass customisation is large and the volume per product variant is relatively small" [6, p.126].

The industrial production shift from mass production to mass customisation was already forecasted in 1987. The ability to produce customised products that meet each consumer's requirements at near mass production costs is the ultimate goal of mass customisation. Giving customers the chance to have a product wherever they want it, any way they want it, and whenever they want it, resonates well with customers. The quantity of mass customised products is gradually increasing as are the customised services. This kind of production paradigm is called *mass personalisation* [18, p.313].

Mass customisation and mass personalisation lead to a particularly challenging production demand problem: high-mix low-volume [19]. It is characterised by a large number of items being demanded, in small amounts each one, and with variation not depending on seasonal trends, making its forecast difficult and inefficient.

Increasingly smaller production lot sizes or even fully personalised singular products stress the necessity for manufacturers to design and operate the production systems, and assembly operations in particular—being the last part of the production chain—with a clear goal of being able to thrive in a high-mix low-volume demand context, for which flexibility is a key characteristic. To stay competitive in such a context, manufacturing companies will need to increase their productivity while becoming more flexible. Fortunately, several new digital technologies are expected to prove useful in achieving this [8].

In the last decades, digital technological advances have opened new possibilities for a variety of economic sectors. Service providers were the first to benefit from them. Later, the potential advantages of implementing such solutions in the manufacturing business in Europe were recognised by the German government, who coined the expression '*Industrie 4.0*' [20] to conceptualise the projected 4th industrial revolution: a manufacturing paradigm change which would leverage digital technologies allowing Germany—and Europe—to maintain a leadership position in the manufacturing landscape, by becoming more agile and efficient, and focusing in high-value high-tech production [21]. Other leading manufacturing countries, such as the USA, China, Japan and India have also established similar strategic plans that stress the importance of leveraging new digital technologies to drive their industries [22].

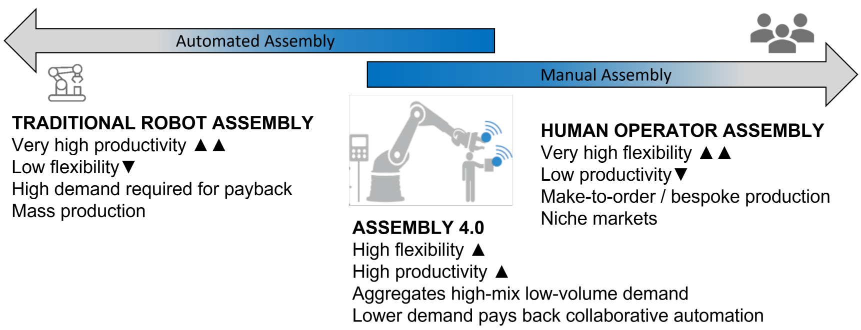


Figure 1.2: Industry 4.0 technologies could help address the dichotomy between productivity and flexibility of assembly lines.

Industry 4.0, *smart industry*, *smart manufacturing* or *smart factories*, among others [22], are terms used interchangeably to describe the same vision: increased flexibility and automation; data and information flow across processes, functions and companies; enhanced quality achieving zero-defect production; leveraging big data, neural networks, machine learning and Artificial Intelligence, among other technologies, to maximise efficiency and responsiveness [23]. However, the implementation road to materialise the 4th industrial revolution to assembly operations—*Assembly 4.0* [24], depicted by Figure 1.2—is far from being established. In fact, to profit from the potential benefits of smart technologies it would be necessary to develop assembly systems to a level of operational excellence and Lean maturity that is rarely found in most industries.

As Figure 1.3 illustrates, it seems clear that applying new technologies to digitalise assembly operations can only cause a disruptive advantage if the operational performance of the underlying systems in its entirety—including conventional elements such as machinery, hardware, people or organisational policies—have solid foundations. As Rüttiman and Stöcki put it "if the manufacturing system is poorly conceived, digitalisation will only be able to optimise a bad design" [25].

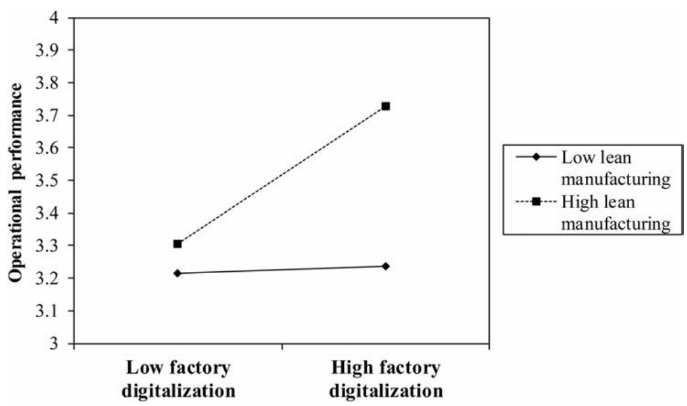


Figure 1.3: Interaction between factory digitalisation and Lean production. *Figure*: Buer et al. [26], CC BY 4.0.

To date, finding effective methodologies for the deployment of Industry 4.0 technologies into assembly operations with a systemic view—in opposition to small, isolated projects with limited productivity gains—remains an open issue. The prize of bridging this gap, however, could be the actual realisation of flexible and productive systems that can cope and even thrive under the most challenging demand conditions.

1.2 Research aim, objectives and questions

The central aim of this thesis is *to understand and define how to design assembly operations to improve flexibility and productivity under high-mix low-volume demand.* To address this goal, three main research objectives were defined, each one providing the groundwork for the following one:

1. Understand the state of the art of the 4th industrial revolution assembly

operations.

- What is the relationship between assembly and mass customisation, lean production and Industry 4.0?
- How could Industry 4.0 technologies improve the flexibility and productivity of assembly operations?
- What role does the human operator play in relation to Assembly 4.0 digital technologies?

2. Develop a method and the tools necessary to characterise and evaluate the performance of different flexible assembly line configurations.
   - How can semiautomated flexible assembly operations performance be evaluated?
   - What combination of input parameters, disturbances and Key Performance Indicators are to be used for such evaluation?
   - What are the key drivers for multi-model assembly line performance under high-mix low-volume demand?
3. Design assembly systems that increase their productivity by at least +25% while facing high-mix low-volume demand, by incorporating a combination of automated and manual workstations.
   - How can semiautomatic assembly lines be configured to achieve large productivity gains and maintain high flexibility when facing high-mix low-volume demand?
   - What key factors need to be taken into account when designing such assembly lines so that digitalisation initiatives can further improve their performance?
   - What technologies could be applied to this particular study case?

1.3 Scope

This thesis is structured in three top-level stages, each one looking into one research objective, as shown in Figure 1.4.

The first stage—Problem definition—defines and delimits the problem, allowing us to gain a better understanding of manual and semiautomatic assembly lines. It also lays the foundation conceptual framework upon which the following stages are built.

The second stage—Analysis tools—introduces, validates and verifies two performance evaluation tools, and uses them in a preliminary study to identify the most critical factors for flexible assembly lines.

The third stage—Improvement—studies the performance of parallel walking-worker line configurations compared to traditional fixed-worker lines. It then expands the simulation models to study the use of milkrun trains for the internal logistics of multi-product assembly lines as a means to deal with disturbances.

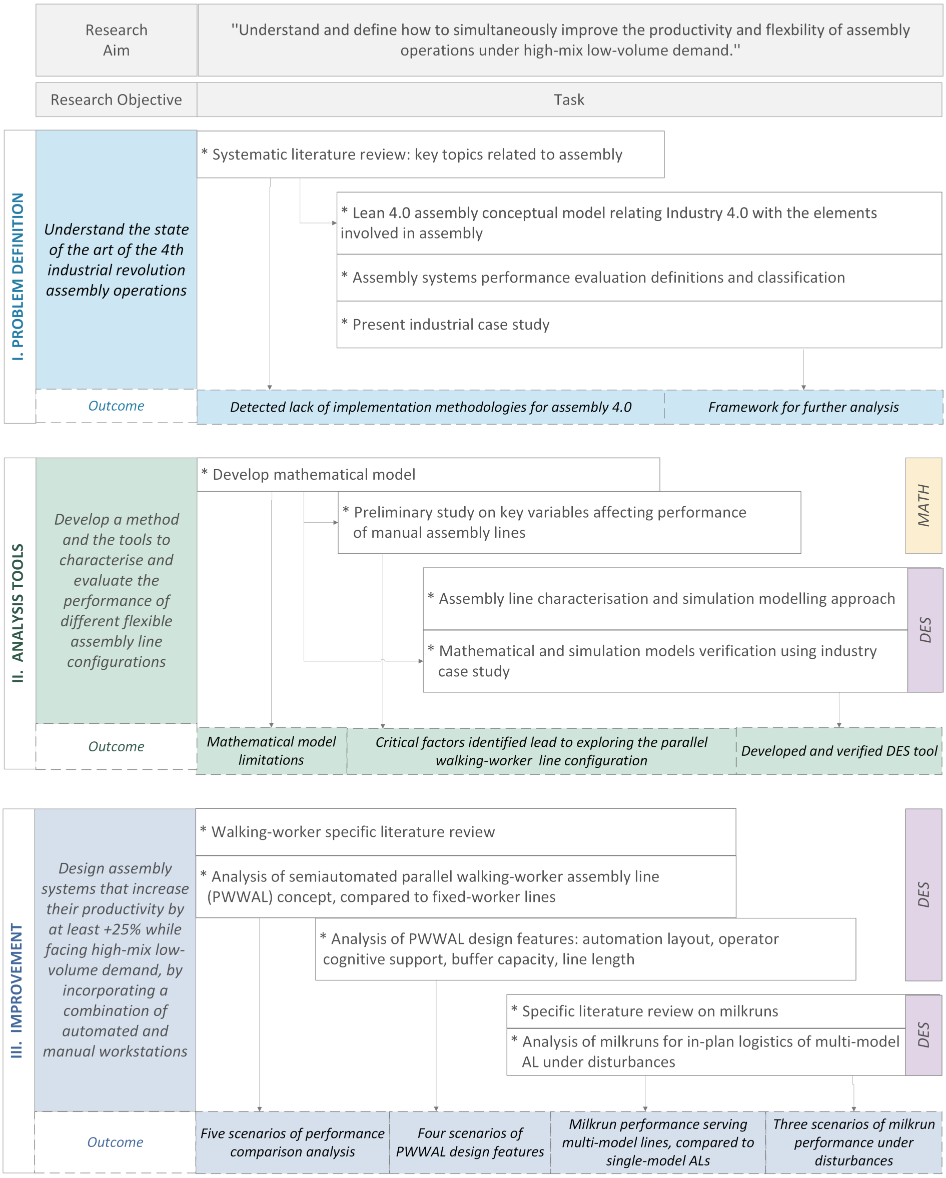


Figure 1.4: Thesis research aim, objectives, scope and outcomes.

1.3.1 Problem definition stage

Derived from the overarching research aim—understanding and defining how to design assembly operations to improve flexibility and productivity under high-mix low-volume demand—comes the first stage of this thesis: *Problem definition*. First, it focuses on gaining insight into the assembly operations' current state of the art regarding five key areas: the mass customisation and mass personalisation demand trends; the new possibilities brought by Industry 4.0 digital technologies; the indicators to be used to evaluate the impact of new technology; the relationship of Industry 4.0 with the Lean Production paradigm; and the role of people in this transformation. A systematic literature review is employed to ascertain the lack of *Assembly 4.0* implementation methodologies.

Resulting from the key findings of the literature review, a conceptual framework is presented, which organises the different layers taking part in assembly operations and highlights their relationships, revealing which Industry 4.0 digital technologies could be deployed and the specific layers affected by them. The methodical implementation of new, disruptive, digital technology to enhance assembly operations require careful evaluation of their potential impact on the system's performance. This would enable digitalisation projects to actually transform the operational performance of the whole system and to avoid only achieving partial or minor gains. To set the foundations of such analysis, the basic definitions and concepts of assembly systems performance evaluation are introduced, and a real industry case is presented, which will be used in the following stages. Derived from the research aim, the scope of such performance evaluation is specifically addressed to manual and semiautomatic assembly systems. The performance metrics focus on measuring productivity and lead time, while the flexibility is assessed by the response of the system to disturbances and challenging high-mix low-volume demand conditions. Both of them contribute to bringing the mass customisation paradigm into the analysis scope. Thus, this paradigm stresses the importance of two key elements: product model changeovers and stochastic variability, which will be integrated into the performance evaluation tools thereafter.

1.3.2 Analysis tools stage

The second stage, *Analysis tools*, is directly related to the second research objective of this thesis: "developing a method and the tools to characterise and evaluate assembly operations for high-mix low-volume production". To do so, two analysis tools are developed. Firstly, a simplified mathematical model is presented. Despite its limitations, related to the complexity of integrating stochastic variables, this parametric model's low computational cost allows carrying out preliminary estimations quickly. It is used to find the most important factors affecting the performance of the industrial study case's assembly systems, thus reducing the number of variables under study. To overcome the limitations of the mathematical model, discrete events simulation modelling is then introduced. To ensure that this modelling approach is suitable for further analysis, as well as to support the findings of the preliminary analysis, both models—parametric and simulation—are then validated and verified against empirical data from the industrial study case. Therefore, this stage provides two analysis tools suitable for evaluating the performance of high-mix low-volume assembly lines, including the potential impact of Industry 4.0 technologies, since the framework presented in the previous stage already identified where would each digital technology sits and which elements would be affected.

1.3.3 Improvement stage

Once the tools for analysis have been developed and tested, the third stage, *Improvement*, addresses the last key research objective—designing assembly systems that increase their productivity by at least +25% under high-mix low-volume demand by introducing a combination of automated and manual workstations. Building on top of the preliminary analysis' previous findings, parallel walking-worker assembly lines are presented. To test the potential gains enabled by this type of assembly line configuration, especially in terms of the duple productivity-flexibility, a comparison is made between fixed- and walking-worker semiautomated lines, measuring their performance against that of a traditional fixed-worker manual line configuration. To broaden the scope of the analysis in terms of the model layers involved in it, further simulation is carried out to analyse the use of a proven Lean tool, milkrun trains, to feed components to multi-model assembly lines. The goal of this study is to assess whether the in-plant logistics would present additional performance constraints to parallel multi-model line configurations, notably when facing high-mix low-volume demand and are subject to disturbances from different sources.

1.4 Structure outline

Following the presented scheme, and to sum up the structure of the thesis, the document is organised as follows:

In Chapter 1, the background and motivation of the thesis have been explained. The research aims, goals and questions have been made explicit, and the scope of the thesis has been outlined.

Chapter 2 presents the state of the art through a systematic literature review to understand the relationship between productivity, flexibility and the new digital technologies for assembly operations. In particular, the review looks into four closely related topics: assembly for mass customisation; Industry 4.0 and performance evaluation; Lean production as a starting point for smart factories; and the implications of Industry 4.0 for people in assembly operations.

Chapter 3 introduces the research framework. Firstly, an operator-centred conceptual model for Assembly 4.0 is proposed. The model organises the components of the assembly operations system along with their interactions among themselves and with new Industry 4.0 technologies. Then, basic definitions and concepts of flexible assembly performance evaluation are explained. Finally, this chapter presents The Cooktop Company industry case study, which will be used across the remaining chapters.

In Chapter 4, a mathematical analytical model which focuses on product changeover of assembly lines is introduced. The model is then employed along with design of experiments techniques for investigating the most critical factors to flexible assembly systems performance. Finally, one of the key modelling assumptions is validated.

In Chapter 5, discrete events simulation models are developed to overcome the limitations of the previous chapter's analytical tool. This chapter covers the main features of the simulation models used in the thesis, the method employed to gather empirical data from The Cooktop Company, and the models' validation and verification against empirical data from the industrial study case.

In Chapter 6, previous insight on flexible assembly lines and the simulation tools already developed are used to study parallel walking-worker lines, which present several key advantages over traditional semiautomated line configurations. This chapter includes a specific, in-depth literature review on the topic of parallel and walking-worker assembly lines, followed by the modelling assumptions and simulation model description. Six scenarios are used to explore the effect of various mass customisation demand conditions as well as the degree of automation introduced to the different line configurations. Four additional simulation scenarios look into different elements for fine-tuning the parallel walking-worker line concept.

Chapter 7 broadens the scope of the analysis by looking into assembly lines in-plant logistics using milkrun trains. Once again, a chapter-specific literature review is included. The milkrun model is detailed, and four simulation scenarios are used to analyse the effect of product mix and three different sources of variability disturbances.

Finally, Chapter 8 summarises the key findings and the contributions of the thesis. It also discusses the main avenues for future research.

CHAPTER 2

State of the Art

This chapter presents a revision of the state of the art by means of a systematic literature review to understand the relationship between productivity, flexibility and new digital technologies for assembly operations.

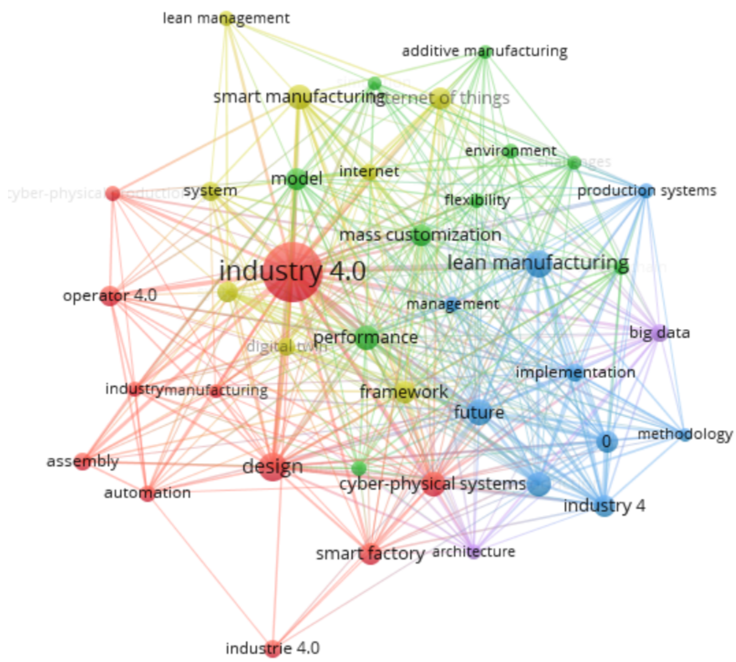


Figure 2.1: Literature review co-occurrence map for the keyword *Industry 4.0*.

The literature review explores the relationship between six key concepts: assembly, mass customisation, Industry 4.0, key performance indicators, Lean and human operators. Figure 2.1 maps the co-occurrence for the keyword *Industry 4.0* with any other keyword, grouping the closer concepts by colours and depicting the frequency of each keyword using the circle sizes. This facilitates understanding how each pair of concepts are related, as will be detailed later in this chapter.

The content of this chapter was published as an article [27], which was part of the Special Issue of the Manufacturing Engineering Society 2020 (SIMES-2020) of the journal *Applied Sciences*. Each section of this chapter corresponds to an article section: Introduction (2.1), Materials and Methods (2.2), Results (2.3), Discussion (2.4) and Conclusion (2.5). Finally, Section 2.6 includes the chapter summary and main contributions.

Article title:

Lean Manual Assembly 4.0: A Systematic Review

Article abstract:

In a demand context of mass customisation shifting towards the mass personalisation of products, assembly operations face the trade-off between highly productive automated systems and flexible manual operators. Novel digital technologies – conceptualised as Industry 4.0 – suggest the possibility of simultaneously achieving superior productivity and flexibility. This article aims to address how Industry 4.0 technologies could improve the productivity, flexibility and quality of assembly operations. A systematic literature review was carried out, including 239 peer-reviewed articles from 2010-2020. As a result, the analysis was structured addressing four sets of research questions regarding (1) assembly for mass customisation; (2) Industry 4.0 and performance evaluation; (3) Lean production as a starting point for smart factories, and (4) the implications of Industry 4.0 for people in assembly operations. It was found that mass customisation brings great complexity that needs to be addressed at different levels from a holistic point of view; that Industry 4.0 offers powerful tools to achieve superior productivity and flexibility in assembly; that Lean is a great starting point for implementing such changes; and that people need to be considered central to Assembly 4.0. Developing methodologies for implementing Industry 4.0 to achieve specific business goals remains an open research topic.

2.1 Introduction

The current situation of assembly operations is characterised by an increasingly varied demand (mass customisation) while the production faces a trade-off between the superior productivity of automated assembly systems and the absolute flexibility and adaptability of manual assembly. Therefore, high-volume production of discrete goods received heavy investments for automation, while low volume, made-to-order or engineer-to-order products were typically assembled manually [13, 28]. In this context, Lean Production (a generalisation of the Toyota Production System) expanded from its origin—Automotive—to many other sectors, and was adapted as necessary to the particularities of each industry or company [5]. Lean Production typically focuses on value as perceived from the customer's point of view, thus it considers that the flexibility to quickly adapt to market demand is critical. For Lean, rigid automation can be seen as a hindrance rather than an advantage, and seeks to incorporate the human factor to automation: *jidoka*, or 'automation with a human touch' [29].

The term Industry 4.0, initially adopted by a German strategic program [22], is used nowadays to express the relationship between different elements of the current manufacturing sector and the new digital technologies. These Key Enabling Technologies are according to [8]: Big Data and Analytics, Autonomous robots, Simulation, Horizontal and vertical system integration, the industrial Internet of Things (IoT), Cybersecurity, The Cloud, Additive Manufacturing and Augmented Reality. Recent research on Industry 4.0 tends to focus on the possibilities brought by a certain new digital technology, or develops a framework to understand what would be the effect of incorporating such new technologies [24]. The arrival of the new digital technologies could address the aforementioned dichotomy of highly-productive yet rigid automation vs flexible but less-productive manual assembly. The quickly developing fields of Human-Robot Collaboration, Virtual/ Augmented Reality and Automated Quality Control, to cite some examples, show promise in bringing forward actually flexible and adaptable automation that has the best of both worlds.

Scarcely explored is the development of implementation methodologies that bridge Industry 4.0 conceptual frameworks with the current state of industrial environments, and the process to successfully deploy new digital technologies that bring the expected returns of investment. Additionally, if the Lean production approach and its techniques are also related to this implementation, the concept of Lean 4.0 could be used as shown in the literature [30]. Since Lean Production and Industry 4.0 certainly have some commonalities [31], Lean could prove useful in providing a starting point for the implementation of Industry 4.0 technologies that improve assembly operations in a mass customisation demand context.

In order to assess the impact of any changes, careful evaluation systems are needed to ensure that technological investments are implemented to solve the problems and address the businesses goals, and not just because they are available or they bring some cosmetic advantage. The 4th Industrial Revolution is expected to transform the role of the people, but to what extent will assembly operators be affected – are humans to be replaced by machines, or empowered by new technology?

The issue that this literature review aims to address is: *How could Industry 4.0 technologies improve the flexibility, productivity and quality of assembly operations?* To look into it, we aim to answer the following questions:

1. What are the characteristics and implications of mass customisation for assembly operations?
2. What new Industry 4.0 digital technologies are relevant to assembly operations? How to make the most out of their potential, and how to measure the improvement?
3. Is Lean Production the best starting ground for implementing Industry 4.0 assembly operations?
4. How would Industry 4.0 affect people in assembly? How to support people transitioning to Assembly 4.0?

To answer these questions, a systematic literature review was carried out. From these four sets of questions, six key concepts are extracted, as shown in Figure 2.2: The scope of this article is limited to *Assembly* operations, particularly focusing on *Mass customisation* demand. Neither fully automated systems nor manual assembly deal comfortably with mass customisation demand, since one lacks flexibility and the other's productivity falls short. *Industry 4.0* aims to address this gap by providing superior connectivity between machines and people. *Lean Production* might serve as a foundation for Assembly 4.0, transversally providing a framework to analyse and conceptualise the new role of *Human operators*. Finally, to evaluate the efficiency of assembly systems, *Key Performance Indicators* are commonly used.

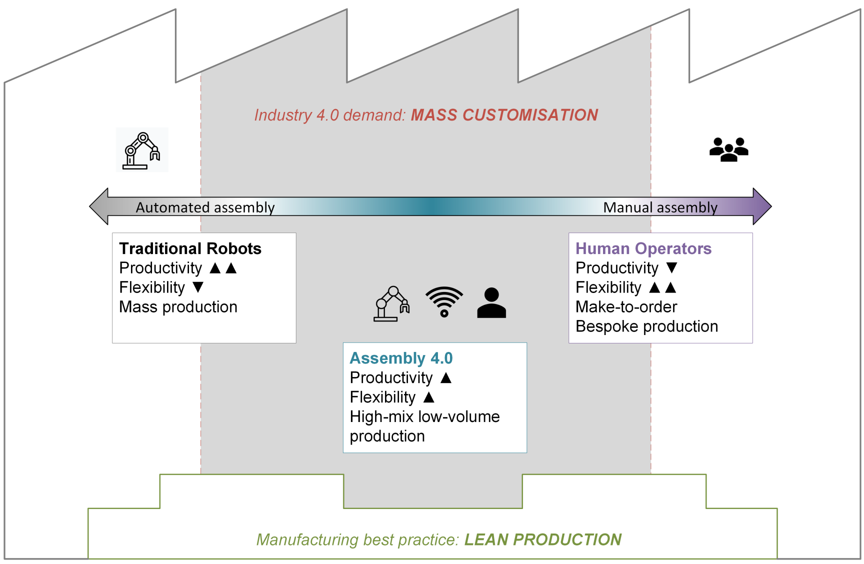


Figure 2.2: Key concepts used for the systematic literature review.

This article is structured in the following manner: Section 2.2 – Materials and

Methods – describes the methodology used for the review, which focuses on the 6 key concepts related to the issue being addressed. This section also includes a brief bibliometric analysis of the references used for the analysis. Section 2.3 – Results – includes the Analysis of Literature, grouped into four main subsections: (2.3.1) Assembly operations, (2.3.2) Industry 4.0, (2.3.3) Lean, and (2.3.4) People. Each subsection focuses on one of the questions that this article aims to answer. Section 2.4 – Discussion – gathers the main conclusions found in the previous analysis and addresses the main issue stated before.

2.2 Materials and Methods

In order to address the issue introduced in the previous section, and to answer the aforementioned questions, a systematic literature review was conducted. This section firstly describes the methodology employed in such review, and secondly offers a brief bibliometric analysis of the results.

The literature review was carried out in four stages – see Figure 2.3: database search, screening, eligibility and literature analysis.

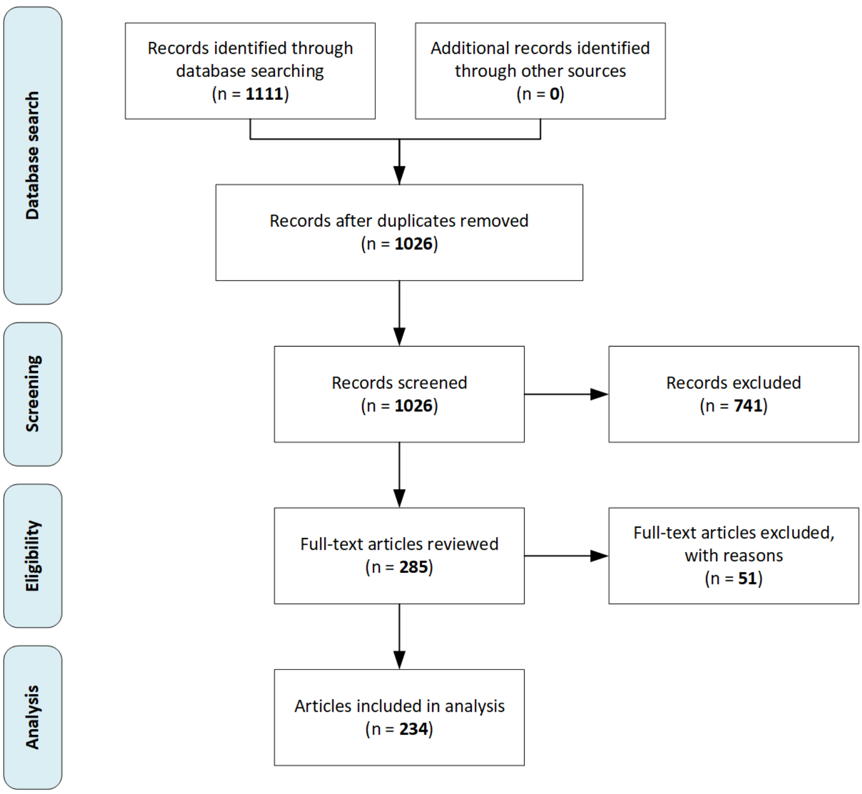


Figure 2.3: Search process and results, adapted from PRISMA [32].

The databases used for the initial stage were SCOPUS (Elsevier) and Web of

Science, and only included relevant publications belonging to the following fields: Manufacturing Engineering, Industrial Engineering, Generalist Engineering, Operations and Management Science. Since the topic under study is the conjunction of several broad subjects, we decided to conduct a systematic literature review that specifically targets their intersections. The 6 key concepts that were used are: Assembly, Mass Customisation, Key Performance Indicator (KPI), Lean Manufacturing, Industry 4.0 and Operator. These concepts were chosen for the search because they are the key ideas in the posed research questions – 'Key Performance Indicators' being used for measuring improvement. The following keywords were used to perform the database search: (1) Lean: *Lean Manufacturing*, *Lean Production*; (2) Mass Customisation: *Mass Customisation*, *Mass Customization*; (3) Industry 4.0: *Industry 4.0*, *Industrie 4.0*, *Smart Factories*; (4) KPI: *"KPI"*, *Key Performance Indicator*; (5) Assembly: *Assembly*; (6) Operator: *Operator*, *People*, *Person*. The keywords were used for Title, Author Keyword and Keyword Plus (in WOS); except for KPI, which was also searched for in the Abstract field. From these 6 key concepts, 15 search groups were defined by intersecting each possible combination of two concepts, as shown in Table 2.1. Duplicates were removed at this point, resulting in 1,026 publications identified.

Table 2.1: Search groups created by intersection of each pair of key concepts, and number of publications found.

Search group	**Publications WOS**	**Publications SCOPUS**	**Publications without duplicates**
Assembly & Mass Customisation	58	52	97
Assembly & KPI	20	19	33
Assembly & Lean	81	106	168
Assembly & Industry 4.0	47	10	55
Assembly & Operator	83	196	268
Industry 4.0 & Lean	48	8	55
Industry 4.0 & Operator	33	16	45
Industry 4.0 & Mass Customis.	17	2	19
Industry 4.0 & KPI	11	2	12
Lean & Mass Customisation	14	19	32
Lean & KPI	31	58	74
Lean & Operator	10	33	40
Operator & Mass Customisation	4	15	15
Operator & KPI	13	98	108
Mass Customisation & KPI	4	3	5

The publications resulting from this search were then screened – based on title, abstract, publication and year – to assess which of them met the inclusion and exclusion criteria shown in Table 2.2, resulting in 741 records being excluded and 285 articles being included.

Finally, the 285 articles were reviewed within each one of the 15 search groups and assessed for eligibility, resulting in 51 articles being excluded because they

Table 2.2: Eligibility and exclusion criteria.

Inclusion criteria	**Exclusion criteria**
Peer-reviewed publications	Book chapters
Recent: published on 2010 or later	Regarding construction, continuous production (e.g. petrochemical), energy efficiency
Language: publications in English	Regarding mathematical models or algorithms for scheduling, line sequencing, or line balancing
	Regarding product design

were not relevant to the key concept being analysed. The resulting 234 articles were analysed, and the outcome of such analysis can be found in Section 2.3 – Results.

The number of articles included in the analysis shows an increasing trend over time, as shown in Figure 2.4. It should be noted that the database search was performed in June 2020, therefore the results shown in this analysis only include articles published up until the first half of 2020. It can be seen that the number of articles related to some key concepts remain constant or grow slightly over time – Assembly, Mass Customisation and Operator – while others grow significantly – Lean and KPI. The number of articles related to Industry 4.0 is rising since 2015, which is consistent with the fact that the term "Industry 4.0" was coined in 2011 [22]. Of the 234 articles included in this review, 54 are conference or proceedings articles (23%) and 180 are journal articles (77%). The articles were published in a total of 117 publications; with 18 journals including 50% of the total articles and 83 publications contributing with just one article to this review. This is consistent with the database search strategy, which looks at the intersections of six different concepts.

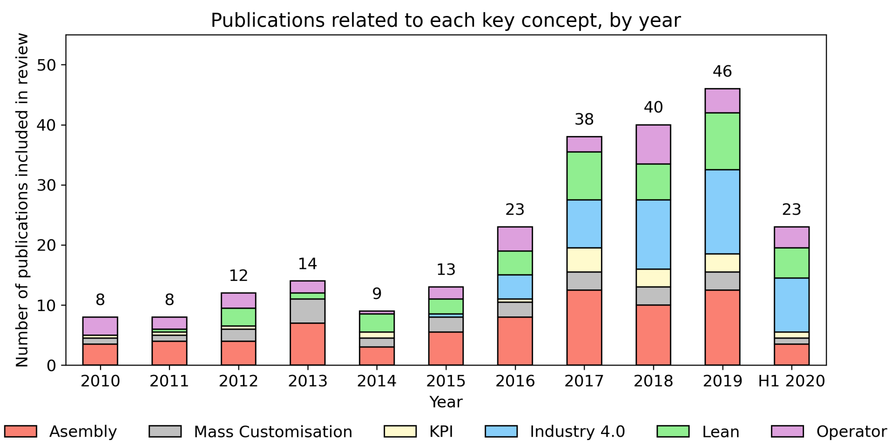


Figure 2.4: Publications related to each key concept, by year.

2.3 Results

This section shows the outcome of the systematic literature review carried out following the methodology described in the previous section, and that addresses the issue of improving assembly operations in terms of productivity, flexibility and quality by using novel digital technologies of Industry 4.0. To look into this question, four specific questions were presented in the first section of this article. In consequence, this section is composed of four parts made of the search key concepts most closely related to each one of the questions, as shown in Figure 2.5. Firstly, looking into 'the characteristics and implications of mass customisation for assembly operations', the key concepts used are 'Assembly' and 'Mass Customisation' (2.3.1). Secondly, to identify 'the new Industry 4.0 technologies, how to make the most out of them and how to measure the improvement', the key concepts used are 'Industry 4.0' and 'Key Performance Indicators' (2.3.2). Then, the key concept 'Lean' is employed to determine whether Lean Production is the best starting ground for implementing the aforementioned technologies (2.3.3). Finally, to explore 'the effect of Industry 4.0 on people in assembly and to find out how to support them in transitioning to Assembly 4.0, the search key concept used is 'Operator' (2.3.4).

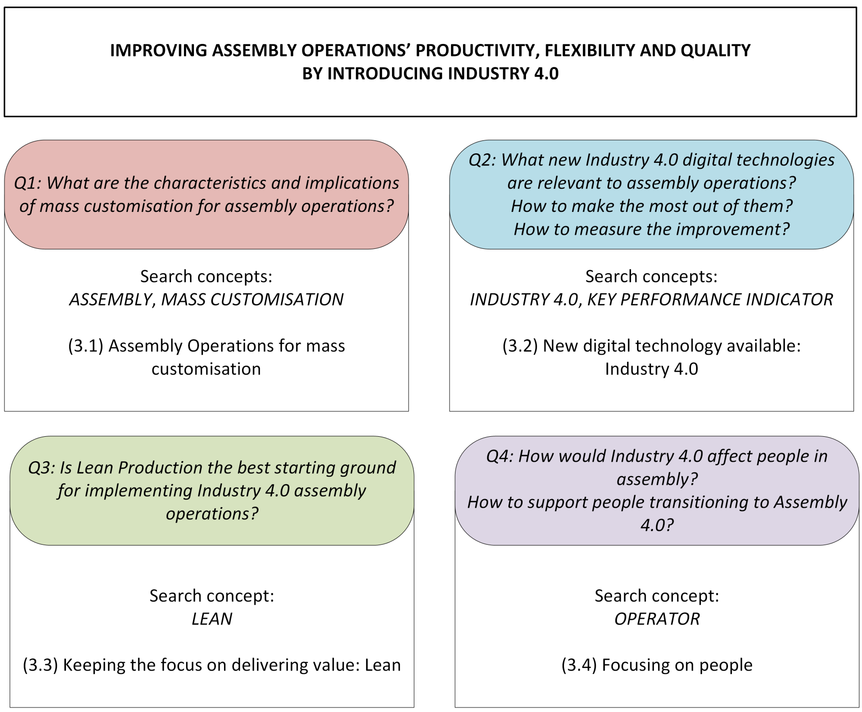


Figure 2.5: Research questions, search key concepts and their relationship to the literature review analysis topics.

2.3.1 Assembly operations for mass customisation

In order to answer the first question "What are the characteristics and implications of mass customisation for assembly operations?", the systematic literature review publications related to the key concepts 'Assembly' and 'Mass Customisation' were analysed. After a brief introduction, the five main topics to be considered will be presented, as shown in Figure 2.6: Modularity and product clustering; Mixed-model assembly optimisation; Customer involvement and postponement strategies; The implications of complexity; and Mass customisation impact on operators. Finally, the key conclusions will be summarised.

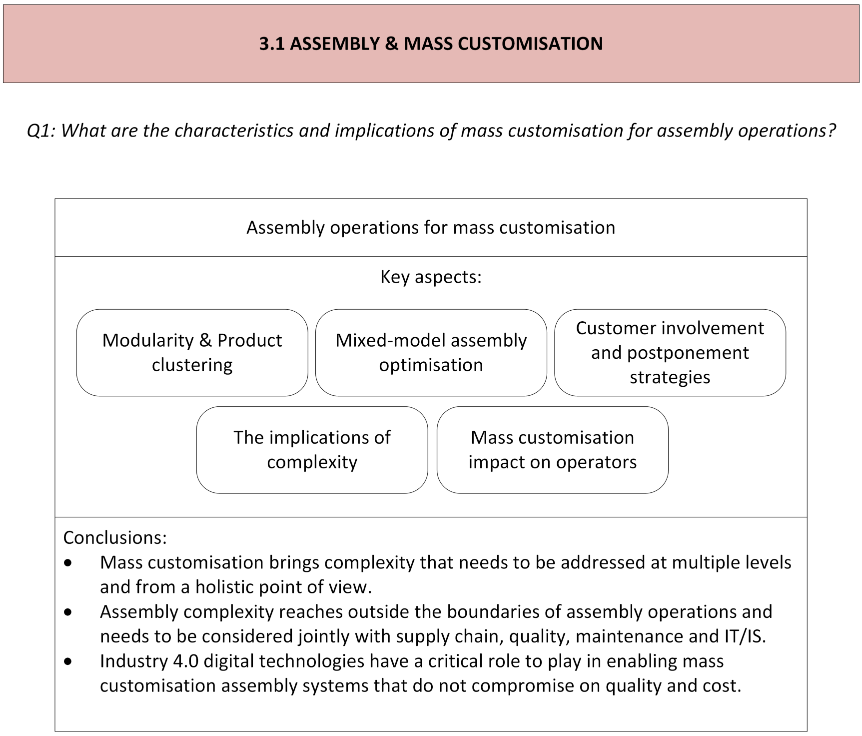


Figure 2.6: Key aspects of assembly operations for mass customisation and main conclusions of the analysis.

Introducing assembly operations for mass customisation

Mass Customisation demand is characterised by a combination of high variety, shorter product life cycles, and variable production volumes (medium or high for platform products, very low for personalised products); compared to Industry 2.0's Stable Market and Industry 3.0's Volatile Market – in terms of product volume, product variety and delivery time. In this new context, Toyota Production Systems (TPS) may prove limited, and its advantages and disadvantages with regards to seru have been analysed by Yin et al. al. [2]. The usage of new key digital technologies will bring forward the 4th Industrial Revolution (Industry 4.0), addressing many of the challenges of production systems for mass customisation [2, 33]. However, looking at isolated systems may not be enough, since increased complexity requires a holistic approach to respond successfully and cost effectively to shifting market demands [34]. Assembly is the final process to create a product, where component sub-assemblies come together into the final product. Demand driven increasing product variety adds complexity, production cost and lead time to Assembly Operations, which goes against its goals. In the mass-customisation landscape, key assembly topics need to be reviewed, evaluated and adapted [13]: assembly representation and sequencing, especially non-sequential assembly; assembly system design – considering line balancing, delayed product differentiation and performance evaluation; assembly system operations –with a focus on exploring reconfigurable assembly planning, mixed-model assembly scheduling, and dealing with complexity resulting from different sources; and the changing role of human operators.

In conclusion, mass customisation brings increased complexity that needs to be addressed at multiple levels and taking a holistic point of view to ensure that optimising a sub-system does not affect negatively another sub-system.

Modularity and product clustering

In order to flexibly assemble many different product variants using the same resources (such as people, equipment, management systems) to keep manufacturing costs down and productivity high. Efficient grouping products into clusters or families is of paramount importance. The variables selected for clustering will depend on the Assembly Operation objectives, for instance: quality and cost to determine product family design [35]; product variety to determine assembly system layout [36]; assembly and disassembly for configuring product variants [37]; procedure, equipment and parts [38]; or involving worker's perspective for actual ease of assembly [39]. Modular production systems would also benefit from automated planning based on individual products CAD files [40].

In conclusion, product clustering, modularisation, reconfigurable assembly systems and delayed product differentiation are valuable tools to maintain competitive assembly in a mass customisation context.

Mixed-model assembly optimisation

Another area affecting greatly the efficiency of assembly lines is its sequencing and balancing. Similarly to clustering and modularisation, different approaches are used depending on the focused goals of the optimisation: cooperative sequencing or workstation analysis for assembly material consumption waviness, setup time and lead time [41, 42]; multi-agent systems analysis for reducing the negative impact of material handling complexity [43]; monitoring manufacturing complexity for workload balancing [44]. New approaches have been also developed to optimise assembly line sequencing [45, 46].

In conclusion, mixed-model assembly is needed to deal with mass customisation while remaining competitive, since it allows to address various operational goals depending on the business needs.

Customer involvement and postponement strategies

Mass customisation may be leading towards mass personalisation, where individual products made to match the exact preferences of each customer are produced in large numbers [28]. Integrating the customer in the design phase could be done using web-based platforms [47]; while Industry 4.0's Cyber Physical Systems (CPS) and a tailored assembly architecture would enable efficient mass personalisation [48]. An alternative strategy is Postponement, which could help with dealing with high assembly complexity [49]. However, it requires designing the assembly line layout for delayed product differentiation [50, 51], and would benefit from reconfigurable assembly stations [52].

In conclusion, assembly operations need to consider the increasing expectations of mass customisation heading towards mass personalisation. In order to adapt to it, Industry 4.0 Cyber Physical Systems could be used to develop reconfigurable assembly stations that can deal with high assembly complexity while maintaining high productivity.

The implications of complexity

Mass customisation brings a great deal of complexity to assembly operations, which affect key elements of the system as well as other nearby areas, such as Quality, Supply Chain or Maintenance. Assembly complexity has can been evaluated from different perspectives: number of product variants [53], induced task differences [54] or product configuration [55]. Complexity has a negative effect on quality, which could be minimised by using cognitive automation [56]. The increasing number of product features to be controlled makes necessary new advanced quality management systems [57]. Supply chain implications of mass customisation assembly range from assembly line feeding problems [58] and modularity-specific issues [59] to assembly supply chain configuration [60] and whole manufacturing networks [61]. Using Automated Guided Vehicles (AGVs) can be used efficiently to feed mixed-model assembly lines [62, 63]. Maintenance resources allocation also needs to be prioritised to minimise the negative effects of increased complexity [64].

In conclusion, assembly complexity reaches outside the boundaries of assembly operations and needs to be considered jointly with supply chain, quality, maintenance and IT/IS.

Mass customisation impacts operators

Fully automated assembly systems bring increased productivity for high-volume production, but lack the flexibility and adaptability of human operators. People are better equipped for assembly tasks with small and frequent variations, but their potential for higher productivity is limited. In a context of market demand characterised by mass customisation which heads towards mass personalised production, reconfigurable assembly systems that incorporate both machines and people can lead to cost effective systems that are flexible and scalable [13]. Automation needs to consider both physical and cognitive abilities of the human operators it supports [65].

In order to improve the yield of assembly operations, providing support to human workers is necessary. Augmented Reality (AR) could be used, reducing the number of engineering/production management resources needed to provide assembly operators with cognitive support to perform their tasks [66, 67]; as well as cognitive/ handling skills transfer systems [68], self-adapting automatic Quality Control [69] or cognitive automation strategies [70]. Automation needs to ensure human safety, which led to research on Human-Robot Collaboration (HRC) plan recognition and trajectory prediction [71], and the concept of "safety bubble" [72]. When employing novel digital technologies for enhancing assembly systems performance, one cannot underestimate the strategic importance of IT/IS systems [73].

In conclusion, in a context of market demand characterised by mass customisation which heads towards mass personalised production, reconfigurable assembly systems that incorporate both machines and people can lead to cost effective systems that are flexible and scalable. Industry 4.0 digital technologies have a critical role to play in making possible mass customisation assembly systems that do not compromise on quality and cost, and that do not achieve increased performance by affecting human operators negatively.

Assembly and mass customisation: conclusions

In a context of market demand characterised by mass customisation which heads towards mass personalised production, the increased complexity reaches the boundaries of assembly operations and needs to be considered jointly with other areas (e.g. supply chain, quality, maintenance, IT/IS) and taking a holistic point of view to ensure that optimising a sub-system does not affect others negatively. To maintain assembly operations competitive despite the increased complexity, product clustering, modularisation, delayed product differentiation, mixed-model assembly, and reconfigurable assembly systems are valuable tools. Reconfigurable assembly systems in which human operators work effectively alongside machines or robots, made possible with Cyber Physical Systems, can lead to cost effective systems that are flexible and scalable. It seems clear that Industry 4.0 digital technologies have a critical role to play in making possible mass customisation assembly systems.

2.3.2 New digital technology available: Industry 4.0

In order to answer the previously presented questions "What new Industry 4.0 digital technologies are relevant to assembly operations?", "How to make the most out of them?" and "How to measure the improvement?"; the systematic literature review publications related to the key concepts 'Industry 4.0' and 'Key Performance Indicators' were analysed. After a brief introduction on Industry 4.0 (I4.0), the eight main topics to be considered will be presented, as shown in Figure 2.7: I4.0 technology for improving processes and decisions; I4.0 technology for mass customisation; I4.0 technology for supporting human operators; I4.0 for mass customisation; Key Performance Indicators for assembly; Key Performance Indicators for I4.0; and Small and Medium Enterprises (SMEs) in the I4.0 era. Finally, the key conclusions will be summarised.

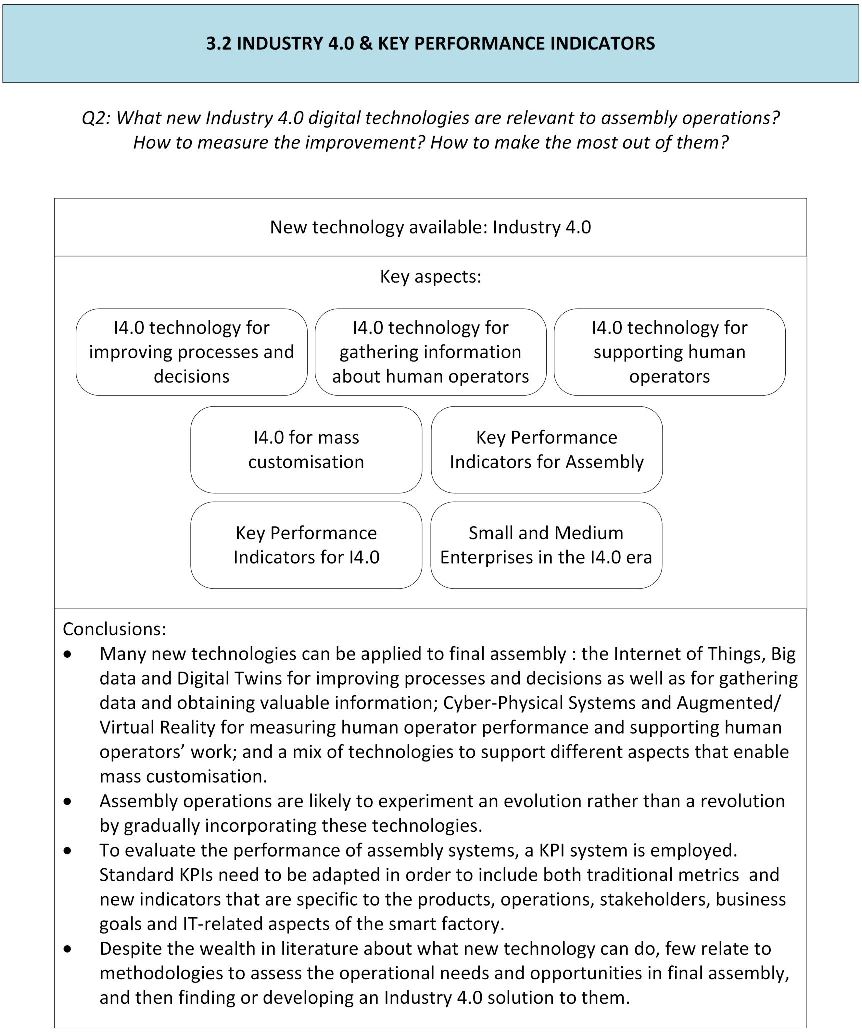


Figure 2.7: Key aspects of Industry 4.0 technologies for assembly operations and Key Performance Indicators (KPIs), and main conclusions of the analysis.

Introducing "Assembly 4.0"

According to Yin et al., industrial revolutions are related to distinct technologies, market demands and production systems. The 4th industrial revolution differs from industry 1.0 - 3.0 because it is expected to happen in the near future, as opposed of the previous three. The deep and intertwined changes in available technology and market demand paradigms create new possibilities; however, the industry 4.0 production systems are expected to be an evolution from the previously existing systems (characterised by seru, flow lines, Toyota Production System or TPS, job shops, cellular manufacturing and Flexible Manufacturing Systems or FMS) enhanced by the novel digital technologies [2].

Bortolini et al. investigated in [23] the impact of the 4th industrial revolution on assembly systems design. The dimensions to consider are six: balancing, sequencing, material feeding, ergonomic risk, equipment selection and learning effect. The evolution of the industrial environment in European countries leads to an aging workforce, re-shoring of production facilities and more efficient and distributed communication networks. In this environment, nine are the enabling technologies of Industry 4.0 that have the most potential to affect assembly systems: Big Data, IoT, real-time optimisation, cloud computing, cyber physical systems, machine learning, augmented reality, cobots and additive manufacturing. The integration of these technologies in the design and management of assembly processes leads to what Bortolini et al. define as *"AS40"*: Assembly Systems 4.0. The main characteristics of *AS40* are assembly control systems, aided assembly, intelligent storage management, late customisation, product & process traceability and self-configured workstation layout [23].

Cohen et al. looked into how assembly system configuration would be affected by Industry 4.0 principles, understood as four incremental stages or steps to achieve the 4th revolution: connectivity, information, knowledge and *smart*, which involves "predictive and automated decision making processes, with possible self-adjustments and reconfiguration of the production system". The new paradigm would reduce the costs of assembly automation; reduce setup costs and learning curves; enable the assembly of small quantities of large products in flow lines; enable the assembly of very different products in the same system; better traceability of failures and defects; and smarter material handling. In the last stage of Industry 4.0 (*smart*), assembly systems would be Self-Adapting Smart Systems (SSAS), and together with continuous support to operators (OSS), flexibility, agility and productivity would be greatly increased [74].

According to Cohen et al. in [24], the main goal of flexible assembly systems in the Industry 4.0 era is to address the mass customisation demand paradigm. At this moment, operational, tactical and strategical issues remain unsolved for implementing "Assembly 4.0". A key aspect is the social effect of Assembly 4.0: the assembly workforce is expected to shrink – at least, in Western countries- but additional technological job positions will appear, partially offsetting the operator reduction. The workforce would experiment a net decrease, thus increasing the productivity per employee. Therefore, the role of people in A4.0 will be increasingly important, which calls for future research that considers human operator back at the centre of the production systems of the future [24]. When looking ahead in the evolution of assembly systems into the 4th Industrial revolution, Cohen et al. identify challenges when integrating new and existing technologies: uncertainty on the synergies of the I4.0 key enabling technologies; the human-automation collaboration; incorporating Artificial Intelligence into assembly systems; and finding, developing and keeping the Assembly 4.0 human specialists. On top of the technical knowledge, Industry 4.0 operators will need a new set of non-technical skills, so education centres and companies will need to work together to meet this demand [11].

Developing an Assembly 4.0 system in a controlled environment, such as a Learning Factory, allows to better understand the complexity of such system. The drone factory developed by Fast-Berglund et al. “focuses on the interaction and cooperation between humans and cobots to create collaborative applications in final assembly tasks”. It was built with operator involvement form the start, and it incorporates a modular and event-driven IT architecture that creates a digital twin of both product and production system, allowing automated planning and preparation of operations [75].

Facing a mass customisation demand, late customisation is a strategy allowing customers to make changes to their orders even when the production has started. Industry 4.0 digital technologies bring additional tools for developing an assembly system able to cope with resequencing the production process [45]. Identifying information and data needs is a key step in the design of smart assembly factories, to ensure that the increased complexity associated to addressing mass customisation production can be managed by the human operators [76]. Additionally, strategies for improving the use of IT/IS systems in assembly need to consider the whole digital strategy of the organisation [73]. Optimising the design of any Industry 4.0-enabled system at early stages is critical for SMEs in the manufacturing sector. Axiomatic design and *Acclaro* software has proven useful [77].

The analysis of literature allowed organise Industry 4.0 technologies in four main categories depending on their goals in assembly operations: improving processes and decisions, gathering information on human operators, supporting people in assembly, and enabling mass customisation. Table 2.3 summarises the references of technologies employed for each goal.

Industry 4.0 technologies for improving processes and decisions

Novel Industry 4.0 technologies can be used to improve processes and gather meaningful data which allows better informed decisions. Big Data can be used to maximise yield and machine uptime in precision assembly processes, by detecting long term errors and enabling predictive maintenance [78]. Sensors from across the

Table 2.3: Technologies of Industry 4.0 by usage.

Industry 4.0 technologies[1]	Improving processes & decisions	Gathering information on human operators	Supporting people in assembly	Enabling mass customisation
Big Data	[78]		[79]	
IoT	[80–83]	[84]	[85]	[86]
Real-time optimisation	[87]	[88]		[45]
Cloud computing				[89]
Cyber-Physical Systems			[90, 91]	[86]
Augmented/ Virtual Reality			[92–101]	[102]
Additive manufacturing				[102, 103]
Digital Twin	[104–106]	[88]		
Other	[107, 108]	[70, 109–111]		

[1] Industry 4.0 Key Enabling Technologies based on [23].

shop-floor can be used in conjunction with an IT/IS service to provide critical information about the processes in the white goods industry [61][80]. RFID can be used to track assembly execution and then to derive guidelines for smart assembly line development [81] and Web based system (*saas*) to control smart internal logistics using mobile robots [87]. Motion Analysis System (MAS) to monitor and evaluate manual production processes [82, 112]. The *Human Factor Analyser* is a software/hardware architecture that can be used for manual work motion and time measurement employing depth cameras and automatic data processing aiming to evaluate work performance quantitatively [83]. Digital Twin of assembly processes can be used to analyse the efficiency of the line [104]; and it would also enable product-centric assembly [105]. Festo's *Cyber Physical Factory* can be used to implement an Industry 4.0 Digital Twin framework [106].

Industry 4.0 technologies for gathering information on human operators

Industry 4.0 technologies allow new ways of gathering information about human assembly operators that are less intrusive, more accurate or more capable than previously existing techniques: Mattson et al. propose a method of measuring the wellbeing and performance of operators at assembly stations [107]. Krugh et al. measure human-machine interaction using the Internet of Things (IoT) to understand the impact of people on Industry 4.0 assembly systems [84]. Eye tracking can be used to analyse the user experience of engineering design & manufacturing [108]. A theoretical human-centred framework for Operator 4.0 using Digital Twin based simulation and real-time human data capture can be used to provide insights on operator ergonomics and mental workload [88].

Industry 4.0 technologies for supporting people in assembly

Cyber-Physical Systems (CPS) for improving operator ergonomics [90]; vision systems for measuring and providing feedback on operator performance [109]; cognitive assistance for rework area [110]; strategies for cognitive automation that allow operators to deal with increased complexity [70]; Augmented Reality (AR) to assist manual assembly [92]; operator training using digital assistance [111]; training using Virtual Reality & process mining allowing to replace traditional inter-personal demonstration and repetition [94] and real-time interface using data from many devices and an algorithm allowing manual assembly operators to deal with requests and report faults [85].

Industry 4.0 technologies for mass customisation

Manufacturing flexibility is a strategic orientation for high-wage countries, and Industry 4.0 technologies bring solid benefits to Operations Management, especially in terms of technology management and Just-In-Time (JIT) production [113]. One technology in particular – Additive Manufacturing, can break the flexibility vs cost trade-off which most industrially developed countries face [103]. Compared to the volatile market of Industry 3.0, characterised by product variety, the smart market of industry 4.0 involves customer participation in individual customisation of products [2]. Industry 4.0 KET enable mass personalisation through short product development cycles [102] and individual customers' input [18, 86]. Rossit et al. propose an approach based on tolerance planning strategies and re-sequencing capabilities to allow changes to the product to be made even after production has started [45]; while Chung et al. envisage a dynamic supply chain design for connected factories through cloud-based information systems as a way to achieve mass personalisation [89].

In conclusion, Industry 4.0 not only offers new alternatives for cost-competitive mass customisation but also opens the door to mass personalisation, where the customer is involved in individual customisation of the product.

Key Performance Indicators for assembly

Key Performance Indicators (KPIs) are employed widely to assess the outcome of assembly systems. New concepts for novel assembly systems need to use KPIs to evaluate their potential performance. In most cases, traditional KPIs are used [114]: cost (investment, labour), quality (first pass yield, final yield) [115–117], throughput time, quantity and lot size; inventory costs [118], line productivity (e.g. OEE – Overall Equipment Effectiveness) [119], energy consumption, cycle time and service level [120, 121].

Integrating KPIs that link design, production and quality goals through the product & process development has proven useful to limit late engineering changes which delay the assembly system development [122]. A combination of economic and structural KPIs can be used to evaluate the adaptability of Reconfigurable Manufacturing Systems [123]. Yang et al. propose that KPI selection for the smart automation of manufacturing systems needs to be company and location specific, and that the KPIs variation and sensitivity to the introduction of new Industry 4.0 technology needs to be a key driver for developing a strategy for smart assembly automation [124]. For evaluating the performance of Line-less Mobile Assembly Systems (LMAS), Hüttemann et al. developed a set of 11 specific KPIs, 6 of which are adapted from conventional KPIs to account for the wide variety of products being made in the assembly system, and 5 are specific to LMAS (e.g. overall travelled distance, number of station configuration reconfigurations) [125].

In conclusion, to evaluate assembly systems, standard KPIs need to be adapted in order to include both traditional metrics (e.g. cost, quality, throughput, inventory, lead time, productivity) and new indicators that are specific to the products, operations context and business goals.

Key Performance Indicators for Industry 4.0

Manufacturing flexibility is a strategic orientation for high-wage countries, and Industry 4.0 Key Enabling Performance measurement is a necessary management tool in any factory transformation. Traditional KPIs are valid to evaluate the impact of Industry 4.0 on production systems. However, new IT-related KPI classes will be required to assess Data management (e.g. IT efficiency, Availability of IT, Correctness of data, Completeness of data), Transparency & connectivity (e.g. Degree of interconnectivity, Digital coverage, Proportion of virtually controllable resources), and Product management [126]. Industry 4.0 technologies bring the possibility of using IoT devices to gather real-time data from an immense number of devices in real time, enabling rapid responses to changing conditions [127]. KPIs for smart factories need to be reliable and targeting the right goals to support Operational objectives. Therefore, correctly identifying the smart factory stakeholders and understanding their requirements is crucial [128]. Transforming a traditional factory —using legacy machines– into a smart factory is possible without buying expensive new machines, employing a continuous improvement approach, the IoT as enabling technology and establishing visible KPIs from the beginning so that the path to Industry 4.0 is clear to all stakeholders [129]. The increased network complexity and data traffic increases the probabilities of IoT failure. To address this, a data anomaly response model was proposed by Hwang et al. [130]. The changes brought by Industry 4.0 could affect people greatly. To make this impact on people more visible, human-centric KPIs have been proposed [131].

In conclusion, traditional and new IT-related KPIs classes (e.g. Data management, Transparency and connectivity, Product management) would be used to assess and control the impact of Industry 4.0 on production systems. Identifying the smart factory stakeholders and their requirements is critical for obtaining meaningful KPIs. The Internet of Things is the Key Enabling Technology that allows gathering data from multiple sources to produce real-time KPIs that allow rapid responses to fast changes in the smart factories.

Small and Medium Enterprises in the Industry 4.0 era

Although large corporations are more likely to benefit from adopting Industry 4.0 technologies, Small and Medium Enterprises (SMEs) could also obtain a competitive edge from lean-digital manufacturing systems [132]; for example, improving the communication between shop-floor and the top-floor [133]. SMEs have different needs and requirements, which should be taken into account when designing smart manufacturing systems [134]. SMEs have started their digitalisation journey, but further Industry 4.0 developments need to align with the particularities of SMEs, and their organisational structures need to fully embrace and support digitalisation in order to benefit from its implementation [135]. Fast-berglund et al. looked at 40 SME and 8 OEMs in order to establish collaborative robot (cobots) implementation strategies and to determine what KPIs to use for this cases [136]. The increasing penetration of intelligent machines to work alongside people and the benefits of *agile* production will turn SME operators into 'Makers', skilled workers whose main activities are no longer assisting or monitoring machines but creative tasks involving a wealth of information, alternatives, criteria and possible solutions [137].

In conclusion, Small and Medium Enterprises (SMEs) operators will be affected differently by I4.0 compared to corporate workers; but it is clear that I4.0 can bring competitive benefits for SMEs.

Assembly 4.0: conclusions

The 4th Industrial revolution demand paradigm means mass customisation of products, made possible by new digital technology. Conversely, production systems are most likely to experiment an evolution rather than a revolutionary change. Two key areas will be subject to change: the role of people in assembly operations – especially in terms of responsibility and skills; and the possibility of automated or hybrid assembly for low-volume production, including multi-mixed model assembly.

To evaluate the performance of assembly systems, standard KPIs need to be adapted in order to include both traditional metrics (e.g. cost, quality, throughput, inventory, lead time, productivity) and new indicators that are specific to the products, operations, stakeholders and business goals. The Internet of Things is the Key Enabling Technology that allows gathering data from multiple sources to produce real-time KPIs that allow rapid responses to fast changes in the smart factories. The smart factory will need to consider also IT-related KPIs to ensure its smooth computer-dependant operations.

There are plenty of examples of new possibilities due to novel technologies applied to final assembly: improving processes, gathering data and obtaining valuable information, measuring human operator performance and supporting human operators' work. However, research articles mostly focus on what the new technology can do, but few relate to following a methodology to assess the operational needs or opportunities in final assembly and finding or developing an Industry 4.0 solution to them.

In order to ensure that the solutions enabled by Industry 4.0 technologies are aimed in the right direction, it is important to keep the focus on Adding Value.

2.3.3 Focusing on delivering value: Lean

In order to answer the third question "Is Lean Production the best starting ground for implementing Industry 4.0 assembly operations?", the systematic literature review publications related to the key concept 'Lean' were analysed. After a brief introduction, the 9 main topics to be considered will be presented, as shown in Figure 2.8: Lean tools for assembly operations; Internal logistics; Ergonomics; Assembly operations layout; Teaching Lean; Evaluating performance; Lean and Industry 4.0 interaction; Lean tools for Industry 4.0; and Lean management. Finally, the key conclusions will be summarised.

Introducing Lean in the era of Industry 4.0

According to Yin et al., one key characteristic of the Industry 3.0 market –product variety– changed is to change in the Industry 4.0 era to mass customisation (customer participate in individual customisation). However, the existing production systems will not change in a great way, as Flow lines, Lean Production, cells and Flexible Manufacturing Systems remain up to date when facing Mass Customisation [2]. On the other hand, Stump et al. propose that despite the fact that Lean Production can be applied easily to manufacturing situations with low levels of customisation (i.e. product variety, Yin's Industry 3.0 market conditions) but increasing levels of customisation make difficult to directly apply Lean principles of establishing flow and keeping low inventory levels [138].

Gunasekaran et al.'s review concludes that Agile manufacturing (which shares with Lean its focus on product value as defined by the customer) is key for sustainable competitive advantages; and identifies five enabling competencies that need to be deployed jointly to achieve its goals: transparent customisation, agile supply chains, intelligent automation, total employee empowerment and technology integration [139]. To cope with mass customisation with Lean objectives of continuous mixed-model flow, Chatzopoulos presented an production system design algorithm that employs production modules connected by Kanban [140].

Lean Production tools for assembly operations

Lean Manufacturing offers an array of tools and techniques to deal with increasing demand complexity and variability which could benefit assembly operations in a

3.3. LEAN

Q3: Is Lean Production the best starting ground for implementing Industry 4.0 assembly operations?

Keeping the focus on delivering value: Lean

Key aspects:

Lean tools for assembly operations	Internal logistics	Ergonomics
Assembly operations layout	Teaching Lean: Learning factories	Evaluating performance
Lean and Industry 4.0 interaction	Lean tools for Industry 4.0	Lean Management

Conclusions:

- Lean Manufacturing offers an array of tools and techniques to deal with the increasing demand complexity and variability, and which could benefit assembly operations in a context of mass customisation: SMED, kaizen events, simulation, standardised work, value stream management.
- While most authors consider Lean Manufacturing as a valid approach for increased complexity of Mass Customisation, others claim that Lean cannot be applied straightforwardly in the Industry 4.0 era (1 out of 12 articles).
- Lean clearly has a positive synergy with Industry 4.0 because new technologies can enhance Lean assembly, and Lean maturity supports the implementation of new technology. However, Lean might not be necessarily the best possible starting ground for smart assembly in every situation, and it is not a prerequisite for implementing Industry 4.0.
- Both Industry 4.0 and Lean consider that people have a central role to play in assembly operations.

Figure 2.8: Key aspects of Lean assembly for Industry 4.0, and main conclusions of the analysis.

context of mass customisation. Although Lean, a generalisation of the Toyota Production System (TPS), originated in the automotive industry, it has expanded to many other manufacturing sectors - e.g. aeronautical, which demand characteristics are not similar to automotive [141]. One classic Lean tool is SMED (Single Minute Exchange of Die), which is still a trending topic according to a recent review [142]. Looking at balancing manual assembly lines with high number of product variants (mixed model assembly), kaizen events and complexity reduction have proven useful since they fill the gap between mathematical balancing models developed by academia, and actual techniques used in industry [143]. Mixed-model assembly lines throughput rate can be increased by using Lean in conjunction with simulation [144]. To increase productivity and reduce the necessary shop floor space, continuous flow can be achieved through the use of Standardised Work, U-shape assembly lines and material handling systems [145]. Continuous improvement tools can be applied to increase throughput and reduce buffer capacity [146]. To address the increasing complexity of Standardised Work (SW) for mixed-model assembly, a reconfigurable approach to SW sheets and Control and Fabrication Instructions has proven useful [147]. Value Stream Mapping (VSM), another classic Lean tool, has been evolved into Value Stream Management at the University of Luxembourg Lean Manufacturing Laboratory [148]. A different approach to VSM is combining electronic-VSM with simulation, resulting in reduced lead times and non-value add activities [149]. Three new methods were proposed to identify non-obvious constraints of mature production process, where traditional Theory of Constraints methods fall short [150].

In conclusion, research on the application of Lean techniques and tools for assembly operations is still an open topic. The digitalisation of some of the tools, such as Value Stream Mapping, has shown some success.

Internal logistics

A key adjacent area to Lean assembly operations is Logistics, which makes the necessary components or materials available for assembly at the right time with minimum waste. Lean supply chain uses 6 classic KPIs: lead time, costs, inventory level, delivery service level and quality [118]. To increase the assembly line's value-add time and ergonomics, and to reduce waste and necessary space, using plastic containers instead of cardboard has been found an interesting option [151]. Looking in to minimising Work in Progress stock (WIP) and the required number of assembly operators, pre-kitting offers advantages as well as challenges [152, 153]. Usta et al. propose a methodology for assessing the best design for part feeding system for lean assembly, considering that the problems of pure kitting could be countered by hybrid systems (human & machine) [154]. Yamazaki et al. present a design method to reduce the cost of flexible automation of material handling systems [155]. In-house logistics for lean assembly require evaluating and selecting from different transportation alternatives in order to feed part supermarkets [156].

In conclusion, internal logistics are tightly associated to assembly, and therefore both should be analysed together since changes to one will affect the other as well.

Ergonomics

Lean production's (LP) impact on ergonomics and psychosocial risks have been studied for decades, and the focus of the studies has varied over time, with a current view that considers that management style can make LP effects either negative or positive [157]. Da Silva et al. develop an index to assess the LP's assembly cell work in terms of ergonomics and psychophysical demand [158]. The impact of line and assembly cells on breaks and worker's health has been assessed, finding that assembly cells tend to have higher Cycle Times, which increase the physicality of the work; while assembly lines posed no risks [159]. A different approach to evaluating the impact of LP on ergonomics is utilising simulation: (1) for analysing the effect of physical overload on assembly line performance, finding that Cycle Times too close to TAKT (i.e. low catch back time) leads to operator overload, which means absenteeism and low productivity in the long term [160]; (2) or for designing efficient hybrid assembly lines that are ergonomically safe [161].

In conclusion, Lean production can affect ergonomics negatively depending on management style.

Assembly operations layout

A key aspect of Lean assembly operations is the production layout. Classic Lean assembly is done in assembly lines or assembly cells. Assembly cells offer various advantages with regards to assembly lines; and a methodology for reconfiguring an assembly line into a cell is proposed by Carmo-Silva et al. [162]. The efficiency of Lean manufacturing production systems can be better analysed when considering assembly as a macro-activity instead of a series of stations; and the wastes identification is fine-tuned to assembly operations [163]. Lean assembly lines typically use Kanban to pull production and create material flow. In his paper, Savino et al. propose a method for using semi-automated parts feeding in O-shaped assembly lines [164].

Yin et al. analysed in [165] the similarities and differences between Lean Assembly (lines and cells), agile manufacturing (Quick Response Manufacturing, QRM) and *seru* manufacturing. They found, based on two key industrial cases (Canon and Sony), that a production system that focuses primarily on responding to quick changes in demand and product instead of prioritising waste reduction (i.e. Lean Production) can be very competitive in high-cost environments. As a result, of this priority, *seru* focuses on "reconfigurability, resource completeness within cells, worker responsibility and buffering as needed to accommodate dimensions of demand variability". However, the applicability of *seru* assembly systems outside of high-cost, high variability, high innovation, short product development cycles remains to be seen [165].

In conclusion, Lean Production systems typically employ assembly lines or cells layouts to establish pull and create material flow. For certain context involving high-cost, high-variability, short product development cycles, *seru* assembly systems are particularly competitive because they are focused on adaptability.

Teaching Lean for assembly operations: Learning Factories

Since operator engagement is at the core of Lean Production, Lean assembly focused training has been explored over the past decades. Academia-driven teaching methods have not always been adequately adapted for non-students. Recreating industrially relevant environments for teaching Lean at Learning Factories aim to bridge this gap [166]. Lean techniques themselves have been used to design a

Learning Factory, using a manual assembly line as starting point, and employing theoretical knowledge as well as industrial experience for evolving the line into a Learning Factory [167].

Learning factories are incorporating Industry 4.0 technologies to their education & research facilities, focusing on dealing with complexity [168], intelligent logistics [169] or intelligent manufacturing in full-scale simulations [170]. Virtual Reality (VR) and Augmented Reality (AR) can be used to enhance the student's experience when learning Lean Manufacturing. Using VR for training and AR for visualising the assembly instructions improved the lessons [171].

In conclusion, Lean Learning Factories need to mimic real-life scenarios to become useful for non-academic learners with industrial backgrounds, such as assembly operators. Industry 4.0 technologies could be used to enhance the training environment of Learning Factories.

Evaluating performance from a Lean perspective

Lanza et al. propose a simulation-based method for assessing the performance improvement of production systems due to Lean techniques. As Key Performance Indicators (KPIs), either direct measures or monetary equivalents are used to compare initial vs future scenarios. To relate cost-savings over time, cost-time profile charts can be employed [172]. Complex coefficient KPIs derived from delivery date and balanced production can be used to assess small-batch mixed-model scheduling models better than simple KPIs, although the potential use of such KPIs in to manage real operations is reduced [46]. Multi-criteria KPIs can be used not only for management and control of operations but at earlier stages of flow planning projects [173]. For practical results, leading indicators are preferred over lagging KPIs [174] so Cyber-Physical Systems (CPS) which lead to intra-logistics evaluation tools that use a wealth of data collected automatically, could be preferred over relying on human input [175].

Evaluating the operational performance of Lean organisations can be done using tree-like KPI structures [176] or integrated performance assessment frameworks [177, 178]. Cortes et al. proposed a "Lean & SixSigma Framework" [179] to evaluate leanness in order to justify future investment – in a similar fashion to Lanza et al.'s [172], and focus on a methodology for a solid KPI definition that allows and enables strategic-operational alignment. Kovacs et al. studied the relationship between lean maturity, operational performance and investment; and concluded that implementing and sustaining Lean practices pays off because new technology cannot improve performance if the processes are not under control in the first place [180].

In conclusion, KPIs and performance assessment frameworks are used to measure the effects of changes in Lean production systems. Establishing a set of KPIs needs to take into account multiple stakeholders and to align the strategic and operational goals of the organisation. Simulations and case studies show the beneficial effects of lean methods, and allow to estimate the economic return of investment of Lean management decisions.

The interaction between Lean Production and Industry 4.0

Lean production is a key characteristic of the 3rd industrial revolution production systems. While other aspects have evolved (e.g. technology, from computers to smart digital devices) or radically changed (e.g. market focus from variety and lead time to customisation and personalisation), Lean is still up to date in the era of Industry 4.0 [2]. Moreover, the relationship between Lean and Industry 4.0 technologies is catching increasing attention from academia in the last decade [181].

The question posed by Mrugalska et al. [182] has been addressed by many authors, both theoretically and analysing use cases across many countries: “Can Lean and Industry 4.0 coexist and support each other, and if so, how?” There are four main lines of thought when answering this question: (1) Lean techniques and Industry 4.0 technologies interact in a positive way, and there are many cases to illustrate this [30, 31, 183, 184]; (2) Lean facilitates the change towards Industry 4.0 [185, 186]; (3) Industry 4.0 supports Lean, i.e. makes the factory Lean [187–191]; (4) although Lean and Industry 4.0 aim for the same goals, their approach is essentially different regarding digital technology [192].

Five articles looked at answering Mrugalska et al.’s question [182] by surveying the industrial reality of different countries, all of them finding positive interactions between Lean and Industry 4.0 technologies. Dombrowski et al. analysed 260 industrial companies in Germany, and found Lean as an enabler of Industry 4.0 [186]. Tortorella et al. looked into 110 user cases in Brazil, and found a positive Lean-Industry 4.0 correlation, as well as increased benefits of new digital technologies where Lean was also present [193]. Rossini et al. analysed 108 cases of European manufacturers, concluding that Lean allows achieving higher levels of Industry 4.0, while lacking Lean production techniques makes it more difficult to change towards Industry 4.0 [194]. Chiarini et al. investigated 200 cases in Italy, and found that most strategic operational areas benefit from implementing Industry 4.0, such as design-to-cost, supply chain integration or machinery-electronics-database integration [195]. Lorenz et al. analysed user cases in Switzerland, and found that Lean maturity allows greater performance improvements from implementing Industry 4.0 [196].

In conclusion, there is a wealth of evidence showing that Lean Manufacturing is a valid approach to improve assembly operation in a context of mass customisation, and that Lean and Industry 4.0 can benefit from synergies because each one enhances the other. However, according to some authors [192], Industry 4.0 and Lean have essentially different approaches regarding the role digital technologies should have.

While some authors deem that TPS considers robots, machines and computers in the opposing side of *jidoka* ('automation with a human touch'), it should be noted that TPS's lack of enthusiasm towards digital technologies could have been influenced by the current digital technologies of that era (1950-1980s). Since the rate changes in digital technology has been particularly remarkable in the past 4 decades, it seems bold to assume that TPS's views on computers in the second half of the 20th century still apply.

Lean tools for the Industry 4.0 era

The arrival of the 4th industrial revolution could mean changes in the role or the value of existing Lean Production tools. For example, Value Stream Mapping (VSM) could no longer be a sustainable tool, since it might lack flexibility when dealing with digital processes; although evolutionary improvements to this tool could correct this shortcoming [197]. On the other hand, Lean Automation aims at achieving the best possible combination of Lean and Industry 4.0 automation [198]. Industry 4.0 will create new forms of waste, digital waste, and Romero et al. conclude that future research would need to focus on new techniques developed to eliminate it [199, 200]. Using simulation of Lean production environment can be used to find clustering alternatives that reduce the waiting time without compromising the business productivity [201]. Malik and Bilberg proposed a method for assigning tasks to robots or people in Human-Robot Collaborative (HRC) assembly, based on the physical properties of the components, HRC safety, and the dynamics of the HRC environment such as part presentation and feeding [10].The IoT and simulation could be used to support expert-less decision making, in a similar way to the classic Andon tool does [202]. In any case, systems integration will be needed to ensure that Lean Manufacturing Systems meet the Industry 4.0 requirements [203].

In conclusion, classic Lean tools – e.g. Value Stream Map – might need to change in order to remain useful for analysing digital processes. The appearance of "digital waste" should be taken into account, but in general terms, Industry 4.0 technologies are expected to support the ability of people to make Lean-oriented decisions.

Lean Management affected by the 4th industrial revolution

The evolution of Lean Management in the context of Industry 4.0 leads to risks and opportunities. According to Rother et al. [204], the success factors of the coming transformation are three: management engagement, involvement and interaction. Therefore, the proposed approach is to use the technological advances to free up manager time and use it to focus on the human relationships: sharing knowledge, developing the workforce's skills and managing progress [205]. Total Quality Management will need to evolve as Quality planning, Quality Control, Quality Assurance and Quality Improvement are different in a digital manufacturing framework compared to the previous human-capabilities-based era [206].

In conclusion, Management has a key role to play in the successful transition to Industry 4.0. From the Lean perspective, changes brought by Industry 4.0 could be used to free up manager time to be invested focusing on the human relationships.

Lean and Industry 4.0: conclusions

Research on Lean tools for assembly operations is still an open topic. Firstly, it should be noted that since internal logistics are tightly associated to assembly, both should be analysed together because changes to one will affect the other as well. Lean Production systems typically employ assembly lines or cells layouts to establish pull and create material flow. For certain context involving high-cost, high-variability, short product development cycles, *seru* assembly systems are particularly competitive because they are focused on adaptability. KPIs and performance assessment frameworks are used to measure the effects of changes in Lean production systems. Establishing a set of KPIs needs to take into account multiple stakeholders and to align the strategic and operational goals of the organisation. Simulations and case studies show the beneficial effects of Lean methods, and allow to estimate the economic return of investment of Lean management decisions.

The Toyota Production System (TPS) considers robots, machines and computers in the opposing side of *jidoka* ('automation with a human touch'), but it should be noted that their lack of enthusiasm towards digital technologies could have been influenced by the current digital technologies of that era (1950-1980s). Since the rate changes in digital technology has been particularly remarkable in the past four decades, it seems bold to assume that TPS's views on computers in the second half of the 20th century still apply. Currently, there is a wealth of evidence showing that Lean Manufacturing is a valid approach to improve assembly operation in a context of mass customisation, and that Lean and Industry 4.0 can benefit from synergies because each one enhances the other. Some classic Lean tools –e.g. Value Stream Map– might need to change in order to remain useful for analysing digital processes. In general terms, Industry 4.0 technologies are expected to support the ability of people to make Lean-oriented decisions. Management has a key role to play in the successful transition to Industry 4.0. From the Lean perspective, changes brought by Industry 4.0 could be used to free up manager time to be invested focusing on the human relationships. Learning Factories could be a great tool to share the vision of Lean 4.0 assembly, but they need to mimic real-life scenarios to become useful for non-academic learners with industrial backgrounds, such as assembly operators. Industry 4.0 technologies could also be used to enhance the training environment of Learning Factories. Since both Lean and Industry 4.0 stress the importance of people, it seems only natural that supporting human capabilities becomes a priority in Lean 4.0 assembly.

2.3.4 Focusing on people

In order to answer the fourth and last set of questions "How would Industry 4.0 affect people in assembly?" and "How to support people transitioning to Assembly 4.0?", the systematic literature review publications related to the key concept 'Operator' were analysed. After a brief introduction, the 6 main topics to be considered will be presented, as shown in Figure 2.9: Line balancing, sequencing and job rotation; Lean: operators at the centre; Frameworks for operators in Industry 4.0; Automation and Human-Robot Collaboration; Supporting operators with Industry 4.0 technology; and Implications of smart factories for operators. Finally, the key conclusions will be summarised.

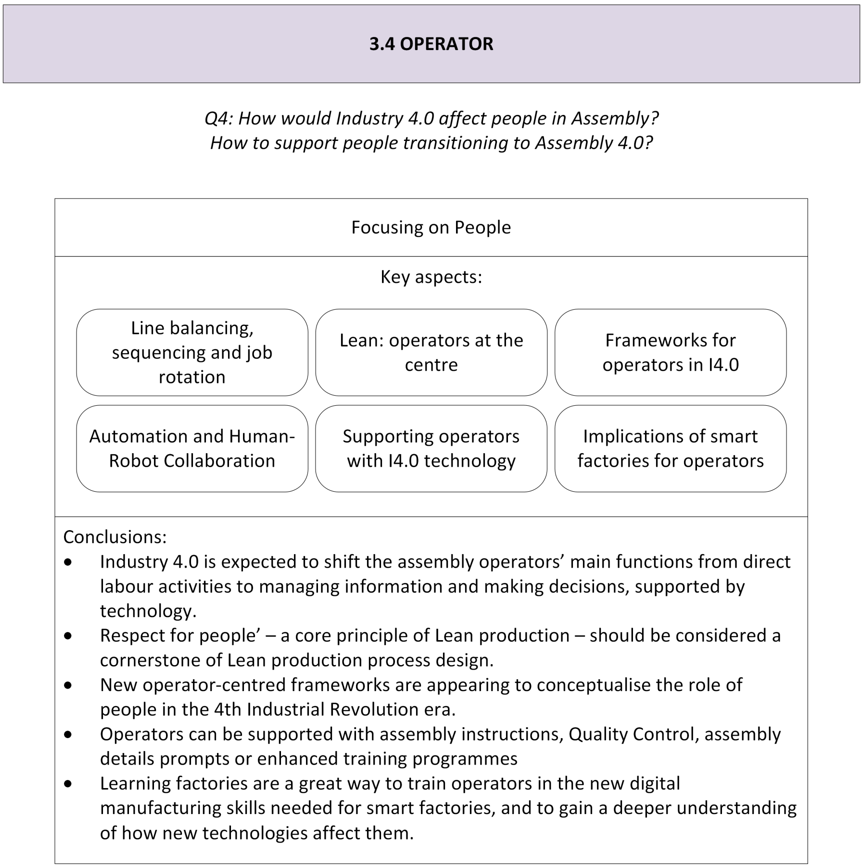


Figure 2.9: Key aspects of Operators in Industry 4.0, and main conclusions of the analysis.

Introducing People in assembly operations

Human operators are critical for competitive assembly systems when considering information flows, competence needs and the requirements for effectively making use of automation. In such an environment, human teams –rather than individuals, are key [207]. The role of operators depends strongly on the type of production system (e.g. high volume production vs low-volume high-variety). Traditional automation allows increased productivity but it lacks the adaptability of human operators. The design of reconfigurable assembly systems by incorporating both machines and people can lead to cost effective system flexibility and scalability. However, the collaboration between people and robots can create safety issues. These can be addressed in two clearly separated ways, according to Hu et al.: (1) employing vision systems to stop robots; (2) robots so light and low force that they can be stopped safely by people. Safely increasing flexibility and efficiency in mixed-model assembly lines is one of the problems that Industry 4.0 technologies seek to address [74].

In conclusion, the role of operators depends on the type of production system, and there is usually a trade-off between the increased productivity of automation and the adaptability of human operators. Reconfigurable, hybrid assembly systems that incorporate machines and people could lead to cost-effective flexibility and scalability. However, the collaboration between people and robots can also create safety issues.

Line balancing, sequencing and job rotation

Having a flexible and cross-trained workforce is a recurrent approach to deal with the complexity and changing demand conditions of mass customisation [208–210]. Operator job allocation can also be adjusted to address an array of situations: one-of-a-kind production [211], minimising costs in *seru* production systems [212], high turnover and slow learning processes [213], heterogeneous workforce with varying degrees of absenteeism [214], or remarkable ergonomics and walking costs [215], or operator-intensive assembly optimisation –along with sequencing [216]. Alternatively, sequencing algorithms can be used for minimising operator headcount in reconfigurable assembly systems [217]. Although line reconfiguration is a common approach in mixed-model assembly, output can be increased in peak demand without it [218].

Analysing the human operator characteristics and the process complexity can be used to maintain the process KPIs [219], to predict operator overload [220], or to assess human-originated quality problems [221]. Operator walking distances are a key input for kitting vs line stocking decisions [222]; and JIT kitting can be optimised by incorporating hybrid HRC systems [223].

In conclusion, a flexible and cross-trained work force is key for dealing with changing demand conditions, allowing dynamic job assignation and efficient line balancing and sequencing.

Automation and Human-Robot Collaboration

Human-Robot Collaboration (HRC) expects to obtain the best of both human and automation worlds. Costa Mateus et al. developed a methodology for transitioning from manual to HRC assembly: (1) operation decomposition, (2) resource evaluation, (3) resource allocation, (4) collaborative assembly operation. [224]. However, HRC brings quality and reliability problems associated with robots and human operators separately, on top of their interactions, which needs to be addressed when establishing Quality Control [225]. Additionally, collaborative work with a robot has been found to cause stress in operators [226]. Moreover, operator safety remains a key concern for HRC systems. A safety strategy for HRC should consider the following key design areas: human-robot collaboration spaces, robot safety systems, vision monitoring of safety conditions, and an operation control system that coordinates human-robot interaction [227]. Regarding the vision monitoring of safety conditions, Anton et al. used depth sensors so that robots avoid collisions with operators [228]. Another way of ensuring human operator safety in HRC would be the "safety bubble" concept, which is based on live data sharing between reconfigurable assembly systems [59].

In conclusion, Human-Robot Collaboration aims to obtain systems that are both flexible and highly productive. However, quality, and safety concerns are yet to be solved.

Lean: operators at the centre

One key aspect of Lean Production Systems (LPS) implementation is *respect for people*, which has been typically overseen [229]. Worker development define the Toyota Production System (TPS) culture of respect and teamwork, and although it does not directly relate to bottom-line results, it is an integral component of the TPS implementation of *kaizen* (continuous improvement) [230]. There are simple ways to involve operators and supervisors in the continuous improvement journey, and they are built on showing the importance and effect of everyone's actions towards addressing the problems together [231]. One-point lessons have been found effective in sustaining the standardisation and optimisation in LPS [232].

There must be a balance between worker autonomy and creativity versus process and cost control, and De Haan et al. found that "challenging and enabling workers to creatively use their talent and skills in daily work will most likely lead to positive results" [233]. Another tension exists related to judgement-based operator adjustments to processes, which could be considered as tampering from the Statistical Process Control (SPC) point of view. Operator adjustment is not always bad, but a necessity in real production plants, and there are methods to determine whether the operator judgement was appropriate or not [234].

Romero et al. looked towards *Jidoka* (or "automation with a human touch") when analysing the future relationship of people and machines in the emerging 4th Industrial Revolution. They stress that *Jidoka* needs to be understood not only as an approach to automation, but also as a "learning system" in which machine and human benefit from each other [4]. 'Employee Development System', as tool of

Lean Production Management can be used to enhance problem solving capabilities of the workforce, which leads to improved results measured by KPIs [235].

New frameworks consider people as the cornerstone of LPS: either depicting them as one of the fundamental pillars –alongside Process and Tools [236]; or directly as the centre of a layered model for lean factory design [237].

In conclusion, 'Respect for people' –a core principle of Lean production– should be considered a cornerstone of Lean production process design. There must be a balance between worker's autonomy and process control, keeping in mind that operators' involvement in the Continuous Improvement journey is necessary for success in the long term.

Frameworks for operators in Industry 4.0

The concept of Industry 4.0 appeared to provide cohesion to different visions of regarding the future of manufacturing, connected by Key Enabling Technologies (KET). Alongside the development of such technologies, recent research has focused on theoretical frameworks to conceptualise the use of the KET and its impact on human operators. Lindblom et al. [238] studied how to evaluate the Human-Robot Collaboration in terms of safety, trust and operator experience; Golan et al. [239] looked into the future Industry 4.0 interaction between operator and workstation, composed of three subsystems: observation, analysis and reaction.

The key role of operators in the era of the 4th Industrial Revolution has been identified by numerous authors, coining the term *Operator 4.0* [240]. Industry 4.0 technologies should support operators in their tasks, either by directly helping them or by providing meaningful information to assembly system design engineers. Peruzzini et al. developed a theoretical human-centred framework for Operator 4.0 using Digital Twin based simulation and real-time human data capture can be used to provide insights on operator ergonomics and mental workload [88]. In a similar way, Mattson et al. propose a method of measuring the wellbeing and performance of operators at assembly stations using electro-dermal activity [107]. Industrial IoT is another technology that can be used for capturing of human and machinery data for understanding human impact on Industry 4.0 assembly systems [84]. Understanding the operator's information needs is vital for the design of smart assembly factories [76].

In conclusion, new operator-centred frameworks are appearing to conceptualise the role of people in the 4th Industrial Revolution era. The key role of operators has been identified by numerous authors, coining the term Operator 4.0 [240]. Industry 4.0 technologies should support operators in their tasks, either by directly helping them or by providing meaningful information to assembly system design engineers.

Supporting operators with Industry4.0 technologies

Industry 4.0 technologies offer new ways to support human operators in their duties – see Table 2.3: training can be made easier with Virtual Reality (VR), Augmented Reality (AR) and motion tracking [94–96]; instructions can be generated in real-time and displayed using AR [97–99]; or projection AR can be used to provide process information [100], assembly assistance [101], safety in HRC 'chaotic' smart warehouses [241], shipyard worker assistance [242] or to enhance the operator's capabilities and competencies [93]. In general, human operators are positive about the use of AR for assembly support [243]. The technology-enhanced operator is a growing field of research, with many other Industry 4.0 KET involved to achieve varied goals: IoT-based Human-Cyber Physical Systems for providing feedback to operators working in an intelligent space [91]; reducing Big Data to Smart Data to assist people [79]; software robots (softbots) to interface between machines and computer information systems [244]; mobile devices in order to allow dynamic job rotation in multi-variant assembly lines [245]; verbal and visual prompts for assisting workers with intellectual disabilities [246]; wearables for audio commands [247] or detecting potentially hazardous or risky situations [248]; or a combination of many technology-enabled tools [249–251].

In conclusion, varied Industry 4.0's Key Enabling Technologies can be used to support production operators to obtain different benefits. In particular, Virtual and Augmented Reality and wearable devices have attracted great attention. Operators can be supported with assembly instructions, Quality Control, assembly details prompts or enhanced training programmes; which can be provided in a way that is satisfactory for the users.

Implications of smart factories for human operators

Digital technologies progressive presence in factories will change the role of human operators, which will shift from work-focused activities towards coordinating tasks, supervision and decision activities [252]. Operators will therefore need more information than ever before, and this requirements need to be carefully assessed [76]. Considering the operator at the centre, human activities with Cyber-Physical Systems (CPS) have been modelled, and new KPIs proposed to make visible how business and operational decisions affect operators [131]. Empowering operators seems one possible way of making Smart factories happen, and such empowerment will make visual computing technologies necessary, according to Segura et al. [253].

Digital technologies can also be used to obtain insights into human-machine interactions [84] or worker's wellbeing [107], which then lead to forming strategies for cognitive automation [70]. Despite recent advances, digital maturity in manufacturing companies has a long way to go, and most operator-machine interaction is done by mouse and keyboard hardware instead of by using CPS [254].

In conclusion, human operators will need to receive and manage more information than ever before, make decisions and supervise instead of focusing on mechanical work related activities. Therefore, empowering operators to act more autonomously and supporting them accordingly seems necessary. To understand the situation of Industry 4.0 operators can be done using new digital technologies, obtaining meaningful data in ways that were not possible before.

Focusing on people: conclusions

The role of operators depends on the type of production system, and there is usually a trade-off between the increased productivity of automation and the adaptability of human operators. Reconfigurable, hybrid assembly systems that incorporate machines and people could lead to cost-effective flexibility and scalability. However, the collaboration between people and robots can also create safety issues. There must be a balance between worker's autonomy and process control, keeping in mind that operators' involvement in the Continuous Improvement journey is necessary for success in the long term. 'Respect for people' –a core principle of Lean production– should be considered a cornerstone of Lean production process design. A flexible and cross-trained work force is key for dealing with changing demand conditions, allowing dynamic job assignation and efficient line balancing and sequencing. New operator-centred frameworks are appearing to conceptualise the role of people in the 4th Industrial Revolution era. The key role of operators has been identified by numerous authors, coining the term Operator 4.0. Industry 4.0's Key Enabling Technologies can be used to support production operators to obtain different benefits. In particular, Virtual and Augmented Reality and wearable devices have attracted great attention. Operators can be supported with assembly instructions, Quality Control, assembly details prompts or enhanced training programmes; which can be provided in a way that is satisfactory for the users. Human operators will need to receive and manage more information than ever before, make decisions and supervise instead of focusing on mechanical work related activities. Therefore, empowering operators to act more autonomously and supporting them accordingly seems necessary.

2.4 Discussion

This section outlines the key ideas of the four areas considered in the previous section, organised as answers to the four sets of questions posed in the introduction.

Assembly & Mass Customisation

The question related to Assembly and Mass customisation is: "What are the characteristics and implications of mass customisation for assembly operations?"

Mass customisation brings increased complexity that needs to be addressed at multiple levels and taking a holistic point of view to ensure that optimising a sub-system does not affect negatively another sub-system. Assembly complexity reaches outside the boundaries of assembly operations and needs to be considered jointly with supply chain, quality, maintenance and IT/IS. Industry 4.0 digital technologies have a critical role to play in making possible mass customisation assembly systems that do not compromise on quality and cost.

Industry 4.0 & Key Performance Indicators

The set of questions related to Industry 4.0 and KPIs are: "What new Industry 4.0 digital technologies are relevant to assembly operations?", "How to measure the improvement?" and "How to make the most out of them?"

There are many examples of new technologies applied to final assembly – see Table 2.3: the Internet of Things, Big data and Digital Twins for improving processes and decisions as well as for gathering data and obtaining valuable information; Cyber-Physical Systems and Augmented/Virtual Reality for measuring human operator performance and supporting human operators' work; and a mix of technologies to support different aspects that enable mass customisation. However, assembly operations are likely to experiment an evolution rather than a revolution, by gradually incorporating these technologies. Two key areas will be of particular interest: enhancing the role of people in assembly operations –especially in terms of responsibility and skills; and making possible human-machine hybrid systems, capable of efficient low-volume high-variability production.

To evaluate the performance of assembly systems, a KPI system is employed. Standard KPIs need to be adapted in order to include both traditional metrics (e.g. cost, quality, throughput, inventory, lead time, productivity) and new indicators that are specific to the products, operations, stakeholders, business goals and IT-related aspects of the smart factory.

Despite the wealth in literature about what new technology can do, few relate to methodologies to assess the operational needs and opportunities in final assembly, and then finding or developing an Industry 4.0 solution to them.

Lean Assembly for Industry 4.0

The question related to Lean Production is: "Is Lean Production the best starting ground for implementing Industry 4.0 assembly operations?"

Lean Manufacturing offers an array of tools and techniques to deal with the increasing demand complexity and variability, and which could benefit assembly operations in a context of mass customisation. While most authors consider Lean Manufacturing as a valid approach for increased complexity of Mass Customisation, others claim that Lean cannot be applied straightforwardly in the Industry 4.0 era. Lean might not be necessarily the best possible starting ground for smart assembly in every situation. However, it clearly has a positive synergy with Industry 4.0 because new technologies can enhance Lean assembly, and Lean maturity supports the implementation of new technology. Moreover, both Industry 4.0 and Lean consider that people have a central role to play in assembly operations.

Assembly operators in Industry 4.0

The questions related to human operators are: "How would Industry 4.0 affect people in assembly?" and "How to support people transitioning to Assembly 4.0?"

Industry 4.0 is expected to shift the assembly operators' main functions from direct labour activities to managing information and making decisions, supported by technology. A flexible and cross-trained work force would be key for dealing with changing demand conditions, allowing dynamic job assignation, line balancing and sequencing. Learning factories are a great way to train operators in the new digital manufacturing skills needed for smart factories, and to gain a deeper understanding of how new technologies affect them.

2.5 Conclusion

This article looked at the issue of how Industry 4.0 technologies could improve the flexibility, productivity and quality of assembly operations. To do so, a systematic literature review was carried out, and 239 articles were analysed. The resulting analysis was structured into four main topics, each one addressing one of the questions posed in the introduction.

It was found that mass customisation brings complexity into assembly operations, which need to be looked at from a holistic point of view –joining assembly, supply chain, quality, maintenance and IT. New technologies –such as Big Data, the Internet of Things, Real-time Optimisation, Cloud Computing, CPS, Virtual/ Augmented Reality, Additive Manufacturing and Digital Twins– allow obtaining meaningful information in real time about the assembly operations, making better decisions and supporting human operators in their activities. A combination of conventional and new KPIs, to evaluate IT-related aspects of the smart factory, will be needed to measure the impact of these technologies. Although it might not necessarily be the best starting point in each and every situation, Lean is definitely a great starting ground for smart factories. Since both Industry 4.0 and Lean consider that people have a critical role to play in assembly operations, frameworks that place human operators at the centre of Lean 4.0 have started to appear. This focus will need to be translated into supporting people to acquire the digital manufacturing skills they will need. Learning Factories are great to this end.

The literature analysis also uncovered the relative lack of methodologies for implementing Industry 4.0 technologies in assembly operations to address concrete business goals, which remains an open question. There is also room for developing operator-centred frameworks for Industry 4.0 that are specific to assembly operations in the demand context of mass customisation.

2.6 Summary

In this chapter, a systematic literature review uncovered several key findings for improving the flexibility, productivity and quality of assembly operations with new digital technologies: (1) Mass customisation brings complexity to assembly systems, which need to be analysed holistically; (2) new digital technologies allow to have better, real-time information to support decisions made by people; (3) new KPIs, linked to digital aspects, may be needed along conventional performance metrics; (4) Lean is a great starting point for deploying the 4th industrial revolution technologies; (5) both Industry 4.0 and Lean consider people as a key element of production systems; and (6) there is a lack of specific methodologies for implementing Industry 4.0 digital technologies on assembly operations.

Resulting from these findings, it seems that the increasing focus on mass customisation and complexity leads to high-mix low-volume demand conditions dominance over other aspects. In consequence, assembly systems would need to be adapted, designed and/or optimised to be flexible. Specifically, they need to be capable of performing efficiently under high product variety, frequent product changeovers and small batch sizes. Flexible assembly systems would also need to stress the Lean-to-Industry 4.0 journey, a relationship that focuses on firstly implementing and sustaining operational excellence initiatives before a digitalisation strategy can be deployed holistically –i.e., at a systemic level, and not just as a collection of small disconnected projects.

It is worth noting that although the period considered for the systematic review was 2010–2020, the interest in the topic keeps growing. Industry 4.0 and Assembly 4.0 are no longer key subjects by themselves but have become the foundations for a fast-growing field. The capital importance of people is highlighted in the newly-coined term *Industry 5.0* [255], proposed by the European Commission to stress the human-centric orientation of European industry.

The main contributions of this chapter are two key findings about state-of-the-art *assembly systems 4.0*:

1. The systematic literature review carried out evidences a lack of specific methodologies for the implementation of Industry 4.0 digital technologies on assembly systems.
2. Key literature on the topic shows that mass customisation and personalisation demand trends lead to more complex assembly systems. These systems include many different layers that need to be addressed holistically. To gain perspective from multiple angles of how the several layers affect one another, sets of performance measures ought to be used.

Resulting from these key conclusions, the following Chapter 3 includes Section 3.1, which presents an assembly-specific operator-centred conceptual framework for implementing Industry 4.0 digital technologies. Section 3.2 expands on the available tools for evaluating the performance of flexible assembly operations, a crucial step for assembly systems design. Later, Chapter 4 presents a systematic approach using design of experiments to uncover the most critical factors to flexible manual assembly systems for high-mix low-volume demand, a first step towards designing flexible assembly systems that are capable of benefiting from new digital technologies.

CHAPTER 3

Framework

This chapter introduces the conceptual framework to be used in the rest of the thesis. It is composed of three clearly differentiated elements.

Resulting from the main conclusions of the previous chapter, Section 3.1 introduces an operator-centred Lean assembly 4.0 conceptual framework, which allows us to delimit the scope of the following chapters' analysis tools and studies. It also leads to conclusions on the type of Industry 4.0 digital technologies that could be used to enhance the performance of each layer of an assembly system.

Section 3.2 presents general definitions, an assembly line classification taxonomy, and the basic concepts of manual and semiautomatic assembly performance evaluation, which will be used in the following chapters of this thesis.

Section 3.3 introduces The Cooktop Company industrial study case. This study case, which will one of the fundamental pillars of the analysis developed in this thesis, presents a classic situation of mass customisation demand to which the assembly operations need to adapt. This section describes the starting situation, explains the study case main characteristics, analyses the demand to identify mass customisation patterns, and describes the product changeover situation to determine which product-mix assumptions need to be used later for modelling the performance of the system.

Finally, Section 3.4 features the chapter summary and key contributions.

3.1 Operator-centred Lean assembly 4.0 framework

The conceptual model presented in this section, which was presented at the 54th CIRP Conference on Manufacturing Systems (Athens, Greece/online, 2021), and later published in *Procedia CIRP* [256] builds on the previous work carried out by Gil-Vilda et al. regarding a human-centred model for Lean factory design [237]. In consequence, each one of the subsections here corresponds to a section of the conference article: Introduction (3.1.1), Operator-centred assembly 4.0 model (3.1.2) and Conclusion (3.1.3).

Article title:

Operator-centred Lean 4.0 framework for flexible assembly lines

Article abstract:

This article provides a starting point for developing a methodology to successfully implement Industry 4.0 technology for assembly operations. It presents a novel multi-layer human-centred conceptual model in line with Lean philosophy which identifies the assembly operator functions and relates them to other production departments, identifying how they would be affected by incorporating new digital technologies. The model shows that assembly operators would only be directly supported by hardware digital technologies; while the production support departments would mainly employ Industry 4.0 software technologies. The work presented here paves the way for developing a methodology for implementing Lean Assembly 4.0.

3.1.1 Introduction

The term Industry 4.0, initially adopted by a German strategic program [22], is used nowadays to express the relationship between different elements of the current manufacturing sector and the new digital technologies. Recent research on Industry 4.0 tends to focus on the possibilities brought by a certain new digital technology or develops a framework to understand what would be the effect of incorporating such new technologies.

Scarcely explored is the development of implementation methodologies that bridge Industry 4.0 conceptual frameworks with the current state of industrial environments, and the process to successfully deploy new digital technologies that bring the expected returns of investment [27]. Additionally, if the Lean production approach and its techniques are also related to this implementation, the concept of Lean 4.0 could be used as shown in the literature [30].

This article aims to provide a starting point for developing a methodology for successfully implementing Industry 4.0 technology for assembly operations, in line with Lean production principles. To do so, the model presented here links assembly elements and ancillary departments to Industry 4.0 Key Enabling Technologies for assembly operations, considering the operator as the centre of the model, which is coherent with Industry 4.0 principles [240, 257], Lean manufacturing [237] and the EU prospects for Industry 5.0 [255].

In Section 3.1.1 changes in demand trends are presented, introducing a particular issue resulting from mass-customisation: high-mix low-volume. Then, it describes the focus shift towards people in both Lean production and Industry 4.0. Finally, it introduces the role of new technology to support humans in assembly: Operator 4.0. Section 3.1.2 introduces an operator-centred Assembly 4.0 model which identifies which digital technologies have a place in supporting operator functions and interactions in the Industry 4.0 factory. Finally, Section 3.1.3 presents the conclusions of the article.

Demand trends: mass customisation requires flexibility

Although a clear segmentation traditionally existed between mass-produced goods and made-to-order products, the market trends have been shifting towards the customisation of mass-produced items [28]. Despite this not being economically sustainable in the past; technological advances have made it possible. Managing the complexity associated with mass customisation remains one of the main challenges for global production networks [258]. In the near future, mass customisation could not only become desirable, but expected of any company wanting to remain competitive. In this context, adaptable, changeable and decentralised manufacturing networks will possess key competitive advantages [258, 259].

Mass customisation leads to a particular production demand problem, high-mix low-volume: a large number of items being demanded, in small amounts each one, and with a variation not depending on seasonal trends, making its forecast difficult and inefficient. To stay competitive in such a context, manufacturing companies will need to become more flexible without compromising their productivity. Fortunately, several Industry 4.0 digital technologies are expected to prove useful in achieving this as already shown in the literature [11, 31, 260].

Production evolution: Lean 4.0 and focusing on people

New digital technologies have set the landscape for a fourth industrial revolution, conceptualised as Industry 4.0, which describes a vision of increased flexibility and automation; data and information flow across processes, functions and companies; enhanced quality achieving zero-defect production; leveraging big data, neural networks, machine learning and Artificial Intelligence, among other digital technologies, to maximise efficiency [257].

Lean manufacturing, a generalisation of world-leading Toyota Production System, has proven its efficiency in high demand variability, shorter new product development cycles and customer-focused, highly competitive environments [5, 261]. It is therefore a solid starting ground for any manufacturing system evolution seeking to improve productivity and flexibility at the same time. One of the key characteristics that set apart Lean production systems is its respect for people and people's key role in their company's continuous improvement journey [3, 262].

Hence, Lean production needs to be the cornerstone on which Industry 4.0 technologies rely to enhance production. Lean automation is then the synergy between the Lean approach and the new digital technologies – Lean 4.0 [31]. According to Kolberg and Zühlke [263], Computer Integrated Manufacturing (CIM) failed due to the complexity required for the automation technology, while the Lean approach was successful because of its high effectiveness, achieved by reducing complexity and avoiding non-value-added processes.

Although Industry 4.0 solutions to specific Lean production issues may prove useful, either replacing or enhancing existing Lean tools, it is looking at the production system from a holistic perspective where the maximum benefits of disruptive digital technologies could be achieved [30, 31].

Assembly and Operator 4.0

The goal of flexible assembly systems in the Industry 4.0 era, named 'Assembly 4.0' by Cohen and Faccio in [74] –a term that will be used in the present article– is to address the mass customisation demand paradigm. The most relevant key enabling technologies for assembly are –according to [24]– the Internet of Things, Big Data, Real-time optimisation, Cloud computing, Cyber-Physical Systems, Machine Learning, Augmented Reality, Cobots and Additive Manufacturing.

Considering the critical role of assembly line level operators on Lean production systems performance, it is only natural to consider how new digital technologies would enhance the human operator best traits, and help to cover their weaknesses, aiming for a 'human-automation symbiosis' [240]. To analyse this human-technology interaction, it would be useful to start from the operator's perspective to ensure that the implementation of changes does not affect negatively people, but supports them [252].

As proposed in this novel work, keeping the operator at the centre is the focus of the methodology approach proposed and described in the following section, where all the interactions between an assembly operator and production activities and its environment have been established and analysed.

3.1.2 Operator-centred assembly 4.0 model

Due to the success of Lean production systems and because respecting people is one of its key features, human operators need to be at the centre of any methodology seeking to integrate Industry 4.0 digital technologies for assembly operations. This model aims to explain, from the point of view of the assembly operator, which of its productive functions would be affected by Industry 4.0 technologies, and how. It also explains how new digital technologies would affect the material and information flow between the operator and the main Departments which support assembly operations, such as Logistics & Planning, Maintenance and Quality Control.

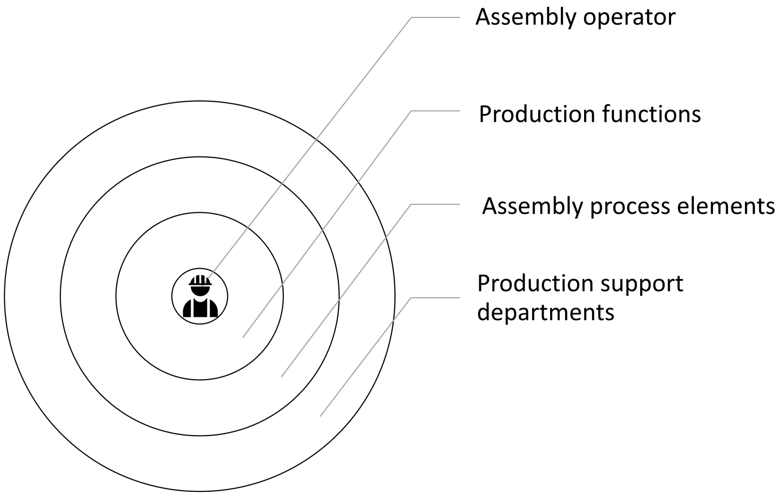


Figure 3.1: First stage of the human-centred model of assembly systems.

The model proposed consists of two stages. The first stage (see Figure 3.1) develops three concentric layers: the productive functions carried out by the operator, the elements used to do so and the Production Support Departments involved with the operator; along with how they interact with the operator. The second stage relates Industry 4.0 digital technologies with its specific point of application from the first stage (Figure 3.5, Section 3.1.2).

Production functions

The first layer considered in the model presented in Figure 3.1 –the most closely related to the operator– consists of the production functions. Manual assembly operators carry out four main productive functions:

- Assembly (AS): attachment of parts together or to the previously processed unit, including manipulation of the units into and out of the workstation;
- Quality Control (QC): building quality in each process step, along with the required tests performed by the operator;
- Changeover (CO): adjustments to the workstation, tools, parts and fixtures to assemble a different product model;
- Communication (CM): recording, sending and receiving data or information.

Assembly process elements

To develop these production functions in Subsection 3.1.2, several assembly process elements are used, which constitute the second layer, as shown in Section 3.2:

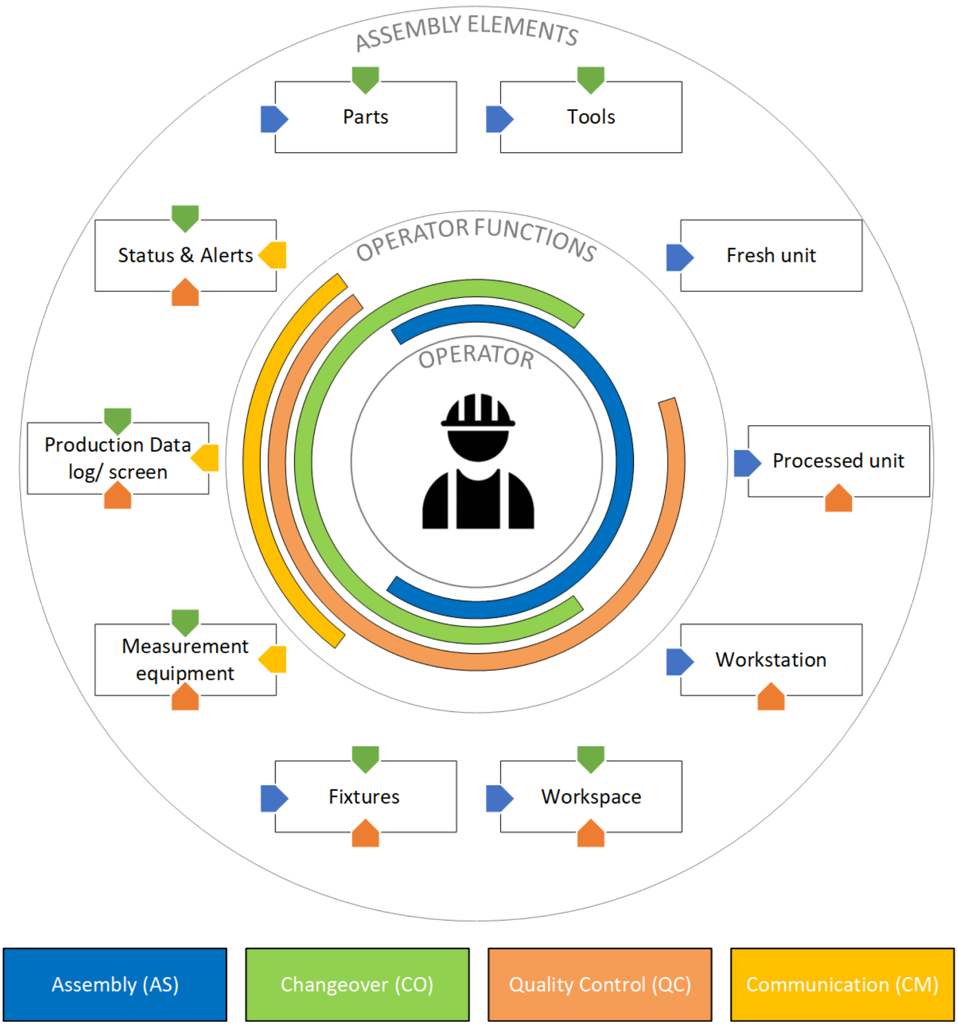


Figure 3.2: Assembly operator functions and process elements utilised to perform them.

- Workspace: the actual space in which the assembly task is carried out. Involved in AS, QC and CO.
- Workstation: the physical space where the in-process unit is held while parts are assembled. Involved in AS and QC.
- Fresh unit: the next upcoming unit to be processed. Involved in AS.
- Processed unit: the previously assembled unit. Involved in AS and QC.
- Tools: devices employed to attach parts to the unit. Involved in AS and CO.
- Parts: components to be assembled to the in-process unit. Involved in AS and CO.
- Status & alerts display: devices which function is to inform of the production status and visually or audibly alert of any anomalous situation. Involved in AS, CO and CM.

- Production data log/ screen: physical or digital means of tracking the production schedule, recording data and displaying supporting information. Involved in AS, CO and CM.
- Measurement equipment: devices utilised to gauge or test relevant characteristics of the in-process unit. Involved in QC, CO and CM.
- Fixtures: devices employed to hold the unit while performing assembly or QC operations. Involved in AS, QC and CO.

Production Support Departments

Assembly operators are supported by five key departments of the organisation: (i) Assembly: other operators, situated upstream, in parallel or downstream in the process stream; (ii) Production Management: including team leaders and assembly managers, they typically deal with non-conforming situations; (iii) Maintenance: they ensure the tools, fixtures and machines; (iv) Quality: they establish Quality Control policies, calibrate and validate testing equipment; (v) Logistics & Planning: they provide the correct materials and parts at the right time, retrieve empty packaging and schedule production.

Operator – Supporting Departments interaction

As Figure 3.3 and Figure 3.4 depicts, operators interact with the supporting departments using a combination of process elements. White arrows indicate material flow, while black arrows indicate data flow.

As shown in Figure 3.3, operators receive fresh units from upstream process steps; and send processed units towards downstream process steps. Information relating non-conformities or upcoming changeovers in shared typically verbally in an informal manner. Formal information about the production status is shared using Status & Alerts process elements, such as Andon lights or display screens. Operators also exchange information formally with Production Management using Production Data logs and screens. Measurement equipment often sends test data to an IT system that stores it and provides Data Analytics.

Operators and Quality exchange information via Status & Alerts, Production Data log/screens and Measurement Equipment. Additionally, Quality provides and maintains the Measurement Equipment (see Figure 3.3) that Operators use to perform QC.

Operators and Maintenance exchange information via Status & Alerts and Measurement Equipment (see Figure 3.4). Also, Maintenance provides and maintains Tools and Fixtures, in response to the operator's information regarding its state.

Figure 3.4 shows that Logistics & Planning provide the operator with parts to be assembled onto the unit, and they retrieve empty packing (material flow) Along with parts or empty boxes, information is transmitted, e.g. when using a Kanban or

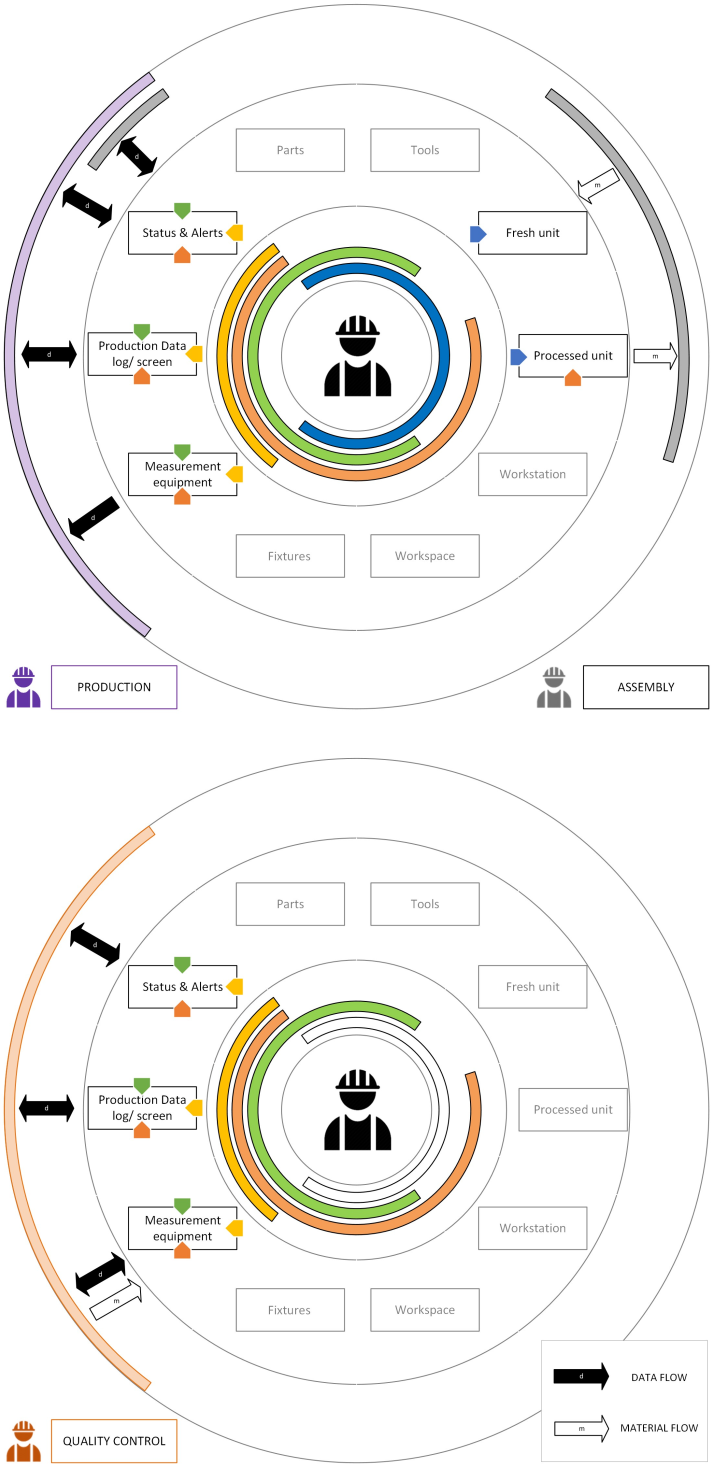


Figure 3.3: Operator – Supporting Departments interaction: Production Management, Assembly and Quality Control.

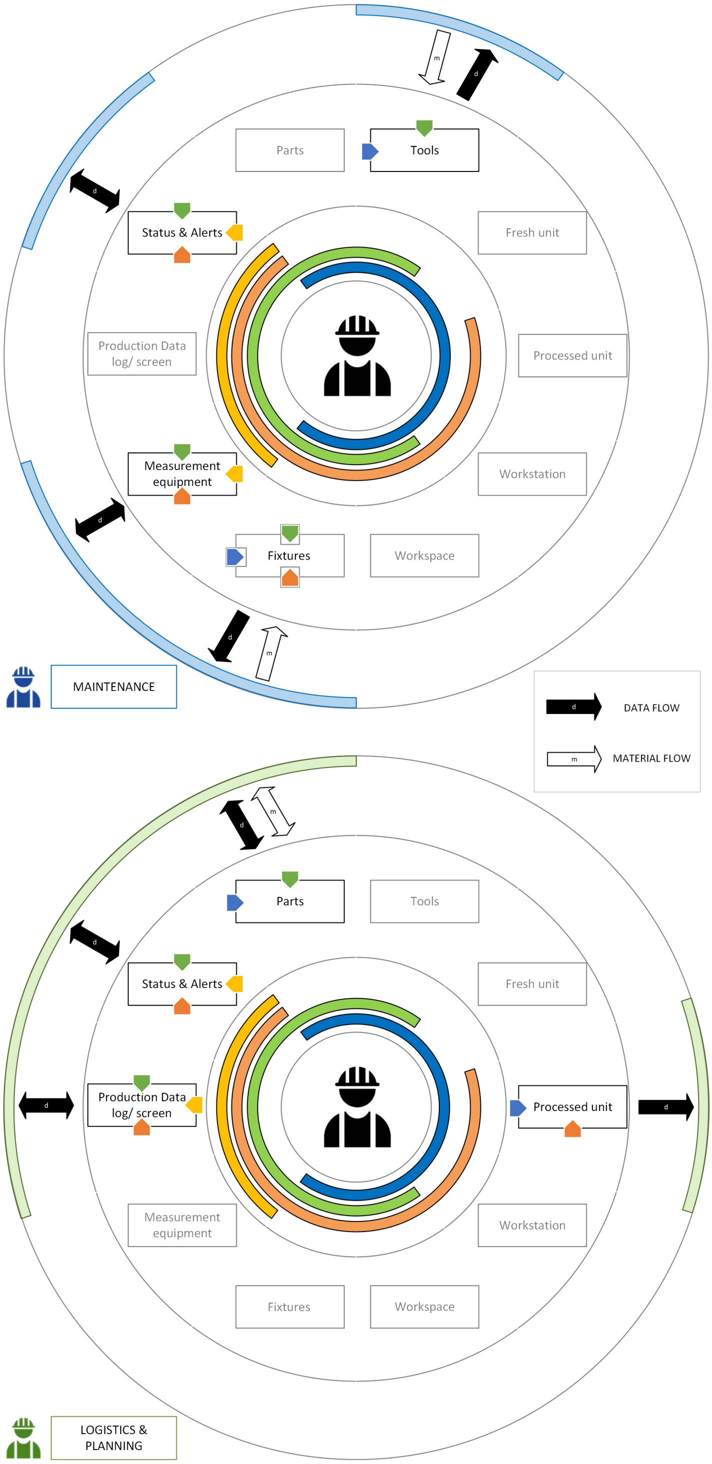


Figure 3.4: Operator – Supporting Departments interaction: Maintenance and Logistics & Planning.

a twin-bin system. Operators also provide implicit information through successfully processed units, which are a measure of production output. They also exchange information via Status & Alerts, Production Data log/screens. A key piece of information provided by Logistics & Planning is the production schedule, specifying batch sizes and changeovers, which can impact the operator's productivity.

Industry 4.0 enabling technologies for Assembly

To connect the proposed model with Industry 4.0, nine enabling technologies have been considered as particularly relevant for Assembly Systems [24]. Six of them are software technologies (Internet of Things, Big Data, Real-time optimisation, Cloud computing, Cyber-Physical Systems, Machine Learning), and three are hardware technologies (Augmented Reality, Cobots, Additive Manufacturing).

While the assembly operator's main functions are not expected to change due to the availability of new digital technologies, the way these functions are developed will need to evolve to enjoy its benefits. The relationship with Supporting Departments also shows potential for improvement. Lastly, Supporting Departments are expected to integrate new digital technologies to obtain increased benefits. Although the latter technologies will not be employed directly by the assembly operator, they will affect his work. Therefore, the implementation of new digital technologies at all levels needs to consider the impact on assembly workers to be successful. Figure 3.5 depicts which Industry 4.0 digital technologies would be beneficial at each layer of the model.

Three key technologies could be used by operators to carry out its functions, as shown in Figure 3.5: Augmented Reality or Mixed Reality (AR/ MR) [264], collaborative robots (cobots) [265] and Cyber-Physical Systems (CPS) [198]. Aiming to support the assembly operator main functions (see Section 3.1.2), Augmented Reality/Mixed Reality could be widely used: enhancing the operator cognitive ability while performing a changeover –which would need to be streamlined and mastered to achieve mass customisation, and supporting a zero-defect assembly and Quality Control, as introduced in [66]. Cobots are to be used not only for assembly tasks, but also to flexibly present the unit-in-process in the best orientation and position for an ergonomic human operation or inspection; even contributing to quick changeovers. Finally, CPS would gather and receive data, reducing the cognitive load of the operator while ensuring the quality and reliability of the data captured and sent in the workstation.

Regarding the Operator's interaction with the Supporting Departments, the Internet of Things could be employed to communicate the vast amount of data required to and from them. Industrial IoT can be combined with Augmented Reality technology to provide real-time maintenance assistance remotely to assembly operators, reducing the equipment downtime in the event of a breakdown, in a similar fashion to systems used to facilitate engineering knowledge to maintenance technicians [266]. Augmented Reality can also provide enhanced tools for communic-

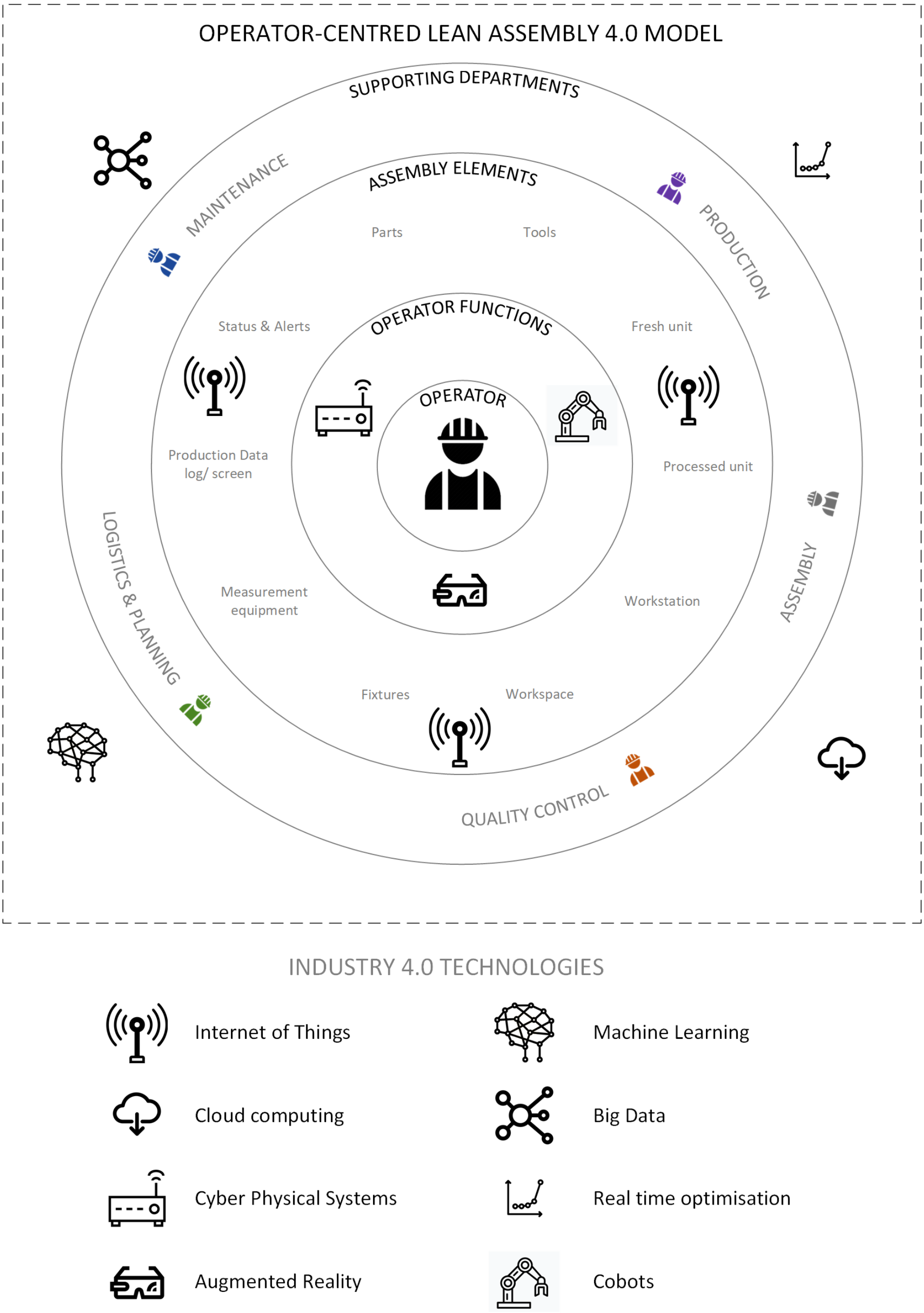


Figure 3.5: Industry 4.0 technologies to be employed at each layer of the Human-Centred Assembly 4.0 model.

ation between Operators and the Supporting Departments, enabling collaborative assembly process design, analogously to the product process design presented in [267].

Finally, Supporting Departments could benefit from using Cloud computing, Big Data, Machine Learning and Real-Time optimisation, which would affect assembly operations positively in the long term. These software technologies would influence greatly the bottom-line results, but these will not be directly perceived by assembly operators since they will not be in close contact with such technologies. For example, Big Data and Digital Twins for Logistics & Planning would help optimise in-factory stock levels while ensuring reliable feeding of components to assembly cells, but this optimisation is hardly seen from the operator point of view.

Discussion

The multi-layer model presented previously explains an Assembly operator functions, the tools utilised for such end, and its interactions with the Production Support Departments, from a human-centric perspective. It then establishes which of the previous layers could be affected by Industry 4.0 digital technologies, and which technologies would enhance each particular function or relationship.

As Figure 3.5 shows, there is a clear differentiation between the technologies used by the operator to perform its functions (hardware technologies), and the technologies used by the Production Support Departments – not directly by the operators (software technologies).

Although this model does not reveal how to successfully implement Industry 4.0, its necessary prerequisites, or the expected order of magnitude of the benefits it would bring; it does identify which technologies could be used to support each one of the operator's duties, making it a solid starting point for future research.

This model is builds on top of the foundations laid by solid previous research: the central role of people for Industry 4.0 [240, 257] and for Lean assembly systems [237], as well as the EU prospects for Industry 5.0 [255]. However, it has not been validated experimentally to date.

To determine the prerequisites and the potential benefits of implementing Industry 4.0 technologies according to the framework presented here, validation in an industrial real study case is deemed necessary.

3.1.3 Conclusion

Aiming to achieve mass customisation, production systems in the Industry 4.0 era will need to support the Assembly operators when and as needed. The importance of people in Manufacturing systems was already a key point in successful Lean production systems, and Industry 4.0 technologies need to embrace this perception.

A human-centred model was presented, explaining, from the point of view of the assembly operator, which of its productive functions would be affected by Industry 4.0 technologies, and how so. One clear differentiation appears between the technologies used by the operator to perform its functions (hardware technologies), and the technologies used by the Production Support Departments – not directly by the operators (software technologies).

This model does not aim to be exhaustive for all kinds of manual assembly process, but it does include everything related to most manual high-mix low-volume processes, and it is open enough to allow additions from specific processes to adapt it where necessary.

Future lines of work would employ this model to develop an explicit methodology for implementing Industry 4.0 digital technologies aiming to support the human Assembly operator and evaluating the potential gains in industrial contexts, thus providing empirical validation in real industrial study cases. This would correlate Assembly 4.0 implementation to key operational KPIs (e.g. productivity, on-time delivery, first time yield) when analysing a particular case study, whose boundary conditions and approach could be properly established by the model.

3.2 Performance Evaluation of Flexible Assembly Operations

This section introduces an assembly line classification, the basic concepts of assembly systems performance evaluation, and the definitions of the most relevant parameters used in the models used in later chapters.

3.2.1 Assembly line classification

Assembly line features can be classified according to three main sets of characteristics, according to Boysen et al. [268, p.678–682], whose definitions are listed below. Concerning the work presented in subsequent chapters of this thesis, the following six assembly line attributes are of capital importance:

1. Product precedence:
    - Mixed-model line: "Varying models are manufactured on the same production system, the production processes of which are similar enough so that setup times are not present or negligible. Thus, the units of the different models are produced in an arbitrarily intermixed sequence."
    - Multi-model line: "Different products are manufactured in batches. Whenever another batch is to be processed, a setup occurs which requires time and resources."
    - Single-model line: "A single product is manufactured or the production processes of multiple products are (almost) identical so that they need not be distinguished."

2. Processing times:
   - Stochastic processing times: "It is assumed of processing times follow a known (or even unknown/partially known) distribution function."
   - Dynamic variations of processing times: "These variations are, e.g., due to learning effects of operators."
   - Processing times are considered to be static and deterministic.
3. Movement of workpieces:
   - Paced workpiece movement: where a cycle time restricts the product advance.
   - Asynchronous unpaced movement: "As soon as a station completes its work, the workpiece is moved to the next station or a buffer in front of this station unless blocking occurs."
   - Synchronous unpaced movement: "the movement of workpieces is coordinated between stations. The workpieces are transferred to the respective next station when all stations have completed their current workpiece."
4. Line layout:
   - Single line: "The stations are arranged in a serial manner along the flow of the line."
   - U-shape: "U-shaped line layout with at least one crossover station is used."
5. Parallelisation:
   - Parallel lines: "More than one parallel line is to be considered or the number of lines installed as part of the decision problem."
   - Parallel stations: "When stations are parallelised, their resources and work contents are duplicated so that they process all assigned tasks alternately."
   - Parallel tasks: "parallelised task is assigned to more than one station. In addition to their regular work content, stations process the parallelised task interchangeably."
   - Neither type of parallelisation is present.
6. Buffers:
   - Unlimited/limited capacity buffers: When in-process workpieces can be stored between stations.
   - Unbuffered line: When a station can only move the finished workpiece forward if the following station is empty, or at a synchronised time.

The assembly systems analyses of this thesis employ slightly different assumptions depending on the goal and scope of each case.

3.2.2 Performance evaluation models

The general framework for analysing the performance of an assembly system consists of a series of *inputs*, interpreted by a *model* representing the system, which in turn produces an *output*, depicted by Figure 3.6. Such output can be evaluated using different measures, or Key Performance Indicators (KPIs).

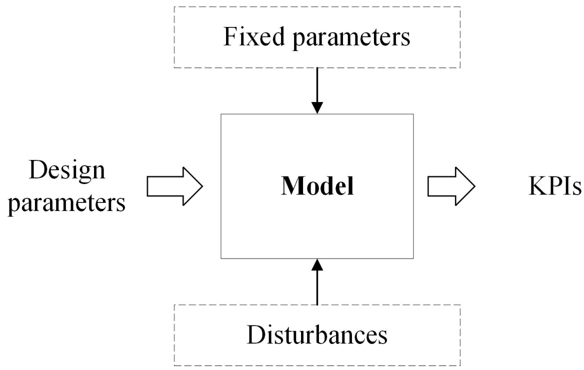


Figure 3.6: Assembly systems performance evaluation general framework of analysis.

Input parameters

Regarding the input variables (or parameters), it is possible to differentiate two main groups: design and fixed parameters, which will be explained together, and disturbances.

Design parameters describe aspects of the assembly system relatively under control or that can be directly modified to obtain the desired outcome. On the other hand, fixed parameters cannot be easily altered, because they depend on external factors –e.g. the customer demand or the work content of a certain product– or changing them is beyond the scope of the analysis at hand. In consequence, some variables, such as the number or layout of manual assembly stations, can be considered fixed or design parameters depending on the investigation goals and scope.

The following list includes most of the design/fixed parameters and notation employed. Note that some additional, analysis-specific variables will be defined and used in subsequent chapters.

BC	Buffer capacity: maximum number of work-in-process units between workstations.
B_{CO}	Number of batches of the same product family before changeover.
CT	Cycle time
J	Number of automated workstations.
K	Number of manual workstations in an assembly system.
L	Number of assembly lines.
LB	Line balance.

M	Number of product models. Depending on the scope of a certain analysis, this number can refer to final product variants (i.e. references) or product families, each one sharing the main production characteristics.
Q	Batch size
T_s	Setup time: necessary to adapt the workstations in order to produce a different product model.
T_p	Processing time: Time necessary to perform the assembly tasks assigned to a workstation.
T_t	Milkrun transportation time: Time required by the milkrun train to cover the route between the in-plant warehouse and the points of use at the assembly line.
T_h	Milkrun operator handling time: Time required by the milkrun operator to load or unload component containers to the points of use.
W	Number of workers. Usually (but not always) equal to the number of stations.
WC	Work Content: Total aggregate processing time to assemble a product from the beginning until it is finished.
WC_R	Work Content ratio: Ratio between the largest and the smallest work content among the products of an assembly line.

Disturbances are different from other input variables because they present a *stochastic* behaviour. Stochastic variables can be described using a random probability distribution that may be analysed statistically, although it is not predictable. These parameters are used to represent the non-deterministic nature of manual processing times and quality control rates, among others. While discrete events simulation models are designed to incorporate stochastic parameters, analytical mathematical models are considered to be more limited in this regard [269, 270].

The following parameters express the ratio between the mean and standard deviation of the probabilistic distributions used to model stochastic disturbances.

CV_p	Processing time variability
CV_s	Setup time variability
CV_c	Conforming pieces per container variability
CV_q	Batch size variability

Models

In opposition to *optimisation* models—which generate a set of decisions or courses of action to maximise the performance of production systems—*performance evaluation* models "estimate the measures of a system performance for a given set of decisions and system parameters. These models rely on techniques of stochastic processes, probability, and simulation." [271, p.4]. There are many different tools of evaluative models for discrete production systems. A top-level categorisation would differentiate between analytic models and simulation models, among others [272]. These are the two types of performance evaluation models that have been used in this thesis: mathematical and simulation.

Analytic models - which include capacity analysis, queueing, and mathematical programming - are typically very fast, and can capture accurately some advanced features such as rework, batch processing or re-entrant material flows. Their results, consisting of a single number for each KPI, are easy to interpret. However, these models usually rely on restrictive assumptions, meaning that they are not appropriate for all kinds of production scenarios.

Simulation, on the other hand, "in this context refers specifically to computer-based discrete event simulation" [273, p.18]. This modelling tool can capture virtually any level of detail, including both dynamic and stochastic (random) behaviour. Its downside is that it requires superior computational power, takes longer to run, and its results can be more difficult to interpret because it requires statistical analysis of the simulation outputs [272].

The specific features of the models used in this will be detailed in Chapter 4 and Chapter 5.

Output variables

Modern assembly operations require multi-faceted measurements to fully understand the performance of such systems. While the first industrial focus was to control and minimise production costs, later productivity (or production efficiency) became the key measure [12]. Lean Production highlighted the importance of minimising the delivery time to customer orders and used lead times as well as inventory measures as indicators of efficiency. In recent times it is considered that a set of KPIs is needed to assess the operational situation of a production system.

Assembly performance measures typically look at efficiency measures such as "assembly throughput, capacity, lead-time, in-process inventory, availability, flexibility, quality, cost per assembly" [9, p.36], depending on the situation-specific goals. The selected KPIs need to keep a balance between simple and easy-to-understand measures (which are directly applicable by industry practitioners) and more complex, compound indicators that can depict better a particular situation.

The KPIs used in this thesis are derived from the following three main performance measures [9, p.36]:

1. Throughput (Th): "the rate of good-quality assemblies produced by an assembly system". The maximum throughput is also named line capacity. Over a fixed period, the aggregate throughput is the total output of the system. Improvement goal: increase throughput.

2. Productivity (P): the ratio between the production rate and the input resources required. Improvement goal: increase productivity.
3. Lead time (LT): "total time required to produce one assembly including all waiting time." Improvement goal: decrease lead time.

The three main performance measures have been related to nine Key Performance Indicators:

$Output$	Output: Total number of conforming units produced.
Th	Throughput: Production rate of conforming units.
P_{Line}	Line productivity: production rate of conforming units per operator.
P_{Labour}	Labour productivity: percentage of time that operators spend adding value to the in-process units.
P_S	Surface productivity: production rate of conforming units per operator and surface unit.
U	Milkrun utilisation: fraction of total available time that the supply chain operator is busy (picking components at the warehouse, driving the milkrun train and handling containers to load/unload components).
S	Stock at assembly line: stock level of components held in the assembly line.
LT_B	Batch lead time: time for a batch of units to be finished from the moment the last unit of the previous batch is finished.
LT_U	Unit lead time: time for a unit to be finished from the moment it starts being assembled.

3.3 Industry case: the Cooktop Company

This Section introduces the study case: industry, product, production system, demand (Subsection 3.3.1), and then introduces the assembly line under study (Subsection 3.3.2).

3.3.1 Introduction to the industrial study case

As part of the DIGIMAN4.0 consortium, this thesis project could collaborate with an industrial partner, the Cooktop Company, which is a global enterprise designing, manufacturing and distributing white goods. The home appliance industry is a highly competitive market, which drives cost efficiency. The study case analysed here corresponds to a manufacturing facility which specifically deals with gas cooktops (discrete manufacturing). Gas cooktops deal with a particular global market with multiple national and international regulations and technical specifications which add variability to the global mass customisation demand trend.

Product and assembly system: gas cooktops

The Cooktop Company production plant located in the North of Spain has a gas cooktop product portfolio of c. 500 references. The references are grouped in product families and product lines depending on some key product characteristics such as its size (e.g. 30, 60, 75 or 90 cm), number of hobs (from 1 to 6 per cooktop) or the hob top material (e.g. steel, ceramic, glass) and finish (e.g. enamel). There are seven distinct product lines (PL) in this facility, and each product line is comprised of 5 to 20 product families (PF). In turn, each product family consists of up to 25 product references. Each product line is assembled in an assembly line, capable of efficiently handling a vast number of related products.

All seven product lines add up to an aggregate demand of over 500k units per year. While some product lines experience high demand, others add up to as little as one production batch per year. The product line-family demand pattern is also replicated at a product family-reference level and will be looked at in further detail later on. The variable demand pattern drives the reduction of production batch sizes to limit the low-demand references shelf time and warehouse occupation. However, smaller production batches decrease the production productivity and thus increase the average production cost of such references, which if transferred to the final customers further reduces their demand, especially in a strongly commoditised market such as home appliances.

The top three most demanded product lines are assembled in semi-automated lines, which have cycle times of approximately 70 to 120 seconds. They consist of eight manual stations alongside several partially automated stations (e.g. for screw fastening after manual placement of the components) and three fully automated stations which perform laser engraving and in-line quality control tests. Semi-automated lines present shorter cycle times and increased line productivity and therefore lower costs per unit. However, these traditionally automated stations require heavy investments demanding high production volumes of very similar products, which restricts them from assembling cooktops of a single product line.

On the other hand, the product lines presenting lower demand are produced in fully manual assembly lines, which have cycle times in the range of 150 to 280 seconds, and consist of 3 to 5 workstations. They leverage the inherently superior flexibility of human operators. The absence of rigid automation allows them to deal with extended product lines, but their lower productivity places these products at a competitive disadvantage in terms of production cost.

Demand profile

The demand patterns faced by The Cooktop Company are quite common across other industries. Figure 3.7 shows a Pareto chart of the cooktop demand volume per product line. Note that the three product lines with higher demand (above 100k units per year) were already been produced in semiautomated assembly lines;

since the higher production volume allowed them to benefit from the increased productivity brought by automation. Product lines 4 to 7, on the other hand, each present such a low demand volume that introducing traditional automation would not be economically viable.

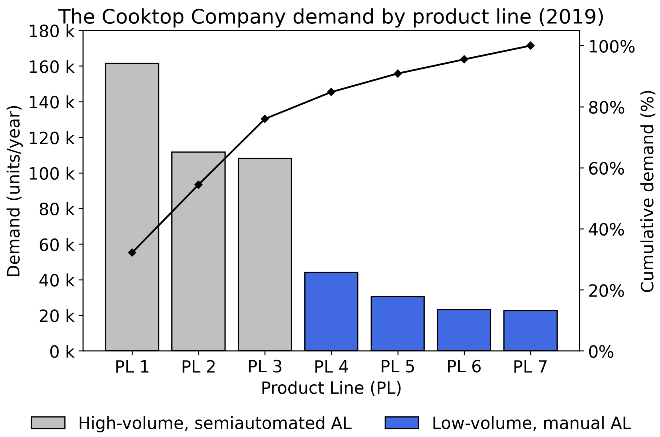


Figure 3.7: Demand by product line (PL) at The Cooktop Company (2019). Product lines 1–3 (grey) correspond to already semiautomated assembly lines. Product lines 4–7 (blue) are low-volume, and were assembled on manual assembly lines.

Furthermore, Figure 3.8.a and Figure 3.8.b drill down on the demand volume of the two product lines with lower demand. These Pareto charts reveal a similar demand volume distribution pattern: a few (three) product families account for the majority (70-80%) of the demand volume. A more detailed look at the number of product references in each product family highlighted that the demand of the high-runner product families is atomised as well. This allows us to conclude that The Cooktop Company faces high-mix low-volume demand, in line with the framework of mass customisation.

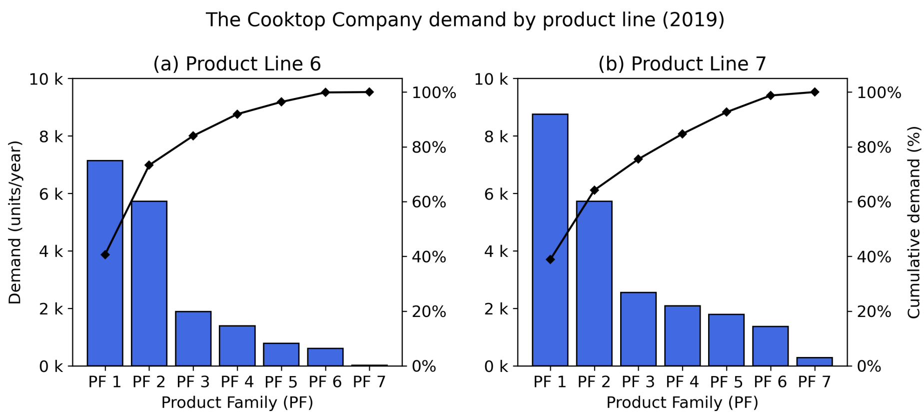


Figure 3.8: Demand by product family (PF) at The Cooktop Company (2019): (a) product line (PL) 6, (b) product line 7.

3.3.2 Manual assembly line under study

Among the assembly lines of The Cooktop Company, three manual assembly lines are analysed in this subsection, and its main features are characterised, building up the industrial study case to be used in later chapters. Firstly, the lines will be described and classified using the previously defined framework, focusing on the key assumptions that analytic or simulation models will use. Then, changeover setup times data will be explored to stress the multi-model aspect of these lines.

Product lines no.4, 6 and 7 manual assembly

This thesis focuses on the high-mix low-volume assembly lines and the ways to integrate automation to increase their productivity while maintaining a high degree of their current flexibility. Figure 3.9 and Figure 3.10 illustrate the state of the lines during the thesis project. Figure 3.11 shows schematically the layout of the assembly lines, which will be modelled in subsequent chapters.

Figure 3.9: Product line no. 7 manual assembly line (on site).

The classification framework introduced in Section 3.2 can be applied to these manual assembly lines. Regarding the product precedence, they are multi-model lines, since each of them deals with a product line consisting of many different product families. Detail on the setup times necessary to adapt the workstations to different products will be presented later on.

Their processing times are assumed to be stochastic since the assembly time data suggests that considering variability is necessary to model the assembly system realistically. Later Section 5.3.2 details the analysis carried out to characterise the manual assembly time variability. The workpiece movement is asynchronous unpaced since workers are not limited by cycle times and can push the processed workpiece to the buffers in-between stations. The assembly lines under study, as

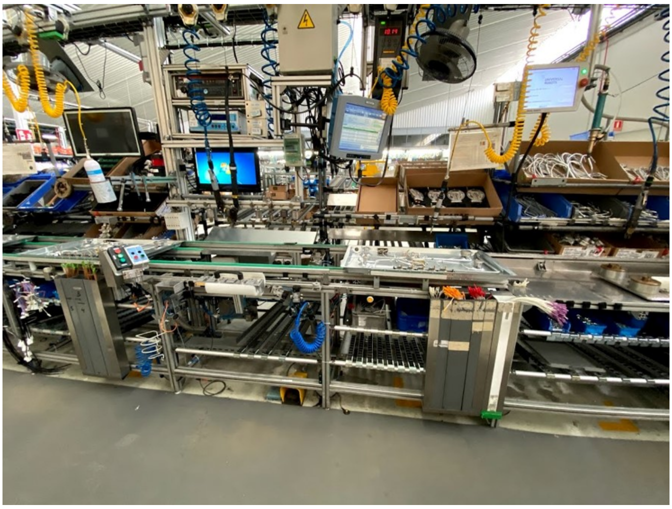


Figure 3.10: Product line no. 4 manual assembly line (on site).

shown by the diagrams in Figure 3.11, present a single-line layout, without any type of parallelisation in their current state. This potential aspect will be explored further in Chapter 4 and Chapter 6. Finally, these are buffered lines with limited capacity. The buffers between stations can typically hold a maximum of one in-process unit, which allows to mitigate the worst effects of processing time variability without excessively increasing the assembly line floor space.

Later Chapters 5–7 describe in further detail the assumptions made to model these assembly lines.

Setup times of multi-model assembly lines

Every time an assembly line switches from producing a product reference, assembly operators need to perform a series of change operations to adapt the stations to the new (incoming) product model.

Setup time is defined as the time employed by assembly operators to change over the fixtures, tools, quality control equipment and component containers (i.e. boxes, pallets, trays).

The elements to be adjusted on each workstation belong to two distinct groups: (1) fixtures and tools, which are present on all workstations, so that the total setup time increases if the number of stations rises; and (2) component containers and quality control equipment, whose total number is independent of the number of workstations. This distinction will be important for the modelling assumptions in Chapter 4.

Setup times typically depend on both the outgoing model (*model out*) and the incoming model (*model in*). Table 3.1 and Table 3.2 show the setup times for product lines no. 6 and no. 7, respectively. This data was obtained by the

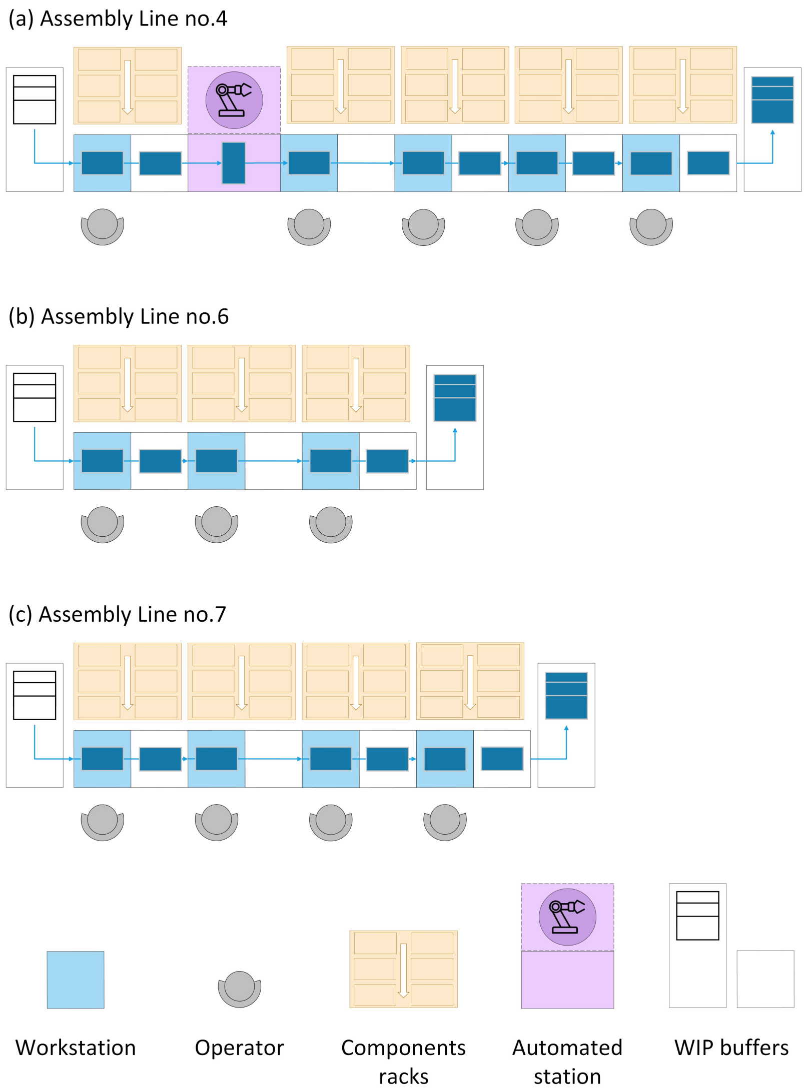


Figure 3.11: Schematic diagram of The Cooktop Company manual assembly lines.

Cooktop Company production department by timing the changeovers. Note that the setup times in the diagonal of the table (i.e. corresponding to a changeover between models of the same product family) are greater than zero. This implies that for product models within a product family—whose cycle times are assumed identical—there are enough differences so that the workstations need to be adjusted. In consequence, the Cooktop Company assembly lines need to be modelled as multi-model AL.

Since the setup time of one station can (and usually is) different from another station, during changeovers it is possible that one or many assembly line operators must wait (*idle*) for an upstream station operator to complete his or her setup,

Table 3.1: Setup time (min), double entry table for product line no. 7.

	Model in					
Model out	*1702*	*1706*	*1703*	*1705*	*1701*	*1704*
1702	3.52	5.20	4.88	7.76	9.20	4.80
1706	4.16	3.44	4.24	6.80	7.44	4.00
1703	4.24	4.88	3.36	8.24	8.00	4.24
1705	4.56	4.56	4.56	4.16	5.76	4.56
1701	4.88	4.88	4.88	5.60	5.04	4.88
1704	5.92	6.72	6.16	9.12	9.76	2.96

Table 3.2: Setup time (min), double entry table for product line no. 6.

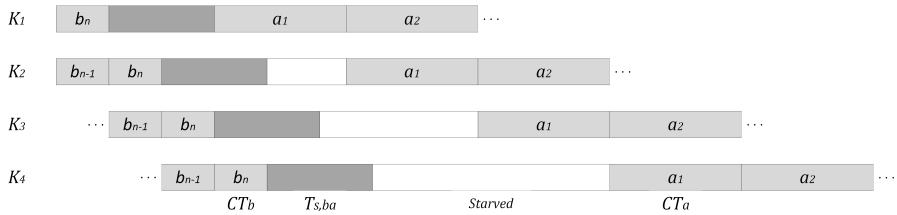
	Model in							
Model out	*2808*	*2802*	*2807*	*2801*	*2803*	*2806*	*2804*	*2805*
2808	4.38	4.56	4.62	5.04	5.16	4.02	4.26	4.08
2802	4.38	4.56	4.44	4.74	4.8	4.02	4.26	3.90
2807	5.10	5.40	4.86	5.16	5.28	4.44	4.68	4.32
2801	4.80	4.98	4.80	5.04	4.80	4.44	4.62	4.26
2803	5.46	5.76	5.10	5.52	4.86	4.74	4.74	4.32
2806	5.28	5.58	5.34	5.76	5.88	4.38	4.98	4.8
2804	5.58	5.88	5.16	5.58	5.70	4.86	4.86	4.68
2805	6.48	6.78	6.12	6.54	5.52	5.76	5.76	4.86

or that an operator becomes *blocked* until a downstream station finishes its setup. This leads to changeover losses, which are always equal to or greater than setup times.

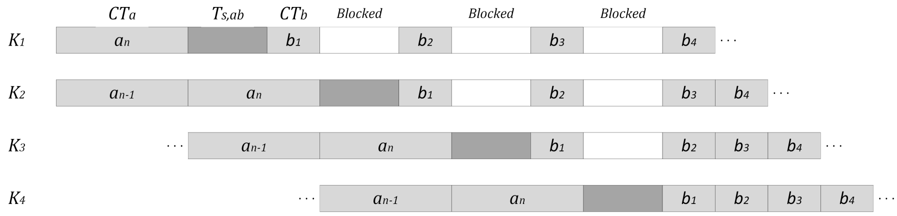
Changeover time is defined as the time employed by the assembly operators from the moment the outgoing product model leaves the line until the first unit of the incoming product model is finished.

Figure 3.12 depicts three product changeover situations when switching from model b to model a (or vice-versa). Product models a and b present different cycle times (CT_a, CT_b). In this example, four workstations ($K_1 ... K_4$) process the last units of a production batch ($b_n, b_{n-1}, ...$) before needing to carry out setup activities of duration $T_{s,ba}$. As soon as possible, each station starts assembling units of the next model ($a_1, a_2, ...$).

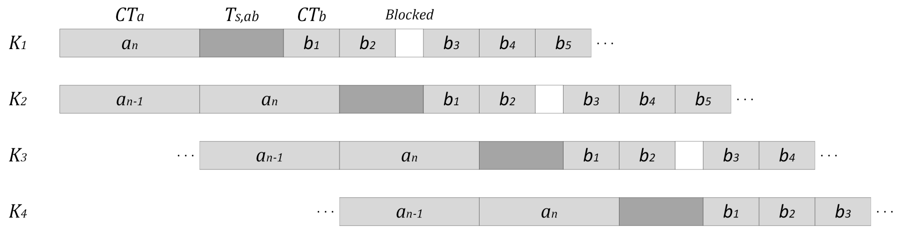
Note that even if all station setup times are equal, changeover losses can occur due to cycle time differences between the incoming and outgoing product models, as shown in Figure 3.12a and Figure 3.12b. Note that buffer capacity (BC) in-between assembly stations protects the line from changeover losses (see Figure 3.12c, but increases the line's WIP and floor space occupation. The analytical model used in the next Chapter 4 specifically focuses on realistically estimating changeover losses because they become increasingly influential on assembly line performance as batch sizes are reduced and product changeovers are more frequent as a result



(a) Changeover with $CT_{in} < CT_{out}$: idle time appears due to starvation.



(b) Changeover with $CT_{in} > CT_{out}$ and no WIP ($BC = 0$): blocking time appears.



(c) Changeover with $CT_{in} > CT_{out}$ and a WIP unit ($BC = 1$): reduced block time.

Figure 3.12: Changeover losses due to cycle time differences between the incoming and outgoing product models. (**a**) Changeover with $CT_{in} < CT_{out}$, which causes the apparition of idle times which propagate as the number of stations grows. (**b**) Changeover with $CT_{in} > CT_{out}$ and no WIP buffer between stations. Operators become blocked. (**c**) Changeover with $CT_{in} > CT_{out}$ and WIP buffer capacity (BC) of 1 unit between stations. Operators block time is mitigated by WIP buffer.

of high-mix low-volume demand.

3.4 Summary

In this chapter, a human-centred model was presented, explaining, from the point of view of the assembly operator, which of its productive functions would be affected by Industry 4.0 technologies. A clear differentiation appears between the technologies used by the operator to perform its functions (hardware technologies), and the technologies used by the Production Support Departments –i.e., not directly by the operators (software technologies). This chapter also introduced the assembly operations performance evaluation framework to be used in all the remaining chapters of this thesis, as well as two key available tools to do so: mathematical (analytical) models and discrete events simulation. Finally, The Cooktop Company industrial study case of assembly operations facing high-mix low-volume demand was presented.

This chapter makes two key contributions towards understanding how to increase assembly operations productivity and flexibility under high-mix low-volume demand:

1. Based on an operator-centred Industry 4.0 framework specific to manual assembly operations, a clear classification between Industry 4.0 digital technologies according to their relationship with assembly operators. Hardware technologies (e.g. collaborative robots, augmented/mixed reality) are in direct contact with the operators, as opposed to software technologies (e.g. big data, machine learning, cloud computing), which are employed by supporting departments and only indirectly affect assembly operators.
2. The most relevant input and output variables to be used using a sound general analysis framework have been established.

The following Chapter 4 employs mathematical modelling for a preliminary evaluation of manual assembly systems to identify the most critical factors affecting these systems' performance. A simulation model is developed in Chapter 5 for a more detailed analysis of flexible assembly operations.

CHAPTER 4

Identifying the critical factors: mathematical model

This chapter introduces a mathematical analytical model which focuses on product changeovers of assembly lines. The model is then employed along with Design of Experiments techniques for investigating the most critical factors to flexible assembly systems performance. The goal of this preliminary study is to lay the foundations for the analysis of improvement opportunities in the assembly line design.

Section 4.1 explains the model's assumptions and scope, based on the framework introduced in Sections 3.1 and 3.2. Section 4.2, which was published as a conference article in 2021, applies the mathematical model to the industry study case of Section 3.3 along with Design of Experiments techniques to identify the most critical factors affecting the system's KPIs. Sections 4.3 and 4.4 expand on the validation of the mathematical model and the significance of one of the modelling assumptions regarding changeover time losses. Finally, Section 4.5 summarises the chapter and presents its contributions.

4.1 Realistic changeover mathematical modelling

A mathematical analytical model was developed, focusing on the product changeover time losses of multi-model assembly lines. It allows us to calculate changeover lost times quickly and accurately, which are typically underestimated by assuming they are approximately similar to setup times ($T_{co} \approx T_s$). This is particularly relevant when considering that high-mix assembly lines imply large variations in product cycle times (i.e. high work content ratio, WC_R) and frequent changeovers.

Moreover, large WC_R results in acute sequence-dependent changeover times which are rarely modelled as such. This simplified mathematical formulation enables a quick initial assessment of the assembly lines' operational KPIs with low computational and professional time costs compared to setting up a discrete events simulation model or employing advanced mathematical formulations.

The main area of application of this model would be high-mix low-volume demand scenarios where product changeovers are very frequent and constitute a major driver of line productivity. Devised as a preliminary assembly operations design tool, this model also allows for a more precise evaluation of changeover times –as a function of incoming and outgoing product models, number of WIP units, number of workstations, etc.– to be used as input data in optimisation techniques for scheduling approaches (e.g. travelling salesman scheduling problem).

The following Section 4.1.1 introduces the model scope and assumptions, and then Section 4.1.2 provides details of the deterministic algorithm that were not included in the conference article of Section 4.2.

4.1.1 Mathematical model assumptions, scope and algorithm

The main disadvantage of mathematical models is their stated assumptions, as they may not be valid in—or accurately represent—the real world [269]. The mathematical model developed is based upon the underlying assumptions, expressed in the terms of the assembly line classification by Boysen et al.[268]:

- Product precedence: multi-model line, since setup times are not negligible and are sequence-dependent. Setup times per station are constant, regardless of the number of workstations.
- Processing times are considered static and deterministic.
- The movement of workpieces is paced, and the time required for it is negligible compared to the assembly processing times.
- Strictly single-line layout.
- Neither type of parallelisation is present.
- Buffers: the model features limited capacity WIP buffers in-between workstations.

The scope of the model can also be expressed using the operator-centred framework detailed in the previous Section 3.1. As shown in Figure 4.1, this model includes the human operators (innermost layer of the framework), three out of the four main operator functions (second layer: assembly, changeover and quality control), and only incorporates the assembly elements of the third layer directly related to the assembly functions: workpieces, workstations, fixtures. Although this mathematical model takes quality control into account, it neither includes any considerations regarding the equipment employed to carry it out nor requires any interaction with the quality control department (fourth layer of the framework).

Figure 4.1: Scope of the mathematical model illustrated using the operator-centred conceptual framework.

Algorithm 1 Deterministic performance evaluation in terms of productivity, throughput and batch lead time in paced multi-model serial assembly lines with K stations, end of line quality controls and changeovers between batches of different product models.

Input: K, Q, $WC(m)$, $LB(m)$, $FTY(m)$
Output: P_{Labour}, LT_B, Th
for all product models m **do**
    Calculate cycle time
end for
for batch i of product model m **do**
    Calculate time to build conforming units
    Calculate time to build defective units
    Calculate total time to build the batch i
    Calculate total time to complete the batch i including changeover
    Calculate time recovered
end for
Calculate average labour productivity
Calculate maximum batch lead time
Calculate average throughput

The mathematical model, whose formulation is listed in the next section (Equations 4.1–4.9), is expressed by Algorithm 1. It uses the following logic, according to the assumptions previously stated:

1. Workpieces are processed in a serial assembly line with buffers between the stations.
2. Each station processes units of a certain product model until a batch is completed.
3. Then, a setup must take place to make the station ready for assembling a different product model.
4. An end-of-line quality control determines if a product is defective. Thus, the assembly line will assemble, on average, more units than the final number of conforming products.

4.1.2 Changeover time estimation algorithm

As mentioned in the previous chapter, the manual assembly lines under study experience changeover time losses due to the necessary setup activities between batches of different products. These activities consist mainly of three groups of tasks: fixtures, tools and component containers.

The necessary time to perform the setup tasks depends on the outgoing and incoming product models as well as the particular workstation. However, while the time required to adjust fixtures and tools depends on the assembly line number of stations, the time needed to swap the component containers only depends on the outgoing-incoming models duple. The mathematical model which will be presented in the next Section 4.2 assumes that the setup time is directly proportional to the number of stations, which might be overstating the setup time losses of longer assembly lines—featuring a greater number of stations—compared to shorter lines. The impact of this assumption will be further analysed in Section 4.4.

Setup time is not the only possible source of changeover time losses. When the cycle time of the incoming product is different from that of the outgoing product, additional losses can occur –illustrated by Figure 3.12– as a result of idle or blocked operators. This effect can be mitigated by the existence and capacity of WIP buffers between stations.

The mathematical model described in 4.2.2 presents the analytical equations to estimate the assembly line performance measures. However, it lacks the formulation of the changeover losses algorithm, which will be used in Equation 4.5, following Algorithm 2 shown below.

The key assumptions for this algorithm are the following:

1. Operators start the setup activities as soon as they finish the last unit of the previous batch $(i-1)$, without needing to wait for the first unit of the incoming model (i) to arrive at their workstation.

2. To start the assembly of the first unit of the incoming product, operators need to have completed the setup of their corresponding workstations, and that the unit has been finished by the previous station.
3. If the incoming model is *faster*—i.e. $CT_i < CT_{i-1}$, the operators may become blocked. For example, if the setup times are equal across all workstations, the first operator would finish the first unit of the incoming batch before the following operator has finished the setup (cf. Figure 3.12b). This is affected by the WIP buffers between stations (Figure 3.12c).
4. If the incoming model is *slower*—i.e. $CT_i \geq CT_{i-1}$, the operators may become idle. This case has a greater effect on changeover losses because the waiting time at each station becomes larger as the number of stations increases (Figure 3.12a).

Algorithm 2 Deterministic estimation of total changeover time losses (T_{co}) from product model $i-1$ to model i in paced serial assembly lines with K stations (index k) and limited WIP buffer capacity (BC) between stations.

Input: CT_{i-1}, CT_i, K, $T_s(i-1, i, k)$, BC
Output: Total changeover time loss from batch $i-1$ to i.
for each workstation k **do**
    if $k = 1$ (first station) **then**
        Start time of last unit of batch $i-1$ set to zero
        Calculate finish time of batch $i-1$
    else if $k \in \{2, .., K\}$ (subsequent stations) **then**
        Calculate start time of last unit of batch $i-1$
        Calculate finish time of batch $i-1$
    end if
    Calculate end of setup
    Calculate start time of first unit of batch i
    Calculate finish time of first unit of batch i
    if $CT_{i-1} \geq CT_i$ **then** ▷ Potential block, see Figure 3.12b
        if $k \in \{1, .., K-1\}$ (any station except the last one) **then**
            Calculate changeover time loss
        else if $k = K$ (last station) **then**
            Calculate changeover time loss
        end if
    else if $CT_{i-1} < CT_i$ **then** ▷ Potential starvation, see Figure 3.12a
        if $k = 1$ (first station) **then**
            Calculate changeover time loss
        else if $k \in \{2, .., K\}$ (subsequent stations) **then**
            Calculate changeover time loss
        end if
    end if
end for
Calculate total changeover time lost

4.2 Labour productivity in manual assembly

This section includes the conference article presented at the 9th Manufacturing Engineering Society International Conference (MESIC) in June 2021 [274].

After the article abstract below, the following subsections correspond to the article's Introduction (4.2.1), Methodology (4.2.2), Results (4.2.3) and Discussion and Conclusion (4.2.4). The following Section 4.3 includes further details of the validation results and the experiment design that were not incorporated in the article.

Article title:

Labour productivity in mixed-model manual assembly 4.0

Article abstract:

Manual assembly lines productivity is threatened by the increased complexity brought by mass customisation demand trends. Industry 4.0 offers potential solutions to address this situation, but the methodology to implement it is still a subject of study. As a preliminary step, this article aims to identify the dominant factors affecting the Key Performance Indicators of mixed-model assembly lines. To do so, parametric and discrete-events simulation models were developed, and Design of Experiments techniques were used. The results show that the key drivers for assembly line performance are number of work stations and batch size, and that increasing the work content ratio of the products assembled does not interact negatively with other factors. The results presented here pave the way for developing Industry 4.0 projects that address specifically the most relevant factors that affect assembly lines performance.

4.2.1 Introduction

The demand trends in the recent decades are the mass customisation of products or even the mass personalisation of goods [28]. The growing number of available options for both final consumers and industrial customers requires focusing on increasing the flexibility of assembly systems while maintaining high productivity levels [13, 165]. The advances in new digital technologies that could bring forward a 4th industrial revolution were conceptualised under the tag 'Industry 4.0' by a German strategic programme, and are namely: Big Data and Analytics, Autonomous robots, Simulation, Horizontal and vertical system integration, the industrial Internet of Things, Cybersecurity, The Cloud, Additive Manufacturing and Augmented Reality [8]. Some of these technologies arrive with the promise of new opportunities for assembly systems design and operations, allowing them to fulfil the latest market requirements [24]. In particular, manual assembly lines and cells show potential for improvement when facing the complexity associated with producing a large number of products – or variants of similar products [74].

Despite new technologies have been developed and their potential benefits have been outlined, implementation methodologies are still a hot topic [27]. The focus in this article is therefore to identify the dominant factors affecting the mixed-model manual assembly lines Key Performance Indicators (KPIs) – such as labour productivity, line capacity and lead time – as a preliminary step in order to ensure that Industry 4.0 implementation projects address the right areas, ensuring that the operational business goals are achieved.

From the initial analysis of the situation, a list of relevant factors was put together along with the operational KPIs that measure the system performance: productivity, lead time and line capacity. Design of Experiments (DoE) is used to find out which factors and their interactions have the greatest effects on the KPIs, and therefore are more important for the system performance. DoE allowed to prepare two phases of analysis: Screening (I) and Interactions (II).

Aiming at exploring how to use a commercial software for mixed-model assembly line simulation, an initial parametric model was used as reference, followed by a second model which uses a commercial simulation package (Methodology, Section 4.2.2). In both cases, parametric—MATLAB®—and simulation—-FlexSim®—-software tools are employed to calculate the Output KPIs from different values of Input factors (Results, Section 4.2.3). The results of the two models are compared and conclusions are extracted, along with a final discussion of the limitations and future outlines of this study (Discussion and Conclusions, Section 4.2.4).

Data from a real case of study is used to validate the results of the analysis. The input data for the simulation is based on the situation of a manufacturer of white goods located in northern Spain. The company is evaluating merging two mixed-model manual assembly lines into one, which would increase the complexity of managing the line, but could bring operational performance benefits if done correctly – especially in terms of labour productivity, without compromising operators working conditions or product quality. Industry 4.0 would be the enabler of such complexity-dealing transformation, but it is deemed necessary to ensure that the investment only targets the critical elements that would allow improving the desired KPIs.

4.2.2 Methodology

This section presents declares the input variables and output KPIs used, describes the two analysis models developed and their verification, and the Design of Experiments to be used in the next section. Figure 4.2 summarises all of this information and schematises the followed methodology considered in this study.

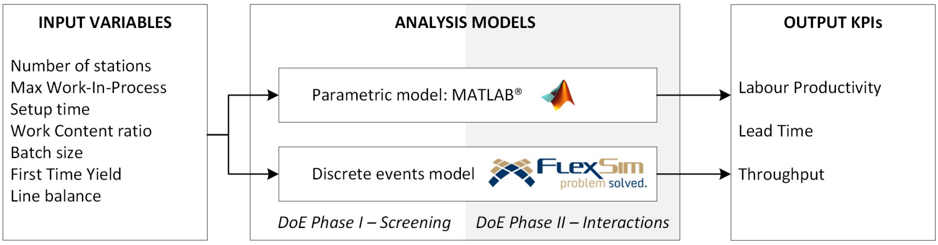


Figure 4.2: Diagram of Input factors and Output KPIs used for the analysis of mixed-model manual assembly lines.

Variables considered

Aiming to explore the effect of various relevant factors on mixed-model manual assembly lines, the following seven were selected for this analysis: Number of workstations, maximum Work-in-Process buffer capacity between stations (BC), Changeover Time, Work Content Ratio between different models, Batch size, First Time Yield (FTY) and Line Balance. Factors related to internal logistics, lack of Quality and Overall Equipment Effectiveness (OEE) of assembly equipment were not considered in this study in order to keep the models simple, and they will be included in future research. The KPIs of interest are three:

- Labour productivity (P_{Labour}, %): ratio of operator value added time over the total time employed.
- Batch Lead Time (LT_B, hours): time to assemble a complete batch of product.
- Throughput (Th, units/hour): average output of the assembly line per unit of time.

Table 4.1 includes the input and output variables with the abbreviations used in this article, as well as the base values from the industrial case study. The work content ratio used is the result of dividing the maximum work content by the minimum work content used in a given scenario.

Models for Analysis

In this work, two models have been used. A simple initial model was developed in order to establish a baseline to which compare later and more complex models. Such model needed to be versatile and scalable, so the parametric tool MATLAB® was used. Aiming at exploring the potential gains of using commercial software for mixed-model assembly line simulation, the free version of the software FlexSim® was chosen.

Parametric model: MATLAB®. A parametric model was employed to calculate the KPI values as a function of the input factors. The software package MATLAB® (R2019b, The MathWorks Inc., Natick, MA, United States) was chosen to implement an algorithm relating the variables presented before.

Table 4.1: Input variables and output KPIs used in models.

Type	Description	Notation	Case study base values
Input	Number of Stations	K	4 stations
	Work-in-Process buffer capacity	BC	1 unit
	Station setup time	T_s	480 s
	Line balance	LB	99%
	First Time Yield	FTY	95%
	Batch size	Q	48 units
	Number of models built in the line	M	4 models
	Work Content	WC	600 ... 1400 s
	Work Content ratio	WC_R	1 - 2
	Cycle time	CT	~ 150 ... 350 s
Output	Labour Productivity	P_{Labour}	~ 90%
	Lead time	LT_B	~ 5 h
	Throughput	Th	~ 10 units/h

Firstly, for each product model m, the cycle time is calculated based on the work content (WC), number of stations (K) and line balance (LB) - Equation 4.1.

$$CT = \frac{WC}{K \cdot LB} \tag{4.1}$$

For each model m, the time employed to build correct and defective units are calculated using Equation 4.2 and Equation 4.3, which use the batch size (Q), number of stations (K), cycle time (CT) and first time yield (FTY).

$$T_{correct} = Q \cdot K \cdot CT \tag{4.2}$$

$$T_{defects} = Q \cdot K \cdot CT \cdot (1 - FTY) \tag{4.3}$$

For each model m, the time used to build the batch is given by the time to build correct and defective units, as shown in Equation 4.4. The time to complete the batch ($T_{complete}$) is calculated by adding the time spent on changeovers (T_{co}) and the time to build the batch, as shown in Equation 4.5.

$$T_{build} = T_{correct} + T_{defects} \tag{4.4}$$

$$T_{complete} = T_{build} + T_{co} \tag{4.5}$$

For each model m, the time recovered (spent assembling correct products) is found using the work content and the batch size, as shown in Equation 4.6.

$$T_{recovered} = WC \cdot Q \tag{4.6}$$

The KPIs can be calculated using Equations 4.7–4.9. Labour Productivity (P_{Labour}) is determined by the sum of time recovered and the sum of time to complete all batches of products. Batch Lead time (LT_B) is calculated as the maximum time to complete a batch, and Throughput (Th) is worked out from batch size (Q), number of models (M), number of stations (K) and the sum of time to complete all batches of products.

$$P_{Labour} = \frac{\sum_{i=0}^{M} T_{recovered,i}}{\sum_{i=0}^{M} T_{complete,i}} \tag{4.7}$$

$$LT_B = \max \{T_{complete,i}\}_M \tag{4.8}$$

$$Th = \frac{Q \cdot M \cdot K \cdot 3600}{\sum_{i=0}^{M} T_{complete,i}} \tag{4.9}$$

Discrete events model: FlexSim®. FlexSim® is a 3D discrete events simulation software for modelling and analysis of manufacturing, operations and logistics systems.

The simulation results were contrasted against the output from the parametric model described in the previous subsection. The free licensing version of the simulation software led to several limitations: (1) a maximum of 30 simulation elements, e.g. stations or buffers; (2) the maximum process flow activities is 35; (3) changeover activities do not start until the new batch of units arrives to a workstation, causing unrealistic additional idle time; (4) the number of different random seeds are limited to just one, preventing any variability analysis.

Due to the aforementioned limitations, two different simulation configurations were used: Configuration A and B. Configuration A maintains the FTY at 100%—disregarding the effects of poor Quality—but in return, allows to overcome the unrealistic changeover limitation mentioned previously. This configuration does not consider BC as a factor neither, since the only source of variability (poor Quality) is neglected. Configuration B considers FTY: two Quality Control checkpoints are implemented in this configuration to evaluate whether a unit has defects, and if this is the case, the unit is sent back to the previous assembly station for in-line reworks, as shown in Figure 4.3.

Verification of the models

In order to compare the two models described previously—parametric and discrete events simulation—a base scenario made of the 7 input factors was used for each

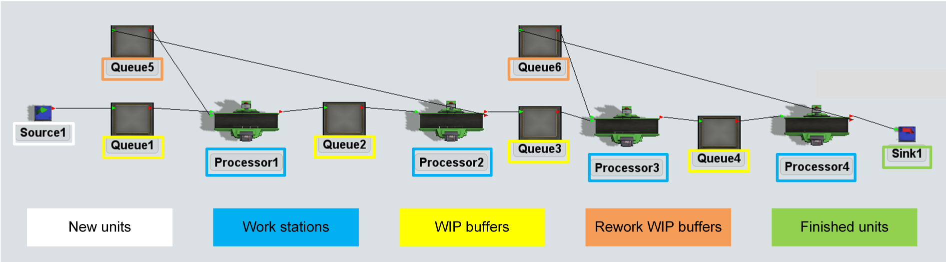


Figure 4.3: FlexSim® simulation model used for Configuration B.

configuration (A and B). From this base scenarios, 24 additional scenarios were generated by changing just one factor at a time (-1 and $+1$ levels), 10 scenarios for Configuration A and 14 for Configuration B. The results of two KPIs (Productivity and Lead Time) were registered to compare the performance of the two models. Both models obtain comparable results for productivity and lead time: the average difference is 2.39%, the standard deviation is 4.58% and the maximum difference is 19.45%, corresponding to the particular case of a large number of workstations, which causes abnormally high idle times during changeovers in the FlexSim® model Configuration B.

Design of Experiments

Considering the relatively high number of factors ($k = 7$ factors, as show in Figure 4.2), the analysis of their interactions and effects on the selected KPIs would require a great number of experiment runs (n^k): 27 = 128 experiments for two levels ($n = 2$) per factor, or 37 = 2,187 experiments for three levels ($n = 3$) per factor. Instead, the analysis was structured in two phases [275]: screening (I) to identify most relevant factors; and analysis of interactions (II) – summarised in Table 4.2.

Table 4.2: Design of Experiments employing two phases due to the large number of factors involved.

Phase	**Goal**	**Experiment Design**	**No. of factors (k)**	**No. of levels (n)**	**No. of runs**
I – Screening	Identify most relevant factors	Fractional Factorial	7	2	16
II – Interactions	Analyse influence and interactions	Full Factorial	3	3	27

The values used for each level (-1), (0) and ($+1$) were chosen by modifying the industry case study values and stretching them slightly beyond what the company considers achievable in the short term, in order to include minimum and maximum range values for each factor.

Phase I – Screening. The Screening phase employs a Fractional Factorial design for 7 factors with 2 levels per factor. Table 4.3 shows the values used for each factor.

Table 4.3: Values used for each factor in the DoE phase I — Screening: Fractional Factorial.

		Values	
Factor	**Code**	−1	+1
Batch Size	A	12 units	48 units
Number of Stations	B	3	8
Max Work-In-Process	C	0	1
Line Balance	D	95%	99%
Station setup time	E	300 s	600 s
First Time Yield	F	95%	97%
Work Content ratio	G	2	3

Phase II – Analysis of Interactions. The Analysis phase consist of a Full Factorial design of 3 factors with 3 levels per factor. The three factors chosen for this phase resulted from analysing the results from the Screening phase. Table 4.4 shows the values used for each factor in phase II - Analysis. The other 4 factors that were not studied in this phase remained fixed at their 0 values.

Table 4.4: Values used for each factor in the DoE phase II – Interactions: Full Factorial.

			Values	
Factor	**Code**	−1	0	+1
Batch Size	A	12 units	24 units	48 units
Number of Stations	B	2	4	8
Work Content ratio	G	1	2	4
Max Work-In-Process	*Fixed*	0	1	
Line Balance	*Fixed*	-	95%	-
Station setup time	*Fixed*	-	480 s	-
First Time Yield	*Fixed*	-	95%	-

4.2.3 Results

The methodology described in the previous section allowed to obtain the following results for each phase of the study.

Phase I — Screening

The experiment results of the design described in Table 4.3 calculated using the MATLAB model described in Subsection 4.2.2 are shown in Figure 4.4 and Figure 4.5.

From the results shown in Figure 4.4, it can be inferred that the two most relevant factors are the Number of Stations (which affects all three KPIs) and the Batch size, which affects Labour Productivity and Batch Lead time.

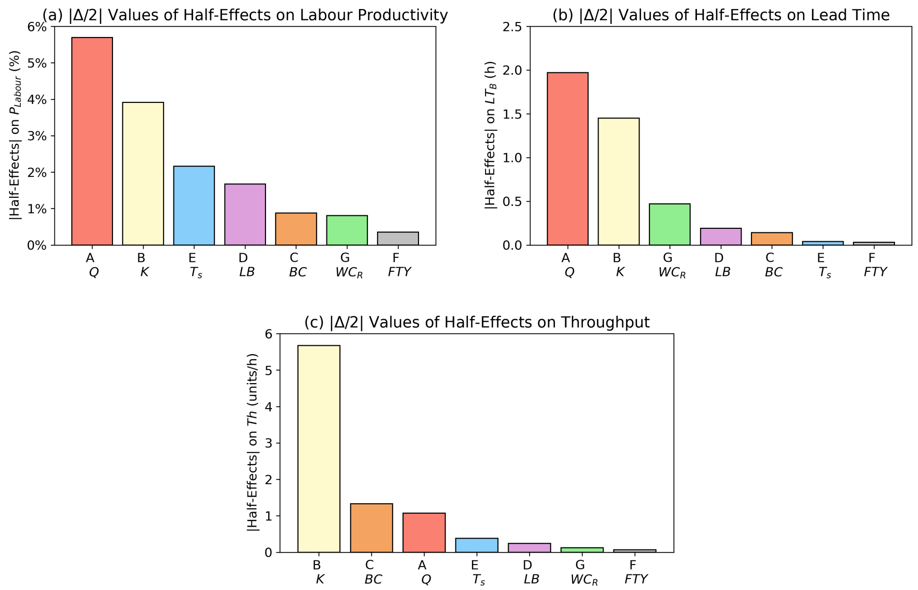


Figure 4.4: Phase I – Screening: Absolute half-effects of input factors on (a) Labour Productivity, (b) Batch Lead Time and (c) Throughput in a Fractional Factorial experimental design.

Phase II – Analysis of interactions

In this phase the focus is the interaction between the most influential factors, namely Number of Stations and Batch size. Since one of the initial goals of the study was to assess the viability of merging two manual assembly lines into one, which would increase the number of models being made and therefore increasing the Work Content ratio of the newly formed assembly line, a third factor—WC_R—was introduced at this stage of the analysis.

The results of the DoE described in Table 4.4 calculated using the MATLAB model described in Subsection 4.2.2 are shown in Figure 4.6. The parametric model was employed because it had been developed specifically to analyse these interactions.

The results presented in Figure 4.6a–c show that although the interaction of factors A (Number of stations) and B (Batch size) is relevant for assembly line Productivity and Lead time, it is secondary to the separate effects of any of the two factors.

4.2.4 Discussion and Conclusions

The results presented in Section 4.2.3, obtained following the methodology described in Section 4.2.2 allow to reveal the most impactful factors affecting the performance of manual assembly lines in terms of Labour Productivity, Batch Lead Time and Throughput. Two models were developed, which results are comparable:

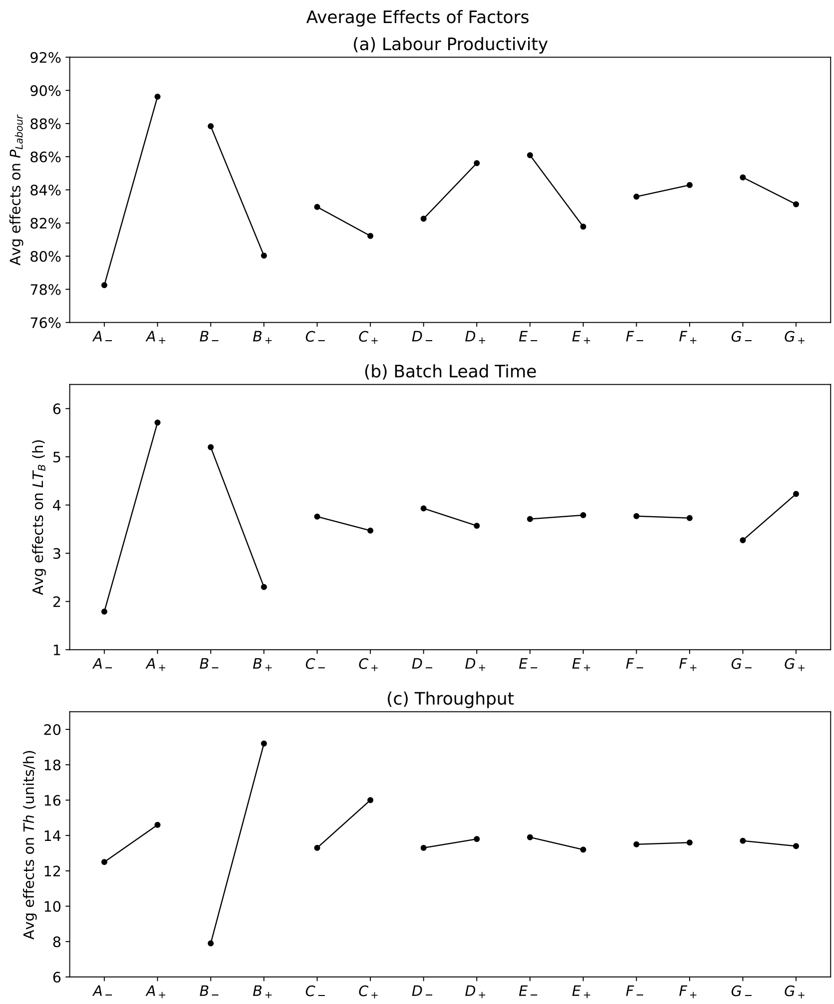


Figure 4.5: Phase I – Screening: Average effects of input factors on (a) Labour Productivity, (b) Batch Lead Time and (c) Throughput in a Fractional Factorial experimental design.

the average difference is 2.39%, the standard deviation is 4.58% and the maximum difference is 19.45%.

It was found that the two most critical factors are the Number of stations and the Batch size. It is important to note that both factors have opposing effects on two of the KPIs – i.e. the increase of Labour Productivity and reduction of Batch Lead Time cannot be optimised simultaneously by changing these two factors alone.

The great importance of the Number of stations is partially explained by the assumption that any additional station needs a changeover time of a similar order of magnitude to that of the existing stations, which may not always be the case. In consequence, the only way of maintaining a high labour productivity when increasing the number of stations (to merge two assembly lines into one or in order

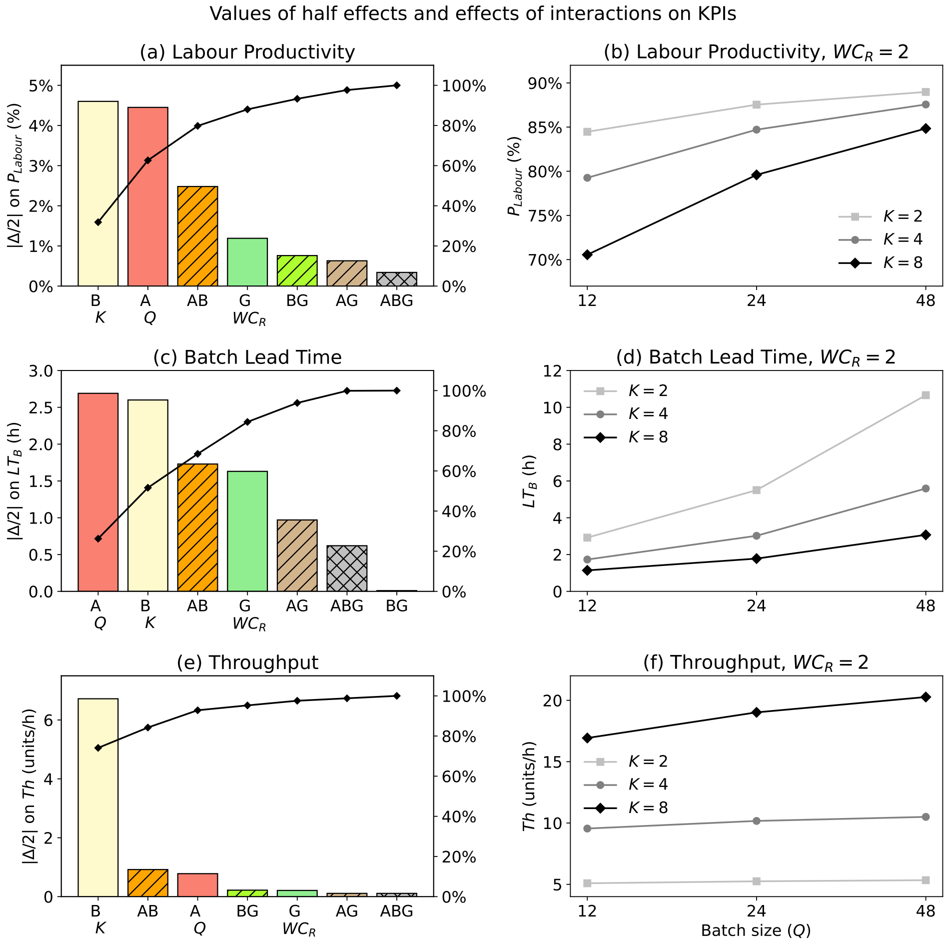


Figure 4.6: Phase II – Interactions: Pareto charts for values of half-effects of number of stations (K), batch size (Q) and work content ratio (WC_R) on (a) Productivity, (c) Lead Time and (e) Throughput; and average effects of K, Q, WC_R on (b) Productivity, (d) Lead Time and (f) Throughput in a Full Factorial experimental design.

to reduce the Lead time) relies on decreasing the changeover time per station to ensure that the total changeover time incurred remains constant or decreases.

The results presented in this article show that an increase in product variety – represented by the variable Work Content ratio – does not interact negatively with any of the two key factors, which suggests that merging two manual assembly lines into one would not suffer from additional Productivity losses. The potential impact of this finding for multi-model assembly lines lies on the assumption that the stations changeover times would not significantly increase as a result of introducing additional models.

In order to maximise the return of investment of any Industry 4.0 solution, they should be aimed at the most influential factors identified before: (1) to address the productivity loss due to the increase in Number of stations required to increase

Throughput and reduce Lead Time, collaborative robots could be integrated in the line. Alternatively, (2) to ensure that the total changeover time remains constant despite an increase in the number of stations, cognitive support to complex or infrequent changeover operations could be provided by Augmented or Mixed Reality.

Future research in this field could focus on enhancing the analysis models by using discrete events software actually incorporating variability, and expanding the model to incorporate the internal logistics constraints due to an increased number of different models in smaller batch sizes. Another potential research route would be scanning the current state of the art Industry 4.0 technologies to find compatible matches for the identified areas as preliminary step before implementing Industry 4.0 technologies in the assembly lines.

4.3 Details of DoE and model verification

This brief section includes some details on the mathematical model verification and the design of experiments used in Section 4.2 that were not included in the conference article [274].

4.3.1 Details of experiment design

Phase I – Screening

Table 4.5 shows the experiment design used for the screening phase of the analysis. It is a fractional factorial design of seven factors ($k = 7$) and two levels per factor ($n = 2$), which results in 16 experiment runs. The factor codification and values used for the experiments are detailed in Table 4.3.

Table 4.5: Phase I - Fractional Factorial experiment design with seven factors and two levels [275].

Run	Q **A**	K **B**	BC **C**	LB **D**	T_s **E**	FTY **F**	WC_R **G**
1	+	+	+	+	+	+	+
2	+	+	+	-	+	-	-
3	+	+	-	+	-	-	+
4	+	+	-	-	-	+	-
5	+	-	+	+	-	-	-
6	+	-	+	-	-	+	+
7	+	-	-	+	+	+	-
8	+	-	-	-	+	-	+
9	-	+	+	+	-	+	-
10	-	+	+	-	-	-	+
11	-	+	-	+	+	-	-
12	-	+	-	-	+	+	+
13	-	-	+	+	+	-	+
14	-	-	+	-	+	+	-
15	-	-	-	+	-	+	+
16	-	-	-	-	-	-	-

Phase II – Analysis of interactions

The second phase of the analysis investigates the interactions between the most important factors identified in Phase I—the number of stations (K) and batch size (Q)—in addition to the work content ratio (WC_R). This phase used a full factorial experiment design with three factors ($k = 3$) and three levels per factor ($n = 3$), which results in 27 experiment runs, as shown in Table 4.6.

Table 4.6: Phase II - Full Factorial experiment design with three factors and three levels [275].

Run	Q **A**	K **B**	WC_R **G**	**AB**	**BG**	**AG**	**ABG**
1	+	+	+	+	+	+	+
2	+	+	0	+	0	0	0
3	+	+	-	+	-	-	-
4	+	0	+	0	0	+	0
5	+	0	0	0	0	0	0
6	+	0	-	0	0	-	0
7	+	-	1	-	-	+	-
8	+	-	0	-	0	0	0
9	+	-	-	-	+	-	+
10	0	+	+	0	+	0	0
11	0	+	0	0	0	0	0
12	0	+	-	0	-	0	0
13	0	0	1	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	-	0	0	0	0
16	0	-	+	0	-	0	0
17	0	-	0	0	0	0	0
18	0	-	-	0	1	0	0
19	-	+	+	-	+	-	-
20	-	+	0	-	0	0	0
21	-	+	-	-	-	+	+
22	-	0	+	0	0	-	0
23	-	0	0	0	0	0	0
24	-	0	-	0	0	+	0
25	-	-	+	+	-	-	+
26	-	-	0	+	0	0	0
27	-	-	-	+	+	+	-

4.3.2 Mathematical model verification results

Several scenarios were used to verify the parametric model output against the simulation model. The details regarding the input factors levels and the results of such a comparison can be found in Table 4.7. A summary of the differences (Δ, relative to the parametric model) can be found in Table 4.8.

Two simulation model configurations were used, A and B, as detailed in Section 4.3.2. The results of two KPIs—labour productivity and batch lead time—were used to compare the performance of the two models. It was found that both models obtain comparable results for these KPIs: the average difference is 2.39%, the standard deviation is 4.58% and the maximum difference is 19.45%, corresponding to the particular case of a large number of workstations, which causes abnormally

Table 4.7: Preliminary verification of parametric and simulation models. Differences are relative to the parametric model.

	Factors							Parametric		Simulation		Difference (%)	
Scenario	Q (units)	K (stations)	BC (units)	LB (%)	T_s (s)	FTY (%)	WC_R	P_{Labour} (%)	LT_B (h)	P_{Labour} (%)	LT_B (h)	P_{Labour}	LT_B
A.Base	48	4	1	95	480	100	1.33	92.0	5.49	92.2	5.47	0.18	-0.4
A.1	**12**	4	1	95	480	100	1.33	84.0	1.71	84.6	1.69	0.78	-1.2
A.2	**96**	4	1	95	480	100	1.33	93.5	10.53	93.6	10.52	0.07	-0.1
A.3	48	**2**	1	95	480	100	1.33	93.0	10.44	93.6	10.41	0.61	-0.2
A.4	48	**8**	1	95	480	100	1.33	89.0	3.02	89.3	2.74	0.33	-9.3
A.5	48	4	1	**90**	480	100	1.33	87.3	5.79	87.5	5.75	0.22	-0.7
A.6	48	4	1	**99**	480	100	1.33	95.8	5.28	95.9	5.27	0.10	-0.2
A.7	48	4	1	95	**300**	100	1.33	93.0	5.44	93.2	5.42	0.19	-0.3
A.8	48	4	1	95	**600**	100	1.33	91.3	5.52	91.5	5.51	0.18	-0.3
A.9	48	4	1	95	480	100	**1.00**	91.9	4.14	91.8	4.13	-0.14	-0.2
A.10	48	4	1	95	480	100	**4.00**	91.8	16.21	92.3	16.15	0.54	-0.4
B.Base	48	4	1	95	480	95	1.33	87.8	n/a	87.8	n/a	0.00	n/a
B.1	**12**	4	1	95	480	95	1.33	80.4	n/a	70.2	n/a	-12.77	n/a
B.2	**96**	4	1	95	480	95	1.33	89.1	n/a	88.2	n/a	-1.03	n/a
B.3	48	**2**	1	95	480	95	1.33	89.1	n/a	86.9	n/a	-2.47	n/a
B.4	48	**8**	1	95	480	95	1.33	85.1	n/a	68.5	n/a	-19.45	n/a
B.5	48	4	**0**	95	480	95	1.33	87.7	n/a	80.5	n/a	-8.22	n/a
B.6	48	4	**3**	95	480	95	1.33	87.8	n/a	86.9	n/a	-0.98	n/a
B.7	48	4	1	**90**	480	95	1.33	83.2	n/a	81.7	n/a	-1.86	n/a
B.8	48	4	1	**99**	480	95	1.33	91.4	n/a	87.6	n/a	-4.16	n/a
B.9	48	4	1	95	**300**	95	1.33	88.7	n/a	89.0	n/a	0.35	n/a
B.10	48	4	1	95	**600**	95	1.33	87.1	n/a	83.6	n/a	-4.02	n/a
B.11	48	4	1	95	480	**75**	1.33	74.1	n/a	73.7	n/a	-0.59	n/a
B.12	48	4	1	95	480	**99**	1.33	91.4	n/a	87.6	n/a	-4.16	n/a
B.13	48	4	1	95	480	95	**1.00**	87.7	n/a	84.1	n/a	-4.12	n/a
B.14	48	4	1	95	480	95	**4.00**	87.5	n/a	86.1	n/a	-1.64	n/a

Table 4.8: Summary of preliminary verification results. Relative difference (Δ) between parametric and simulation models expressed as a percentage of the parametric results.

	ΔP_{Labour} (%)			ΔLT_B (%)		
Model	Mean	SD	Max	Mean	SD	Max
Config. A	0.28	0.25	0.78	-1.20	2.57	-0.09
Config. B	-4.34	5.22	19.45	n/a	n/a	n/a
Total	-2.39	4.58	19.45	-1.20	2.57	-0.09

high idle times during changeovers in the simulation model Configuration B.

Further verification

The verification carried out so far employed two very limited simulation models. In fact, two models were used because a single model could not have all the features that would make it equivalent to the mathematical model. To address this problem, a more complete simulation model was developed employing the same modelling assumptions as the mathematical model uses. The characteristics of that model are detailed in the next chapter's Section 5.1, which provides insight into all the simulation models employed in this thesis.

To perform further verification of the mathematical model, the experimental design of Phase I was adopted. A total of 16 simulation runs were set up using the parameters and levels previously stated, and the results of such simulations were compared against the mathematical model. Figure 4.7 shows the outcome of this comparison in terms of absolute values and differences relative to the parametric model.

These results are summarised in Table 4.9. The results shown here indicate that the absolute relative errors are small—less than 10%—and that, in general, the mathematical model overestimates the value of the KPIs compared to the simulation model. Having established that the parametric model produces very similar, comparable outputs to the simulation model when under the same assumptions, the following chapter will look into leveraging the advantages of discrete events simulation to employ modelling assumptions that can better represent the real industrial situation.

Table 4.9: Summary of further verification results of the parametric model compared to an equivalent simulation model. Relative differences are expressed as a percentage of the parametric model results.

KPI	**Mean $\mid\Delta\mid$ (%)**	**SD $\mid\Delta\mid$ (%)**	**Max $\mid\Delta\mid$ (%)**
P_{Labour}	4.22	1.71	1.38
LT_B	4.88	3.38	1.11
Th	6.66	3.51	1.55

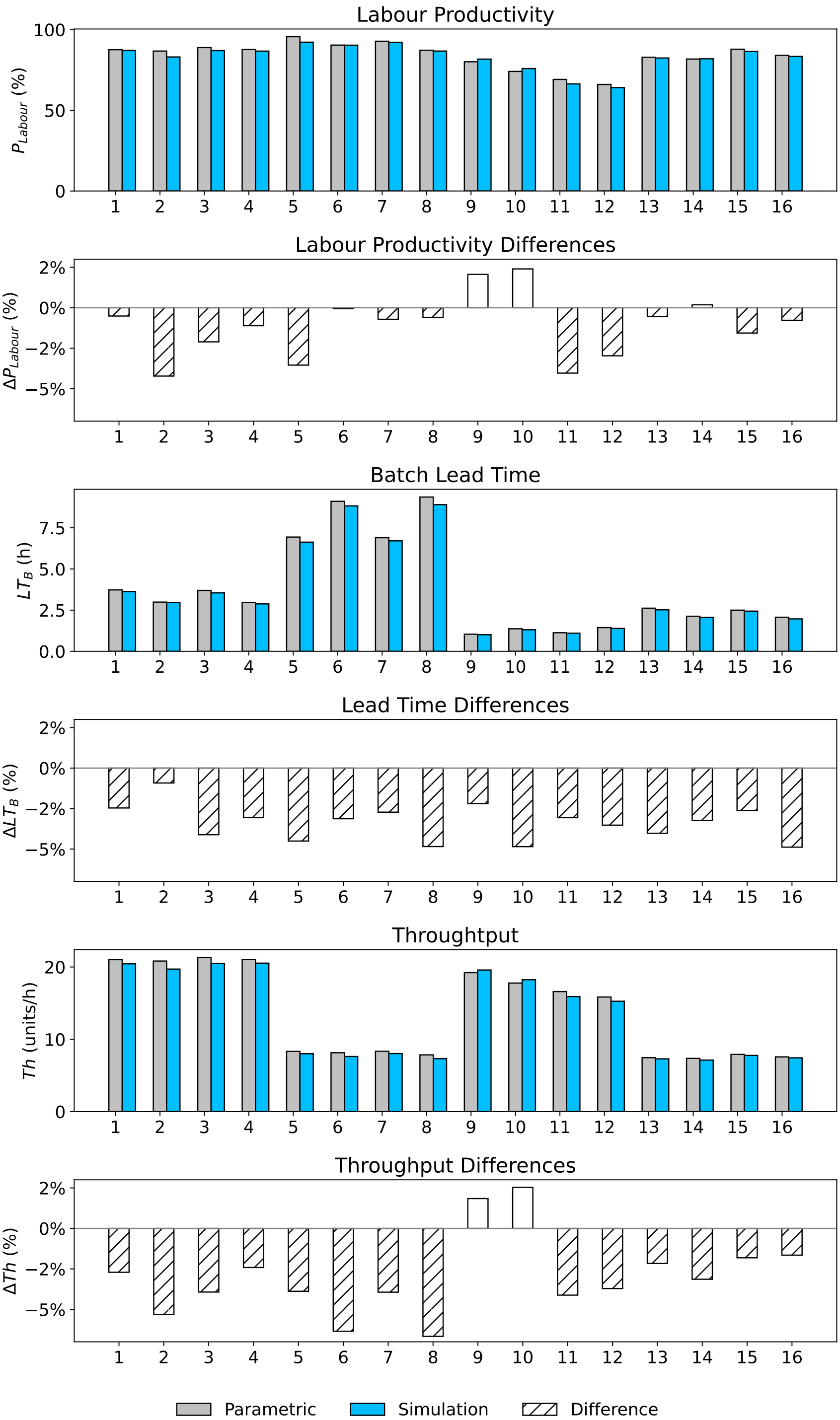


Figure 4.7: Further verification of mathematical model against an equivalent DES model. Relative differences are expressed as a percentage of the parametric result.

4.4 Validation of T_s modelling assumption

One key assumption in the formulation described in Subsection 4.1.1 is that each station's setup time is constant, regardless of the number of stations (K). This assumption is used to model how the setup time would change if the number of stations of a manual assembly line is modified. The assumption used so far implies that the total setup time is directly proportional to the number of workstations (A1: $T_s^{tot} \propto K$). Although this assumption is adequate for modelling assembly stations where fixtures are used on every station, this might not always be the case. In assembly processes where the only changeover activities involve replacing the component containers, a more accurate assumption would be that the total setup time is constant. In this case, each workstation setup time could be estimated by dividing the total setup time over the number of stations (A2: $T_s^{tot} = const$).

Setup time modelling assumptions:

A1: The setup tasks only involve the fixtures on every station. Thus, T_s of each workstation does not depend on the no. of stations. In consequence, the total setup time is directly proportional to K.

A2: The setup tasks only consist on replacing component containers. Thus, the total setup time is constant. In consequence, T_s of each workstation is inversely proportional to the no. of stations K.

To understand the potential impact of this assumption on the DoE results, the screening phase was done over under assumption A2, and its results were compared to the ones already presented in Section 4.2.3. Table 4.10 shows the comparison of the two assumptions for modelling the setup times of the assembly workstations, using parametric and simulation models. This table includes the mean and max absolute differences of three operational KPIs for assumption A2 compared with assumption A1.

Table 4.10: Average and maximum relative differences between modelling assumption A2 compared to assumption A1, calculated using the parametric model.

KPI	Mean $\mid \Delta \mid$ (%)	Max $\mid \Delta \mid$ (%)
P_{Labour}	3.3	11.0
LT_B	3.0	7.7
Th	5.0	9.1

The results shown in Table 4.10 suggest that although the mean differences are relatively small (5% or smaller), the max differences could be considerable, especially for P_{Labour} and Th, which present max relative differences of 11.0 and 9.1% respectively. However, these differences do not necessarily imply that the conclusions of the DoE would change. To ascertain the impact of assumption A2 on the DoE outcome, the average effect charts were plotted in Figure 4.8.

These results suggest that the chosen modelling assumption had little impact

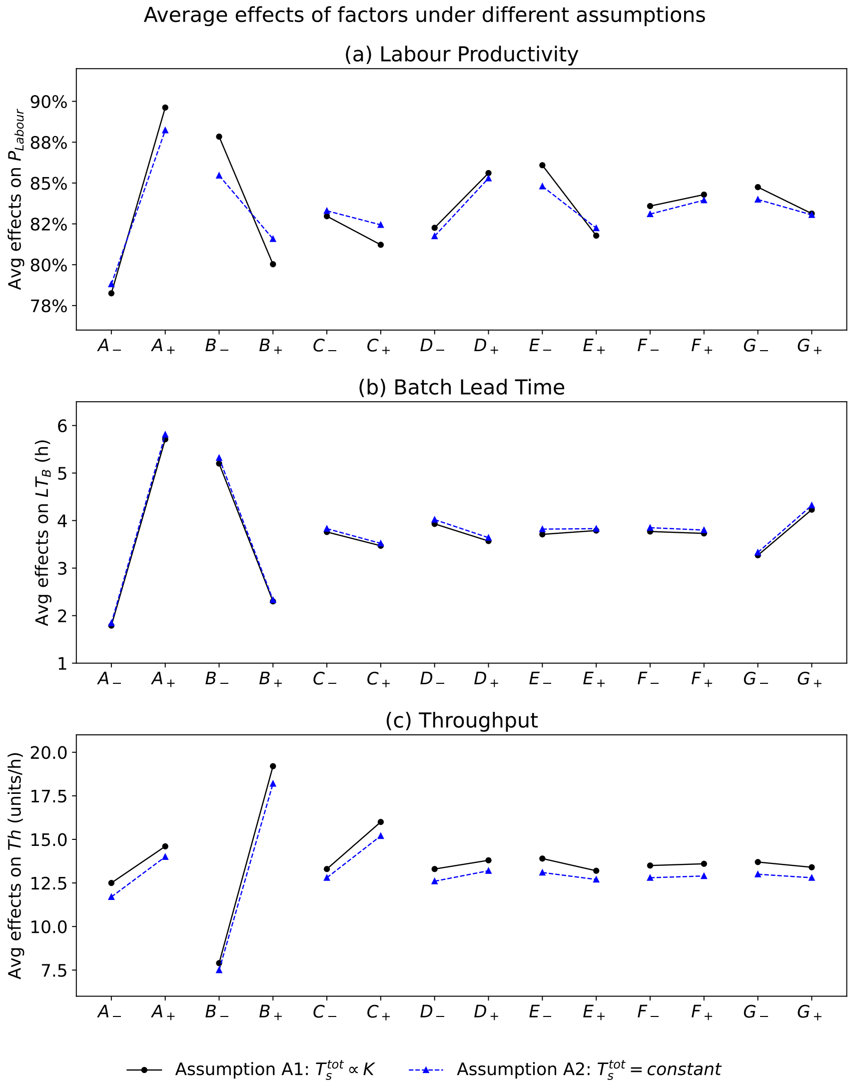


Figure 4.8: Screening Design of Experiments comparison of average effect of factors under two different modelling assumptions. (a) Productivity, (b) Lead Time and (c) Throughput.

on the outcome of the DoE screening phase, because they lead to the same conclusion regardless of the assumption used.

4.5 Summary

This chapter presented a simplified analytic model which uses a set of equations to evaluate the operational performance of manual or semi-automated multi-model assembly lines. Specifically, the model's deterministic formulation focuses on changeover time losses, a key performance driver under high-mix low-volume demand. An exploratory analysis was conducted based on the industrial case study presented in Section 3.3. It employs a two-phase design of experiments to determine the most influential factors on the performance of such assembly lines, measured using three KPIs: throughput, batch lead time and labour productivity.

The results revealed that the two most critical factors are the Number of stations and the Batch size. It is important to note that both factors have opposing effects on two of the KPIs: the increase of labour productivity and reduction of batch lead time cannot be optimised simultaneously by changing these two factors alone.

However, this analytic tool is limited by its inability to easily incorporate stochastic sources of variability and disturbances. To study the cases where variability is a key feature of manual assembly lines, such as the industrial study case of The Cooktop Company, more powerful analysis tools are needed.

Finally, this chapter assessed the impact of a key modelling assumption: the relationship between the number of stations and the total setup time. It was found that this assumption bears no significant weight, and therefore can be relaxed in future modelling situations.

Thus, this chapter makes five key contributions:

1. Proposed a simple analytic model for the performance evaluation of multi-model assembly lines which is easy to implement and sufficiently capable for preliminary analysis.
2. The Design of experiments results show that the two most critical factors for the operational performance of multi-model assembly lines are the number of stations and the batch size. Considering the mass customisation demand trends, there are –and will be– strategic advantages to further reducing the production batch sizes. This leads to the conclusion that looking at designing flexible assembly lines with a reduced number of stations would be a way to enhance productivity and mitigate the negative effect of frequent product changeovers.
3. Since reducing the number of working stations implies a reduction of maximum line capacity, an obvious way to maintain production capacity flexibility would be to consider shorter parallel assembly lines.
4. Further study of the influence of the total setup time - number of stations relationship led to the conclusion that this modelling assumption does not affect the results of the previous analysis.
5. The simplified mathematical model used in this chapter presents limitations making it difficult to incorporate in-depth features, such as variability, and to expand the model to include supporting departments, such as in-plan logistics or maintenance.

The mathematical model's limitations in terms of variability and disturbances led to the development of a flexible assembly model using discrete events simulation, which is covered in the next Chapter 5.

As a consequence of the key finding of this chapter, the assembly lines design presented in Chapter 6 focuses on integrating automated stations with short parallel lines to avoid the negative effects of a high number of workstations while maintaining the capability to change the production rate efficiently.

CHAPTER 5

Simulation approach and models validation

To address the limitations of the mathematical model presented in Chapter 4, this chapter introduces discrete events simulation (DES) models to evaluate the performance of flexible assembly systems. The DES models are capable of overcoming the most important limitations of the analytical model: they can easily incorporate variability and stochastic disturbances, they allow different manners of operator-workstation interaction, and they can integrate supporting departments, such as in-plan logistics or quality control.

First, Section 5.1 introduces the several DES models utilised in this thesis and their key features. Second, Section 5.2 describes the process used to characterised the industrial study case assembly lines variability, so that the simulation models can use accurate distributions to represent it. Then, Section 5.3 presents the validation and verification of the DES modelling methodology using The Cooktop Company case. Finally, Section 5.4 summarises the chapter findings and implications for the following chapters.

5.1 Simulation models used

Multiple simulation models were used to carry out the analysis described in this thesis. Despite their differences, they all share a common modelling methodology and a set of core features because their overarching goal is similar: the performance evaluation of assembly systems for high-mix low-volume demand. Table 5.1 includes a brief overview of the main features of each simulation model.

Table 5.1: Key features of the performance evaluation models employed in this thesis.

	Verification	**Validation**	**AL Design**	**AL Logistics**
	Manual AL	Manual AL	(a) Manual FWAL (b) Semiauto FWAL (c) Semiauto WWAL (d) Parallel WWAL	Manual AL & Logistics
Line Configuration				
No Lines	1	1	(a, b, c): 1 (d): 2	2
No models	4	8 or 6	Input data	Input data
No stations	3 to 8	4 or 3	(a): 2 to 8 (b, c): 8 (d): 16	10
No workers	equiv. K	equiv. K	(a, b): equiv. K (c, d): Parameter	10
No stations auto	-	-	(a): - (b, c): 4 (d): 6	-
WIP buffers				
Max WIP	Parameter	Parameter	Parameter	Parameter
Max WIP auto	-	-	(a): - (b-d): Parameter	-
Demand				
Batch size	Parameter	Input data	Parameter	Parameter
Work Content				
Work Content	Input data	Input data	Input data	Input data
WC ratio	Parameter	Input data	F. of WC, per model m	F. of WC
Processing Times				
Line Balance	Parameter	Input data	F. of K	F. of T_p
Cycle time	Input data	F. of T_p	F. of T_p, per model m	F. of T_p
Process time	-	Input data	Input data, per model m	Input data
Setup time	Parameter[1]	Input data	Input data, per model m	Input data
CO time	Realistic paced[2]	Realistic unpaced[2]	Realistic unpaced[2]	Realistic unpaced[2]
Disturbances				
Quality	Parameter	Parameter	Parameter	-
Rework time	-	-	Out-of-Line[3]	-
Process var	-	Parameter	Parameter	Parameter
Setup var	-	Parameter	Parameter	Parameter
Batch size var	-	-	-	Parameter
Components var	-	-	-	Parameter
Logistics				
In-plant logistics	-	-	-	Y
KPIs				
Output	Y	Y	Y	Y
Throughput	Y	Y	Y	Y
Line Productivity	Y	Y	Y	Y
Labour Productivity	Y	Y	Y	Y
Batch Lead Time	Y	Y	Y	Y
Unit Lead Time	-	-	Y	Y
Milkrun Utilisation	-	-	-	Y
Line Stock	-	-	-	Y
Additional details	Chapter 4	Chapter 5	Chapter 6	Chapter 7

(a) Verfication (b) Validation

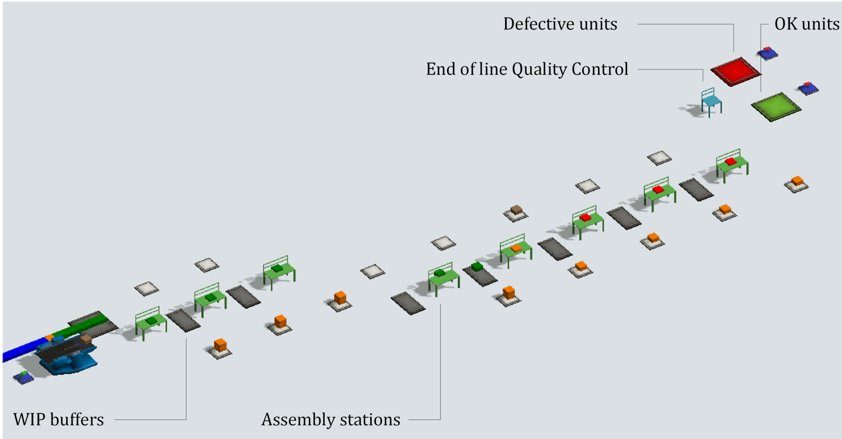
(c) Assembly line design (d) Assembly line logistics

Figure 5.1: Scope of the different simulation models illustrated using the operator-centred conceptual framework: verification (a, yellow), validation (b, blue), assembly line design (c, red) and assembly line logistics (d, green).

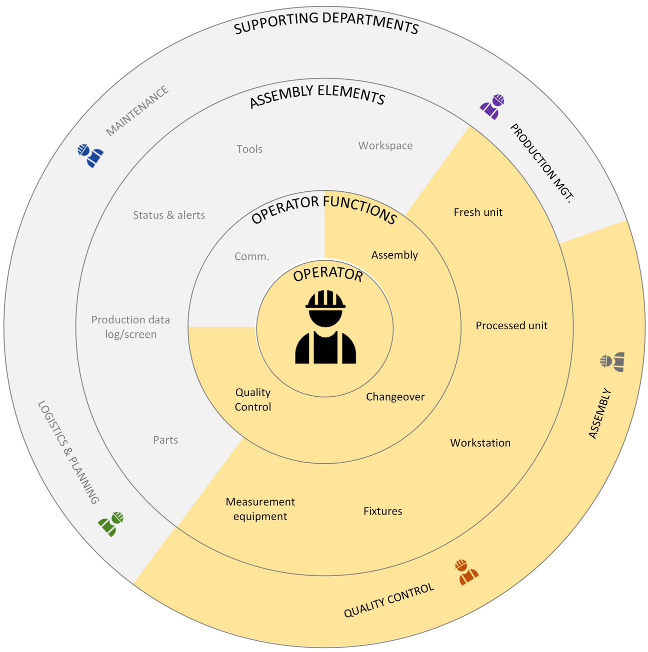
The scope of each simulation model related to the different layers of the operator-centred conceptual framework presented in Chapter 3 is shown in Figure 5.1. Note that the validation model (blue) includes a few more features than the verification one (yellow). In turn, the assembly line design model (red) incorporates one more feature than the previous model, which will be explained later on. Finally, the logistics model (green) presents several fewer features—those related with Quality Control— but expands by including components (parts, third layer) and the logistics and planning department (fourth layer).

The first simulation model of this research project was used for preliminary verification of the mathematical model presented in the previous Chapter 4. The model is shown in Figure 4.3.

[1]Setup time either defined per station or as total T_s
[2]Function of (T_s, m_{in}, m_{out}, WIP)
[3]Rework time mean: 0.5 of WC



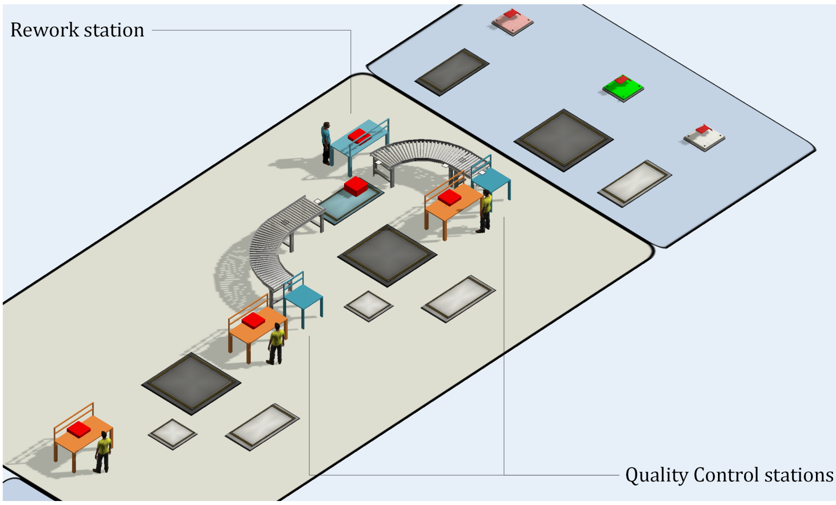
(a) Simulation model used for further verification, 3d view from FlexSim®.



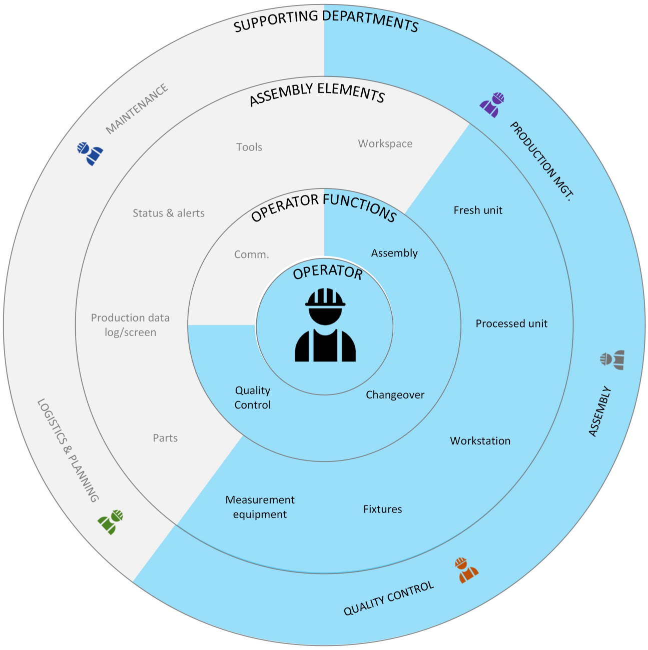
(b) Verification model key features.

Figure 5.2: Simulation model used to verify the mathematical model.

A more complete DES model was later used for a more in-depth verification, as described in Section 4.3. The model employed there, shown in Figure 5.2a, was able to overcome the previous limitations in terms of simulation elements, production defects and the realistic changeover logic. Note that this model features end-of-line quality control and that it can use between three and eight manual assembly stations.



(a) Simulation model used for validation, 3d view from FlexSim®.



(b) Validation model key features.

Figure 5.3: Simulation model used for validation against the industrial case in Chapter 5.

To validate the simulation methodology against the industrial study case, two models were built corresponding to The Cooktop Company's product families no. 6 and no. 7 described Subsection 3.3.2. These DES models present a key difference compared to the previous one: there are two in-line quality control stations, and any defective units detected are sent for rework to a dedicated offline station, as shown in Figure 5.3a. Another difference compared to the previous model is the introduction of process and setup time variability. The characterisation of the industrial case assembly variability will be detailed in the next section.

In terms of the operator-centred framework, shown in Figure 5.3b, this model incorporates the Production management supporting department (fourth layer)—which deals with reworking defective units—and maintains all the features already included in the previous simulation model used to verify the mathematical model.

To analyse the improvement opportunities brought by different assembly line configurations, three main DES models are used: a manual assembly line such as the previously presented, and two new ones which result from the addition of two new features: automated stations and walking-worker interactions between the human operators and the manual assembly stations. Figure 5.4 showcases the semi-automated fixed-worker line, and Figure 5.5a depicts the semiautomated parallel walking-worker lines, whose modelling assumptions will be detailed in Section 6.3.

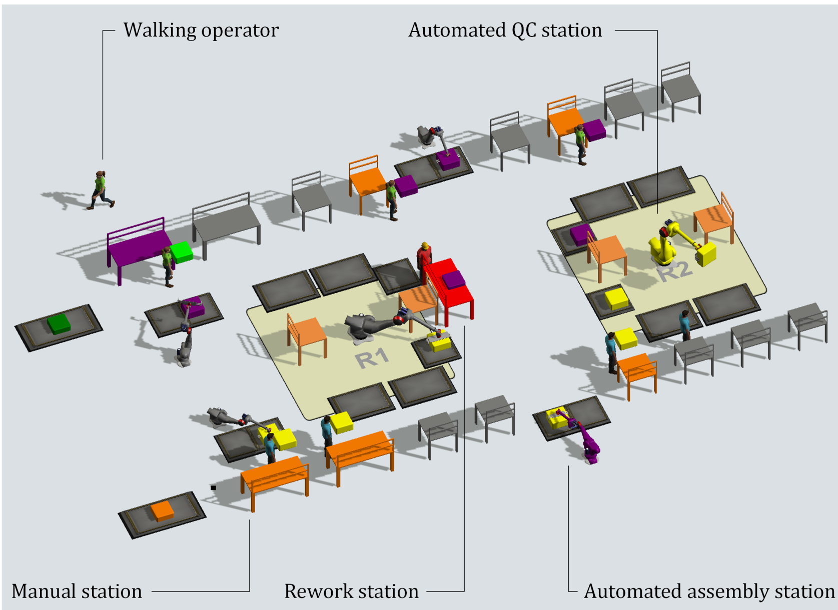
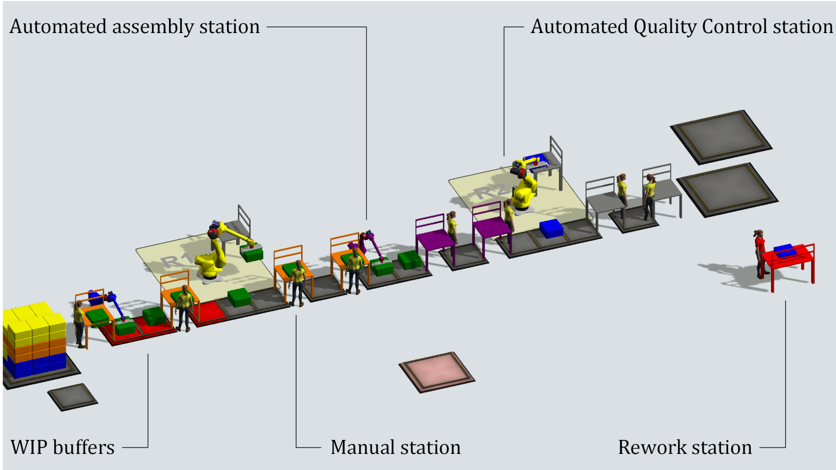


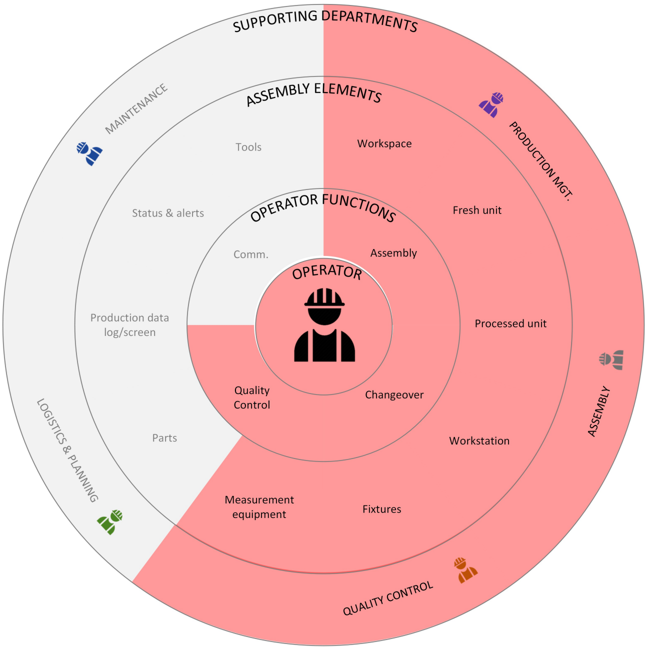
Figure 5.4: 3d view from FlexSim® of the simulation model of a semiautomated parallel walking-worker assembly line (PWWAL), used in Chapter 6.

This simulation models feature unpaced assembly lines with stochastic processing and setup times, which can lead to full WIP buffers (coloured red in the figures) resulting in blocked stations, changeover times (purple stations) and idle operators (grey stations).

As shown in Figure 5.5b, these models expand the scope of analysis by incorporating the workspace element (third layer), necessary to model walking-worker interactions between human operators and assembly stations.



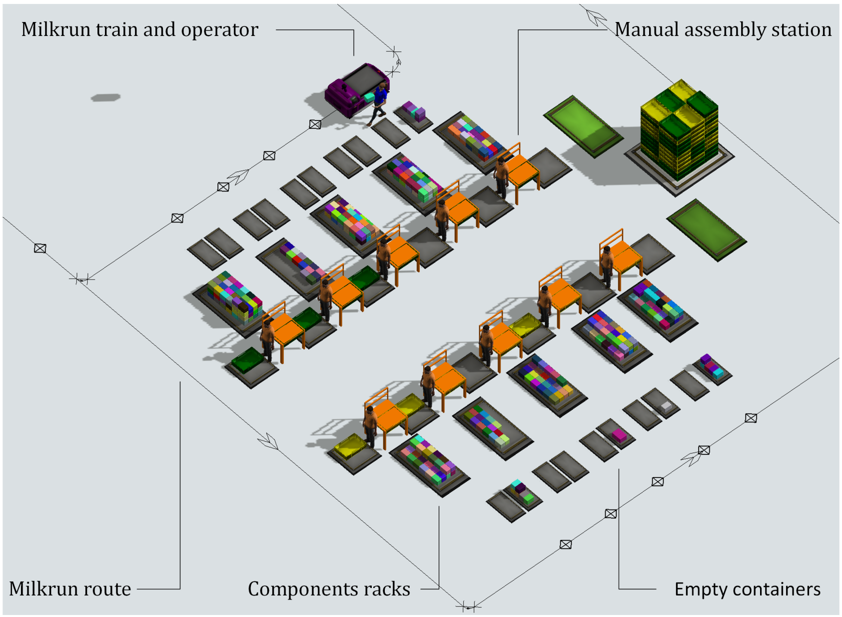
(a) Simulation model of semiautomated fixed-worker line, 3d view from FlexSim®.



(b) Assembly line design models key features.

Figure 5.5: Features of the simulation model of a semiautomated fixed-worker assembly line (FWAL), used in Chapter 6.

Finally, in the logistics model (Figure 5.6a) the scope is expanded. This model, which lacks the quality control or automated stations of the previous ones, adds a layer of complexity by including component consumption by the manual stations. In turn, a milkrun train system feeds the multi-model assembly lines. Figure 5.6b shows the excluded function, elements and supporting department.



(a) Simulation model of in-plant logistics, 3d view from FlexSim®.

(b) In-plant logistics simulation model key features.

Figure 5.6: Simulation model of milkrun trains for in-plant logistics, used in Chapter 7.

5.2 Characterisation of The Cooktop Company assembly lines

Measuring the Cooktop Company manual assembly lines real performance, using the same KPI definitions as in the mathematical or DES models was a critical and necessary step in order to verify the models.

This section first explores the process to transform raw data from the company's MRP into relevant performance metrics using the KPI definitions specified in Section 3.2. Then, another key feature of the manual assembly lines of the Cooktop Company was investigated: the operator's processing time variability. To check whether modelling the assembly line with deterministic processing times was suitable, or stochastic assumptions were necessary, a study to characterise the variability was carried out.

5.2.1 Obtaining empirical industry data for model validation

The dataset employed to characterise The Cooktop Company assembly lines was automatically produced by the MRP system of the company during the month of January 2021. The process to obtain clean data from the raw dataset is described below.

Firstly, it is necessary to extract raw data from the company MRP system, which produces .csv (comma-separated values) files. The .cvs files contain a row per unit produced (e.g. 2,116 units for one assembly line during January 2021) and 19 data columns, including the unit ID number, the company ID code, date and time stamps, product reference code, shipment code, production shift, etc. Secondly, nine duplicated or non-relevant data columns are removed and data formatting is adjusted. It is also necessary to link the raw data to other key information, e.g. to relate each product reference with its product family and standard cycle time. Thirdly, planned stoppages (weekly production schedule, coffee/lunch breaks, shift handover), product changeovers and unwanted minor stoppages are taken into account. This data transformation step is a laborious process because it is difficult to automate. For example, the Cooktop Company morning shift (6:00-14:00) schedules three 12-minute short breaks at 9:15, 10:30 and 12:30. However, these rarely start at the exact scheduled times, and their duration is not always exactly 12 minutes. Maintenance problems and quality control logs also need to be correlated at this stage. Finally, unit production time data is normalised by comparing it against the standard operating procedures (SOP) processing times. At this stage, each data shows the production rate deviation from the expected production rate.

The number of empirical data points collected included 1,680 and 2,116 units produced by two assembly lines over a natural month, which was deemed an adequate sample size. The demand mix of January was considered representative of the annual mix because it included at least one model of each product family that each line could produce.

The data is now ready to perform aggregate calculations for obtaining KPIs at a batch or production shift level. The next Section 5.3 includes the KPI calculation equations and uses the performance measures obtained from the study case data to validate the parametric and simulation models developed. At this stage, the data becomes starting point for the statistical characterisation of the manual assembly variability, which is detailed below.

5.2.2 Variability of manual assembly processes

Having cleaned and processed the study case data, a histogram is used to inspect the distribution of normalised processing times. The data distribution of manual processing times at the Cooktop Company assembly line of product line no.6 (CA28) during the whole month of January 2021 is shown in Figure 5.7. Note that the histogram tail has been placed in an overflow bin for all data points above 2.0 (i.e. whose measured processing times more than double the standard cycle time for the particular unit measured). The data shows a significant degree of variability, so using deterministic times for modelling assembly processing times would limit the simulation results' reliability.

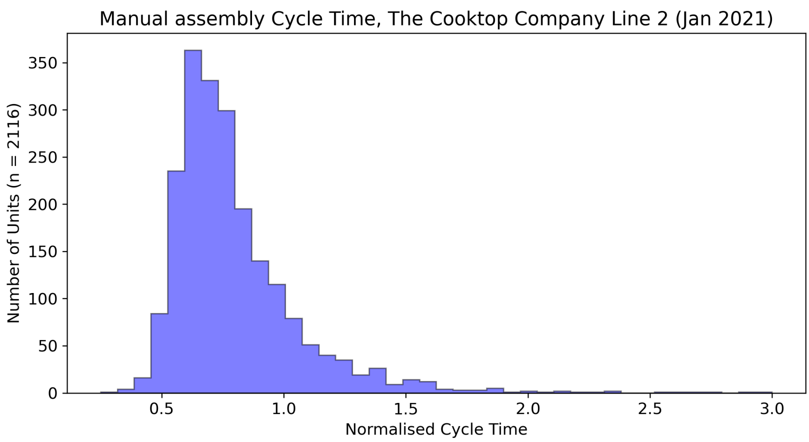


Figure 5.7: Distribution of normalised manual assembly cycle time of Line 2 during January 2021.

The lognormal distribution was chosen for the DES models employed in this thesis. As prescribed by Ginos, the lognormal distribution "is useful in modeling continuous random variables which are greater than or equal to zero. The lognormal distribution is also useful in modeling data which would be considered normally distributed except for the fact that it may be more or less skewed" [276, p. 2]. Manual assembly activities can sometimes be performed more quickly than the standard times (as per the SOP), but it is certainly more common to experience delays. This fact makes the skewed lognormal distribution a good fit for simulating the duration of assembly activities. As Visser puts it:

> The lognormal distribution is a continuous, non-symmetric distribution that is often used to model the duration of activities or tasks. It applies mostly to novice artisans or workers that have to perform non-standard and complex tasks. These tasks often have an overflow especially when something goes wrong. It has two parameters, i.e. the mean value μ and the standard deviation σ. [277, p.2031–2039]

Banks and Chwift discuss in their 2011 article [278] the shortcomings of some of the most commonly used distributions in DES. In particular, for modelling production processing times, they specifically advise against normal distributions, due to a better fit of the lognormal distribution and the fact that normal distributions can generate negative times. Triangular distributions, despite their usefulness in absence of data, present the problem of being bound.

The maximum likelihood estimators of lognormal distributions can be calculated using Equation 5.1 and Equation 5.2 [276, p.8]:

$$\hat{\mu} = \frac{\sum_{i=1}^{n} \ln(X_i)}{n} \tag{5.1}$$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{n} \left(\ln(X_i) - \frac{\sum_{i=1}^{n} \ln(X_i)}{n} \right)^2}{n} \tag{5.2}$$

Applying Equations 5.1 to The Cooktop Company empirical data resulted in the estimation of the variability parameters: $\mu = 1.02$, $\sigma = 0.20$. Figure 5.8 shows the study case distribution of manual processing times measured in January 2021 alongside a lognormal distribution generated with the max likelihood parameters obtained before. Note that the measured data (green) presents a wider and longer tail. This is due to the notably frequent delay events caused by quality control non-conformities, reworks and other production issues.

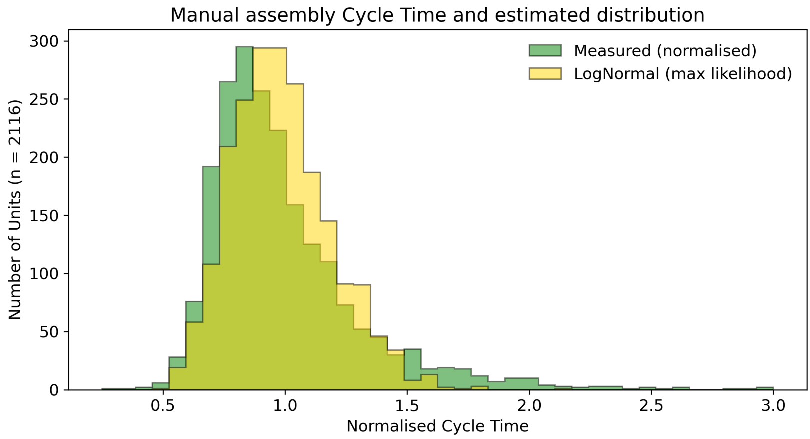


Figure 5.8: Distribution of normalised manual assembly cycle time, comparison between measured (January 2021, green) and generated using max likelihood estimators (yellow).

5.3 Validating and verifying the models

This section presents the validation and verification of the discrete simulation model against the mathematical model described in the previous Chapter 4 and the empirical data from The Cooktop Company study case. The content of this section was presented at the 55th CIRP Conference on Manufacturing Systems (Lugano, Switzerland, June 2022), and published as a conference article [279].

Therefore, the subsections below the article abstract correspond to the article's Introduction (5.3.1), Methodology (5.3.2), Results (5.3.3) and Discussion and Conclusion (5.3.4). Note that the article notation was edited to make its notation consistent with the rest of the thesis.

Article title:

> Models to evaluate the performance of high-mix low-volume manual or semi-automatic assembly lines

Article abstract:

> To address mass customisation demand trends, assembly line flexibility and productivity are critical. Industry 4.0 technologies could support assembly operations to this end. However, clear implementation methodologies are still lacking. This article presents two models for evaluating the most relevant Key Performance Indicators (KPIs) of manual or semi-automatic assembly lines, allowing to maximise the return of investment of any digital technology addition. MATLAB® was used to implement a parametric model, and FlexSim® was employed to build a discrete event simulation model. The models were validated using data from two industrial study cases from a global white goods manufacturer.

5.3.1 Introduction

The current demand trends have been shifting from mass production to mass customisation since the end of the 20th Century, and even further towards mass personalisation [28]. As a result, an increasing number of industries are facing an atomised demand, which could be denoted as 'high-mix low-volume' [13]: a great number of products -and product variants- are in demand in small quantities each. Moreover, the expected shortening of production lead times and reduction of inventory levels put additional pressure on businesses to streamline their processes to compete in the global marketplace [6]. In this context, assembly operations need to be flexible while achieving high productivity, which confronts the traditional dichotomy between manual (highly flexible, not quite productive) and automated assembly (highly productive, not quite flexible).

Since the term Industry 4.0 was introduced by the German government in 2011 [22], it is used to refer to an array of disruptive digital technologies which are expected to bring forward the fourth industrial revolution [8]. Some of these Key Enabling Technologies have been shortlisted to be most impactful on the performance of assembly operations [24]—namely the Internet of Things, big data, real-time optimisation, cloud computing, cyber physical systems, machine learning, augmented reality, collaborative robots and additive manufacturing—by enabling the main characteristics of Assembly 4.0 [23]: late customisation, assembly control systems, aided assembly, intelligent storage management, self-configured workstation layout and product and process traceability.

Nonetheless, questions arise following these analyses, such as the following: Which of the features brought by Industry 4.0 technologies would have the most positive impact on the operational and business goals of assembly operations? What would be the best method of implementing these changes to achieve the maximum return on investment? Previous work [27] established that it is clear that Lean Manufacturing has a critical role to play in this transformation due to the similarities and synergies with Industry 4.0, and that there is a lack of methodologies for implementing the new digital technologies of Industry 4.0 to address concrete business goals.

The main approaches to evaluate alternative scenarios and the impact of design variables on the assembly operations Key Performance Measures (KPIs) include mathematical modelling, simulation, and other techniques such as Petri nets or artificial intelligence, among others [269]. Mathematical models that consider setup times usually do so in a simplified way, as either sequence-independent or sequence-dependent times, although some authors have considered the importance of product change dependent inter-task times [280–282]. On the other hand, Discrete Event Simulation inherently considers the assembly stations waiting and blocking times induced by finite buffers and cycle time differences between distinct products. However, simulation models are more complex and require larger time investments to be built. A simplified mathematical formulation with a focus on changeover losses would allow a quick initial assessment of operational KPIs in a high-mix low-volume demand environment where small batch sizes and frequent changeovers are major drivers of the assembly system's performance.

The goal of this article is to introduce two simple yet comprehensive models that can be used to evaluate the performance of high-mix low-volume manual or semi-automatic assembly lines, allowing to gain a deep understanding of the implications of different parameters on the line KPIs.

The present article is structured as follows: Section 5.3.2 - Methodology - presents the two models developed and the real case from an industrial partner used to validate them. Section 5.3.3 includes the Results and analysis of the aforementioned validation cases, and Section 5.3.4 present the Discussion and Conclusion of the article.

5.3.2 Methodology

Two assembly line performance evaluation models were developed, using MATLAB® and FlexSim® respectively. They consider a series of input parameters that are processed to produce the line KPIs as output.

This section presents the general framework employed, introduces a parametric model implemented using MATLAB®, describes a discrete events simulation model implemented using FlexSim®, compares the advantages and disadvantages of both models, and finally describes the industrial case used to validate both models against real data from the manufacturing plant of a research business partner.

Framework

The models used for evaluating the performance of multi-product assembly lines consider a single linear series of workstations, with one or two quality control (QC) stations integrated with them, as depicted by Fig 5.9.

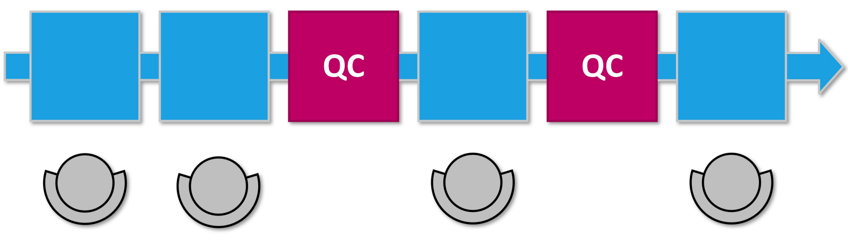


Figure 5.9: Multi-product assembly line with quality control stations.

The model is defined by a set of input variables –divided into design, fixed and disturbance parameters– which produce a set of KPIs as a result, as shown in Table 5.2.

The models consider a manual assembly line capable of producing multiple

Table 5.2: Input variables and KPIs considered in the models.

Variable	**Notation**	**Index**
Design parameters		
No. workstations	K	k
No. of products	M	m
Batch size	Q	
Max. WIP buffer capacity	BC	
Fixed parameters		
Cycle time	CT	
Work Content	WC	
Line balance	LB	
Setup time	T_s	
First Time Yield	FTY	
Work Content Ratio	WC_R	
Disturbances		
Variability of process time	CV_p	
Variability of setup time	CV_s	
KPIs		
Output	$Output$	
Throughput	Th	
Batch Lead time	LT_B	
Labour productivity	P_{labour}	
Line productivity	P_{Line}	

products. After finishing a batch of units of a certain product, the workstations need to change over to the next product, by carrying out a setup. The setup time depends both on the outgoing and the incoming products.

Parametric Model

Firstly, a parametric model was developed to obtain the desired KPIs. It calculates the productive time from the available time minus the changeover time. It then works out the actual productive time of each batch of products by subtracting the time lost due to line imbalance, minor stops and defects, as illustrated conceptually in Figure 5.10.

The software MATLAB® (2019b, The MarhWorks Inc., Natick MA, United States) was used to implement the algorithm described below. MATLAB® was chosen because of its user friendliness since the algorithm presented here does not require the use of an optimised programming language (e.g. C/C++) to complete the calculations in a very short time.

In the first place, the cycle time of each batch (i) of product model m in the sequence is calculated using Equation 5.3.

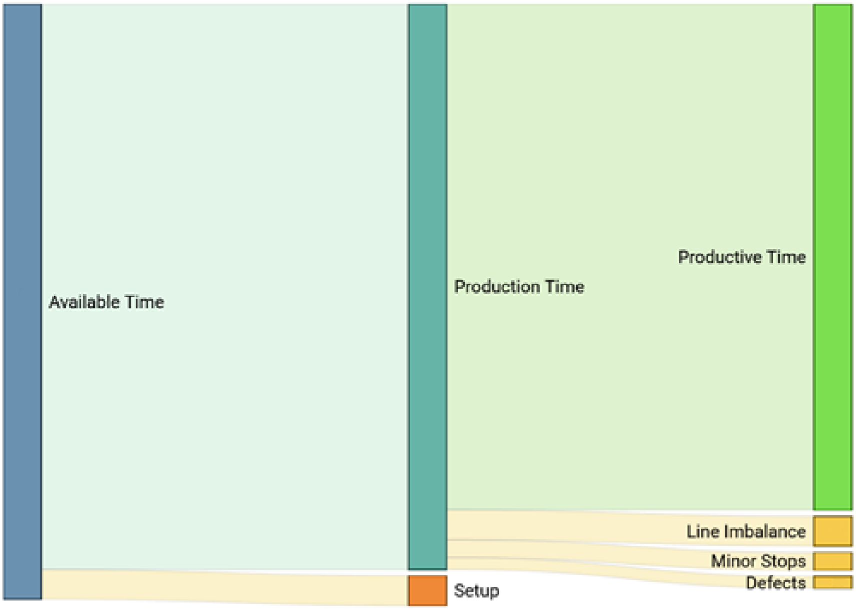


Figure 5.10: Productivity losses in multi-product assembly lines considered in the parametric model.

$$CT = \frac{WC}{K \cdot LB} \tag{5.3}$$

For each batch i, the time lost on changeover depends on the previous $(i-1)$ and the product of the current batch (i). Equations 5.4-5.9 describe its calculation.

For each workstation k, the start and finish times $(t^{start}_{i-1,k}, t^{end}_{i-1,k})$ of the previous batch $(i-1)$ are calculated using Equations 5.4–5.6.

$$t^{end}_{i-1,1} = CT_{i-1} \tag{5.4}$$

$$t^{start}_{i-1,k} = t^{end}_{i-1,k-1} \tag{5.5}$$

$$t^{end}_{i-1,k} = t^{start}_{i-1,k} + CT_{i-1} \tag{5.6}$$

For each workstation k, the finishing time of the setup is given by Equation 5.7.

$$t^{end}_{s,k} = t^{end}_{i-1,k} + T_S(i-1, i, k) \tag{5.7}$$

For each workstation k, the start and finish times of the first unit of the incoming product batch i are calculated using Equations 5.8–5.9.

$$t_{i,k}^{start} = \max\left\{t_{s,k}^{end}\ ;\ t_{i,k-1}^{end}\right\} \tag{5.8}$$

$$t_{i,k}^{end} = t_{i,k}^{start} + CT_i \tag{5.9}$$

In case $CT_{i-1} \geq CT_j$, the changeover time lost on each station k is given by Equations 5.10–5.11.

$$k \in \{1, ..., K-1\}\colon T_{co,k} = \max\left\{0\ ;\ t_{s,k+1}^{end} - t_{i,k}^{end} - BC \cdot CT_i\right\} \tag{5.10}$$

$$k = K\colon T_{co,k} = T_s(i-1, j, k) \tag{5.11}$$

In case $CT_{i-1} < CT_i$, the changeover time lost on each station k is given by Equations 5.12–5.13.

$$k = 1\colon T_{co,1} = T_s(i-1, i, k) \tag{5.12}$$

$$k \in \{2, ..., K\}\colon T_{co,k} = t_{i,k-1}^{end} - t_{i-1,k}^{end} \tag{5.13}$$

Having calculated the time lost due to the changeover for each station, the total time lost is obtained with Equation 5.14.

$$T_{co} = \max\{T_{co,k}\} \cdot K \tag{5.14}$$

For each batch of products (i), a number of units have defects, depending on the product First Time Yield –see Equation 5.15–5.16.

$$N_{defects} = \lceil Q \cdot FTY \rceil \tag{5.15}$$

$$N_{correct} = Q - N_{defects} \tag{5.16}$$

Equations 5.17–5.18 calculate the time employed to assemble defective and conforming units.

$$T_{defects} = N_{defects} \cdot K \cdot CT_i \tag{5.17}$$

$$T_{correct} = N_{correct} \cdot K \cdot CT_i \tag{5.18}$$

Therefore, the time needed to complete each batch of products is given by Equation 5.19.

$$T_{complete} = T_{correct} + T_{defects} + T_{co} \tag{5.19}$$

Finally, for each batch, the recovered –productive– time is calculated using Equation 5.20.

$$T_{recovered} = WC \cdot N_{correct} \tag{5.20}$$

The KPIs shown in Table 5.2 can be now calculated considering the full sequence of NB batches using Equations 5.21–5.25.

$$Output = \sum_{i=1}^{NB} N_{correct,i} \tag{5.21}$$

$$Th = \frac{\sum_{i=1}^{NB} N_{correct,i}}{\sum_{i=1}^{NB} T_{complete,i}} \tag{5.22}$$

$$LT_B = \max \{T_{complete,i}\}_{NB} \tag{5.23}$$

$$P_{Labour} = \frac{\sum_{i=1}^{NB} T_{recovered,i}}{\sum_{i=1}^{NB} T_{complete,i}} \tag{5.24}$$

$$P_{Line} = \frac{\sum_{i=1}^{NB} N_{correct,i}}{K \cdot \sum_{i=1}^{NB} T_{complete,i}} \tag{5.25}$$

Discrete Events Simulation Model

The second model employed to assess the performance of manual multi-product assembly lines uses Discrete Events Simulation (DES) implemented on the software FlexSim® (2021.0, FlexSim Software Products, Inc.). FlexSim® was chosen because it allows recreating the changeover logic matching the mathematical model within the additional complexity of a DES model, as well as defining the KPIs to match the mathematical formulation ones.

The model developed, illustrated in Figure 5.11, consists of 3 or 4 workstations with one operator each, organized in a sequential multi-product assembly line. Each operator, using a workstation (coloured orange in Figure 5.11), processes the corresponding unit for a random period of time which follows a lognormal distribution governed by the mean—cycle time—and the standard deviation -expressed by the process variability parameter as a percentage of the mean: e.g. a process variability parameter value of 0.20 equals to the standard deviation being 20% of the cycle time. Once the unit has been processed, it can be placed in the WIP buffers between stations (coloured dark grey in Figure 5.11) before being processed on the next station. The two quality control stations (coloured blue in Figure 5.11) either reject or accept passing units. The probabilities of each result are governed by the First Time Yield (FTY) parameter. The changeover logic works so that once an operator has finished processing the last unit of a batch, it must set up its workstation for a duration given by a lognormal distribution of mean equal to the setup time parameter (which depends on the outgoing and incoming products) and standard deviation given by the setup variability parameter, similarly to the process variability. The numeric values of both parameters were estimated from real data gathered by the industrial partner, using the maximum likelihood estimators [276].

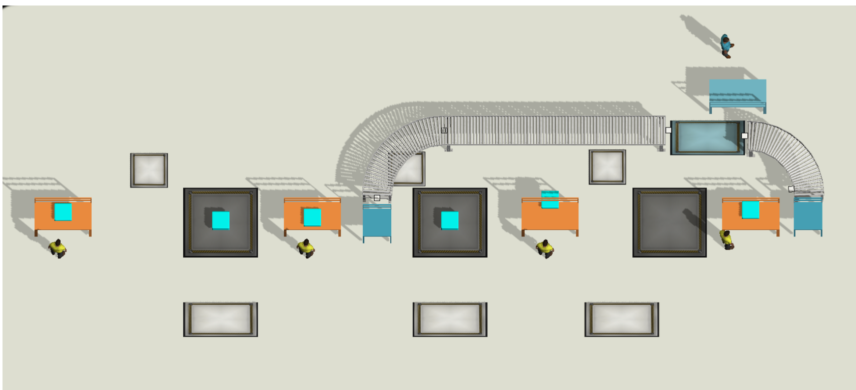


Figure 5.11: Discrete Events Simulation model of Line 1.

Models features comparison

The two models described in Subsections 5.3.2 –parametric– and 5.3.2 –discrete events simulation– aim to calculate the same KPIs using the same input parameters. However, despite sharing some features, they differ in several aspects that make them behave differently under certain circumstances.

The first and most notable difference is that the parametric model does not consider the variability of process and setup times, while the DES model employs lognormal distributions for these times, governed by two variability parameters which express the ratio between the Standard Deviation and the Mean of the lognormal distribution.

The second difference is related to Quality: the parametric model considers an end-of-line quality control, while the DES model features two in-line quality control stations (one located in the middle and the other one located at the end of the assembly line).

The third difference is that the parametric model assumes the assembly stations are synchronous: they start and finish processing products in sync, which might not be the case in industrial environments. The DES model, on the other hand, does not force assembly stations synchronisation, and therefore reflects waiting or blocked times due to the effect of line imbalance, defects and variability.

The last point is changeovers. Both models take into account the workstations blocked and waiting times originated during a product changeover by the cycle time difference between outgoing and incoming products. However, the DES model also accounts for the combined effects of variability, quality issues and out-of-sync, which deteriorate productivity even more than these factors separately.

Having established the key differences, the next Subsection describes the cases used for verifying and validating both models.

Verification and Validation – an industrial real case

To validate the models described previously, they were employed on two scenarios from a global white goods manufacturer site located in the North of Spain, which will be named here as 'Company B'. The scenarios consist of two different manual assembly lines ('Line 1' and 'Line 2') that have not been automated yet due to the substantial number of product variants they produce: around 50 references grouped into 6-8 families on each line. Each family of references has been considered as a single product because the Work Content and assembly sequence of the references within a product family are identical. The low order quantities of each reference and relatively high setup times relative to cycle times, make this case an example of high-mix low-volume demand.

The input data used for both scenarios are summarised in Table 5.3.

Both scenarios were calculated using the parametric and the DES models, and the results were compared against the actual KPIs obtained from the data gathered by the industrial partner.

To verify the models against each other (considering that the parametric model does not include variability of process and setup time), the DES model was used for each scenario with the Variability parameters set to zero.

The following Section 5.3.3 shows the results of the validation and verification against the industrial case described above.

5.3.3 Results

This section includes the KPIs resulting from simulating the two scenarios described in Subsection 5.3.2, named 'Line 1' and 'Line 2'. Figure 5.12 shows the resulting KPIs: Output, Throughput, Labour Productivity and Line Productivity.

Table 5.3: Input data from an industrial real case for validating the models.

Variable	**Units**	**Line 1**	**Line 2**
Design parameters			
No. workstations		4	3
No. product families		6	8
Batch size (avg.)	units	66	64
No. of batches		27	33
Total units ordered	units	1,680	2,116
Max. WIP between stations	units	1	1
Fixed parameters			
Cycle time (avg.)	min	5.42	4.65
Work Content (avg.)	min	21.68	13.95
Line balance (avg.)	%	99.2	98.7
Setup time (avg.)	min	6.85	8.35
First Time Yield	%	99.2	99.8
Work Content ratio		1.33	1.41
Disturbances			
Variability of process time	%	20	20
Variability of setup time	%	20	20

Figure 5.13 below shows the relative error of each of the models when compared with the real industry data (column Company B) for each of the results from Figure 5.12.

The relative errors between real industry data and the KPIs obtained using the models presented in this article are in all cases below 1% for Output, 5% for Throughput and Line Productivity, and 3% for Labour Productivity, which allows considering both models validated. In summary, the average relative error is 1.63% and the maximum relative error is 4.9%.

Moreover, the differences between the results of the parametric model and the DES model with no variability are consistent, not differing more than 3.5% in any KPI. This allows considering that the models are also verified.

It should be noted that both models overestimate Throughput and Productivity since they do not consider any constraints outside of the assembly line such as machine breakdowns, components quality or supply problems.

5.3.4 Discussion and Conclusion

The results shown in Section 5.3.3 allowed validating both models presented in Section 5.3.2 by comparison against real industry data which considers two scenarios. The results also allowed verifying the parametric model against the Discrete Events Simulation model with no variability, since their results differ less than 3.5% for any KPI.

The results show that both models underestimate Output and overestimate

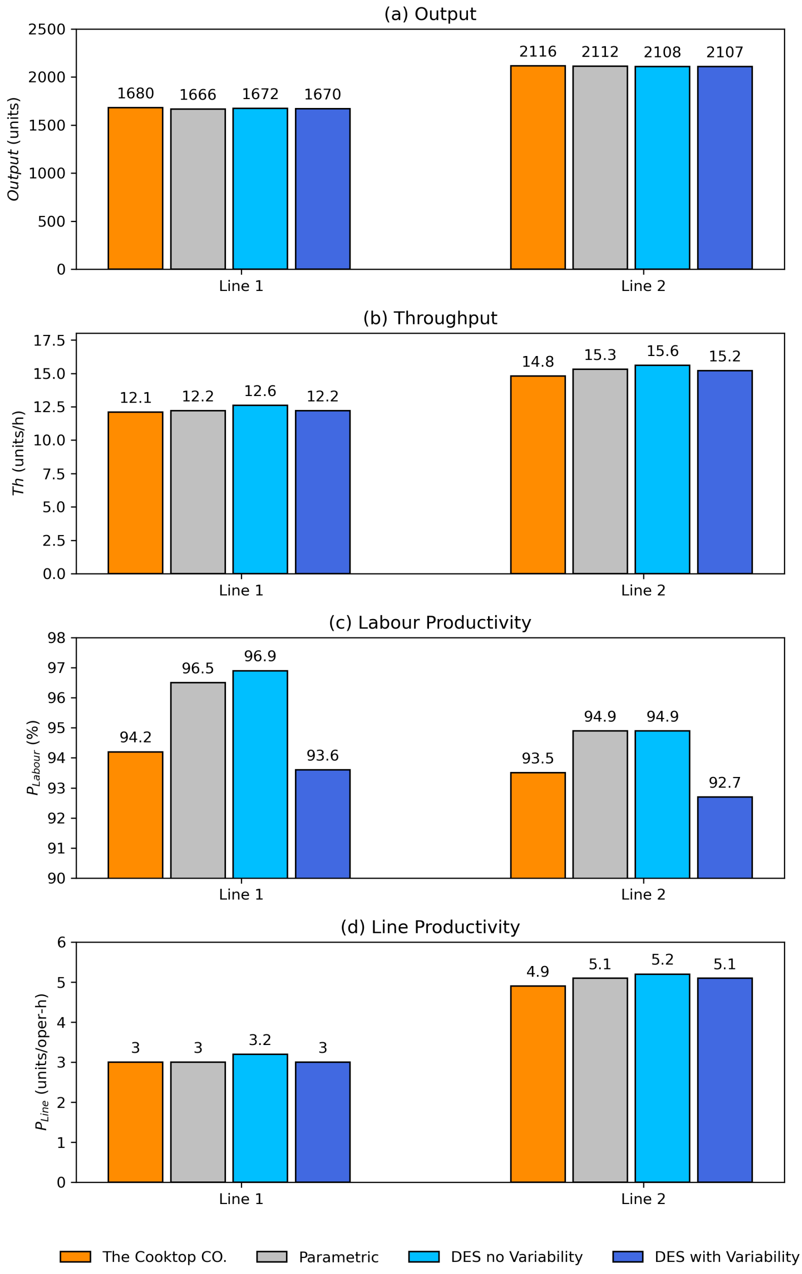


Figure 5.12: Results of validation using a parametric and discrete events simulation model, compared to empirical data from The Cooktop Co. industrial study case: (a) Output, (b) Throughput, (c) Labour productivity and (d) Line productivity.

Throughput, Labour Productivity and Line Productivity. The mean relative error is 1.63% and the max relative error is 4.9%, which means that both models are reliable for high-mix low-volume demand scenarios similar to the ones considered here.

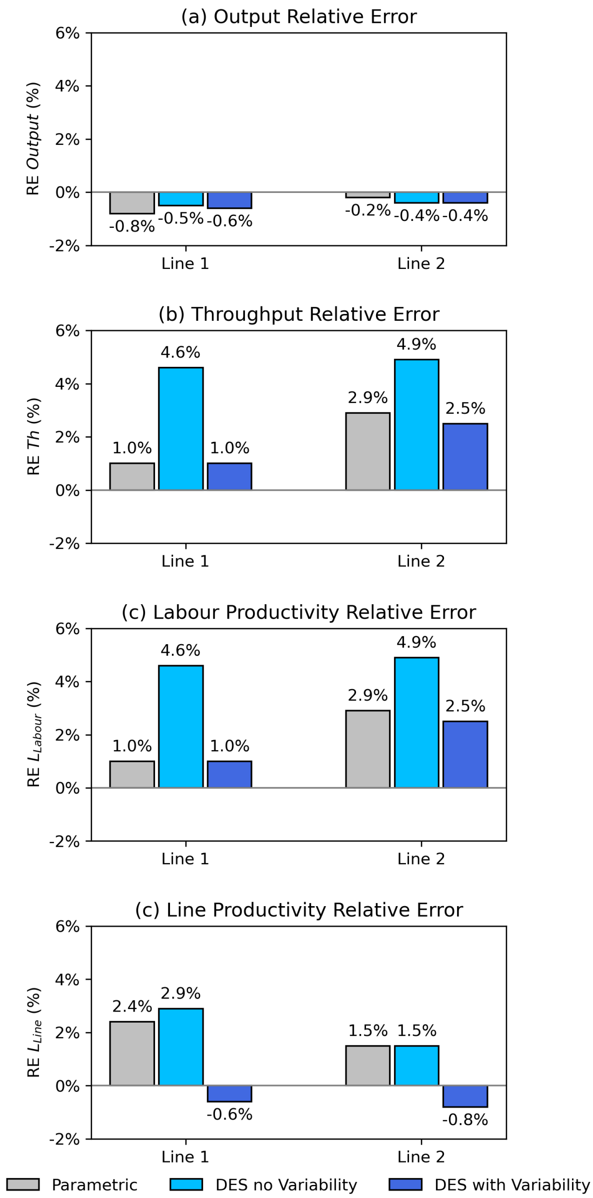


Figure 5.13: Relative error of KPI results using a parametric and discrete events simulation model: (a) Output, (b) Throughput, (c) Labour productivity and (d) Line productivity.

The sources of the errors could be (1) the simplifications that the models entail, such as the lack of process variability in the parametric model or the consideration of non-conforming units as scrap; (2) that constraints external to the assembly line take place: defective components, internal logistics service problems, or quality control equipment breakdown, among others.

Regarding the models' limitations, the parametric model presents great ease of use and speed of calculations, so that it can be used as a preliminary 'enhanced calculator'. Nevertheless, it lacks the complexity to take into account the combined effects of quality issues, variability, changeovers and minor stoppages. In consequence, it can be a useful, yet optimistic tool. The DES model, on the other hand, is already a powerful tool for examining theoretical situations, evaluating assembly line design alternatives, and answering specific questions within a given scenario. Moreover, the DES model can be easily expanded to include automated stations—e.g. collaborative robots [265]—or to take into account the effect of operator cognitive support technologies such as Augmented Reality [264].

Future lines of work would employ the parametric model presented here as a preliminary analysis tool, followed by a DES model expanded from the one described here, but adjusted to evaluate the impact of different digital technologies which would affect certain variables: for example, while employing collaborative robots would increase the line productivity, augmented reality for operator support would reduce the process time variability. Such a model would allow us to understand how to maximise the effect of investments to achieve the desired operational or business goals. Finally, it remains an open topic comparing the estimated improvements to be obtained by implementing Industry 4.0 digital technologies with the actual results in an industrial environment.

5.4 Summary

This chapter focused on the development of discrete events simulation models for the analysis of flexible assembly operations. The limitations faced by the simpler mathematical model presented in Chapter 4 were overcome using the software FlexSim®. Validation of the DES models development methodology was carried out by comparison against empirical data from the industrial study case of The Cooktop Company. The description of both mathematical and DES models as well as the verification and validation results were presented at the 55th CIRP Conference on Manufacturing Systems.

This chapter makes two key contributions:

1. Built DES models to analyse flexible assembly operations with a focus on realistic product model changeovers, suitable for studying high-mix low-volume assembly.
2. Verified and validated them using the previously developed parametric model and the industrial study case of The Cooktop Company.

Having established a methodology to build simulation models and proved that can represent real assembly operations with reduced errors in critical KPIs, this chapter paved the way for designing and analysing assembly line configurations that focus on the most critical factors identified in Chapter 4: number of workstations and batch size. Thus, the following Chapter 6 introduces parallel walking-worker assembly lines which include both manual and automatic stations. Another research patch would be to expand the simulation model to include the outer layers of the assembly systems. Chapter 7 does so by incorporating in-plant logistics into the DES models and analysing key aspects of milkrun trains' performance when feeding high-mix low-volume assembly lines.

CHAPTER 6

Designing parallel walking worker assembly lines

Aiming to increase the productivity of low-volume manual assembly lines, the introduction of traditional automation entails high investment costs, which in turn drive the integration of several product lines to achieve a sufficiently large aggregate production volume. However, fully automated assembly systems typically lack the flexibility necessary to deal with the product variety brought by the integration of multiple product families. The development of more flexible and low-cost automation technologies, such as Industry 4.0's collaborative robots, offers the potential to achieve high productivity even for low-volume assembly.

In Chapter 4, a preliminary study of the most critical factors to assembly line labour productivity concluded that the number of stations and the batch size affect productivity the most. Batch sizes are seldom a design decision, but rather are imposed by the external market demand and the production costs derived, among other factors, from the batch size itself. However, an assembly system capable of producing efficiently (i.e., at low cost) despite small batch sizes is more flexible, since it can address changes to market demand more quickly, and therefore presents competitive advantages to manufacturers facing mass customisation markets.

The other key factor, the number of stations, implies that *longer* assembly lines (i.e., with a larger number of stations) suffer from higher line balancing losses and also higher model changeover losses. On the other hand, shorter assembly lines present reduced line capacity (i.e., lower maximum throughput).

To overcome this problem, which constitutes the core research aim of this thesis, this chapter introduces parallel walking-worker semiautomatic assembly lines, illustrated by Figure 6.1. In particular, this chapter addresses the research objective of designing assembly systems that increase productivity by at least +25% while facing high-mix low-volume demand, by incorporating a combination of manual and automated stations. The DES modelling methodology developed, verified and validated in Chapter 5 is used here to analyse the performance of several assembly line configurations under different scenarios.

Figure 6.1: Parallel walking-worker assembly line simulation model.

The research presented here was published as an article in the journal *Processes* [283], and therefore each section of the chapter corresponds to a section of the article: Introduction (6.1), Literature Review (6.2), Materials and Methods (6.3), Results (6.4), Discussion (6.5) and Conclusion (6.6). Section 6.7 includes four additional scenarios which were used to analyse other aspects of PWWAL design. Finally, Section 6.8 summarises the key findings and contributions of the chapter.

Article title:

Parallel Walking-Worker Flexible Assembly Lines for High-Mix Low-Volume Demand

Article abstract:

Demand trends towards mass customisation drive the need for increasingly productive and flexible assembly operations. Walking-worker assembly lines can present advantages over fixed-worker systems. This article presents a multiproduct parallel walking-worker assembly line with shared automated stations, and evaluates its operational performance compared to semiautomated and manual fixed-worker lines. Simulation models were used to set up increasingly challenging scenarios

based on an industrial case study. The results revealed that semiautomated parallel walking-worker lines could achieve greater productivity (+30%) than fixed-worker lines under high-mix low-volume demand conditions.

6.1 Introduction

Mass customisation and personalisation demand trends drive production operations towards high product variability, smaller batch sizes, reduced inventory, and shorter lead times [2, 28]. As a consequence, an increasing number of industries need to assemble a large number of similar products in small quantities each, which is called high-mix low-volume demand [28]. To succeed under such circumstances, productivity and flexibility are required at the same time, contrary to the existing dichotomy [6]. Reconfigurable assembly systems, first, followed by the cyberphysical or smart assembly systems of Industry 4.0 and the future adaptive cognitive assembly systems, aim to address it [18, 61, 284].

Current manual or semiautomatic serial assembly lines (ALs) present productivity limitations due to the inherent losses of frequent changeovers and the difficulties of balancing a large mix of different products on top of the constraints imposed by automated stations. Moreover, these conventional fixed-worker assembly lines (FWALs) are not highly responsive to demand volume changes since the number of operators cannot be modified without compromising line balance. Unbalanced assembly lines are an open issue [285], and mass personalisation demand trends only aggravate the situation [13, 53]. To address these problems, walking-worker assembly lines (WWALs) present benefits compared to FWALs. WWALs are line configurations in which operators move along the line, moving the products with them, so that each worker performs all assembly tasks on each station until the product is complete, and then starts over again. The benefits of WWALs versus FWALs are [286, 287]: increased flexibility in production level by an easy modification of the number of workers, reduction of WIP inventory, and—most importantly—avoiding the negative effects of workstations imbalance, as long as the number of assembly stations exceeds the number of workers involved. However, WWALs may suffer from productivity losses when in-process waiting times occur because of the stations ahead of an operator being blocked by the other workers [288]. The inclusion of machines within the WWAL can cause additional bottlenecks [289], which can counter the benefits of process automation.

Another take on this problem is parallel assembly lines [290, 291], which increase the reliability and flexibility of the lines, allow better balancing due to superior cycle times and lower number of operators and, therefore, increased productivity at the expense of larger equipment investments and space required. Combining both approaches—WWALs and parallel assembly lines—can provide important benefits in contexts of high-mix low-volume demand.

This article presents a multiproduct parallel walking-worker assembly line (PWWAL) with shared automated stations and evaluates its expected operational performance compared to semiautomated fixed-worker serial assembly lines when dealing with high-mix low-volume demand. The WWAL working logic was chosen due to its advantages over FWAL when dealing with stations balancing under high-mix demand conditions, despite the WWAL's intrinsic inefficiencies due to worker displacements. Additionally, parallel line configurations could prove useful when product changeovers are frequent due to smaller batch sizes, since the number of stations could be reduced, decreasing the changeover losses, which depend heavily on the number of stations when there are large cycle time differences between the models produced by the line.

Discrete events simulation (DES) models were used to perform this study due to their ease of implementation and the possibility to incorporate stochastic parameters [269, 270, 273, 292]. FlexSim® was employed to develop the simulation models. An industrial study case from a global white goods manufacturer was used to build the simulation models, provide input data, and allow validation using historical data. In this industrial case, which is common across many industries, the company goal is to improve the productivity of several manual assembly lines that had been optimised over the years. To achieve this goal, the lines could be merged and upgraded by introducing some automated stations to reduce the manual work content. However, productivity would increase at the expense of flexibility, since line balance deteriorates when increasing product variety. Thus, the motivation for this work is to gain insights into the productivity vs. flexibility trade-off of parallel walking-worker assembly lines in comparison to traditional fixed-worker lines.

The article is structured as follows: Section 6.2 offers a literature review on walking-worker assembly lines. Section 6.3 includes a description of the line configurations modelled, the models' inputs and outputs, and the simulation scenarios employed. Sections 6.4 and 6.5 present the results and discussion of the simulation scenarios, respectively.

6.2 Literature Review

Over the last 25 years, WWALs have been studied using analytical and simulation models, focusing on different aspects of this line configuration performance, and considering different combinations of factors. Table 6.1 summarises the key aspects of the articles selected for this section. It is worth mentioning that none of the articles consider sequence-dependent setup times or automated stations in their WWAL models. Walking times are often considered negligible when the processing times are significantly larger.

Little had been written on walking (moving) worker assembly lines before D.P. Bischak's article in 1996 [286], which points out several advantages of unbuffered WW modules: flexibility in the production level; reduction in work-in-process in-

Table 6.1: Key aspects of selected research articles on walking-worker assembly lines (WWALs).

Author	**Layout**	**Target**	**Method**	**Product**	**Setup**	**Walking Time**	**Automated Stations**	**Variability**
Bischak [286]	U-cell	Max throughput	Simulation	Single-model	No	Negligible	No	Yes
Wang [287]	Linear	Max throughput & line productivity	Simulation	Single-model	No	Yes		
Lassalle [288]	Linear	In-process waiting time	Simulation	Mixed-model	No	Negligible	No	Yes
Wang [289]	Linear	In-process waiting time	Simulation & mathematical modelling	Single-model	No	Negligible	No	Simulation only
Al-Zuheri [293]	U-cell	Line productivity & ergonomic performance	Mathematical modelling	Single-model	No	Yes	No	Yes
Cevikcan [294]	Segmented rabbit-chase	Line balancing	Mathematical modelling	Mixed-model	No	Yes	No	No
Bortolini [295]	U-cell	Max line productivity	Simulation	Mixed-model	No	Negligible	No	Yes

ventories; avoiding the negative effects of AL imbalances produced by the frequent introduction of new products; and improving reported worker morale. On the other hand, the importance of operator cross-training increases as it becomes an enabler of this AL configuration. It was established that WWALs can improve system responsiveness in terms of throughput, and that they work well for unbalanced processing times. The simulation results show a reduced importance of WIP buffers for WWALs versus FWALs, that low variability systems require no WIP buffers, and that buffers would only increase lead time.

Wang and Owen [287] presented a comparison between WWALs and FWALs in terms of line efficiency. Their DES model considered processing times variation and fixed walking times between stations in a linear single-model AL. It was concluded that the WWALs could provide higher output and efficiency than FWALs, and that it has greater tolerance to variations in processing time.

In a later article, Lassalle [288] looked into the details of the in-process operator waiting times of linear WWALs. Simulation was employed, considering negligible walking times and product changeovers. It was found that the productivity loss caused by in-process waiting times is predictable and adjustable, with the workers-to-workstations ratio being its main driver.

In their 2009 article, Wang et al. [289] studied linear WWALs using both simulation and mathematical modelling. They considered a mixed-model AL where workers may have unequal performance, leading to dynamic worker blockages due to the operational rule of not allowing faster operators to overtake slower ones.

Al-Zuheri et al. [293] looked into WWALs to understand their worker productivity and ergonomics performance. Mathematical modelling was used on a U-cell layout, considering process time variability, worker skill level, and walking speed, among other variables. It was found that increasing the workers' walking speed did not improve the productivity of the AL.

Cevikcan [294] presented a line balancing optimisation methodology for multimodel WWALs based on a mathematical model. Bortolini [295] proposed a mixed-model sequencing algorithm for unpaced unbuffered WWALs on U-cell layouts, aiming to optimise line productivity.

In addition, a recent article from Hashemi-Petroodi et al. [296] presented a literature review of different assembly and manufacturing workforce reconfiguration strategies, including walking-worker assembly lines. The authors found that (1) little has been published on multimodel walking-worker assembly lines, and (2) that an open field of research is the consideration of different workforce reconfiguration strategies, including walking-worker assembly lines, in a human–robot interaction environment.

Our article aims to help close this gap by looking into multimodel WWALs, which include manual and automated workstations.

6.3 Materials and Methods

In this article, the performance of the proposed parallel walking-worker assembly line configurations is compared to two fixed-worker assembly line configurations. DES models were used to understand the behaviour of the line configuration alternatives by simulating different scenarios. DES was chosen because it presents important advantages over mathematical modelling when stochastic elements are the main drivers of the system under study [270]. In the AL configurations considered here, the random nature of processing times is combined with random product arrival times to the automated stations. The simulation tool employed was FlexSim® (2022.0, FlexSim Software Products, Inc.). The scenarios are defined by a subset of the input parameters, design parameters. Fixed parameters are common to all models for all scenarios, as well as the disturbances, which govern stochastic features of the models. The performance of the AL configurations is evaluated using several key performance indicators (KPIs), as shown in Figure 6.2.

6.3.1 Assumptions

Figure 6.2 depicts the models employed in this study. All models feature the following general assumptions, following Boysen's classification [268]:

- The production systems are unpaced, buffered assembly lines.
- The number of workstations is constant, and they can only process one unit at a time. For the parallel line configuration, the number of stations refers to the number on each of the two lines.
- The model mix is known, and demand continues for the whole simulation horizon.
- They are multimodel assembly lines: they produce different models of products in batches. Setup is necessary before a batch of different products can be assembled, and it is performed by the operators as soon as possible, i.e., when the last unit of the previous batch has been processed. Setup time depends on the sequence of products, and it is lower when subsequent models are of the same product family.
- No component shortages: components being assembled onto the product are always available at the stations.
- The product sequence is governed by the parameter B_{CO}, which indicates the number of batches of the same family that are produced until a product family changeover occurs (which takes longer than a same-family model changeover).
- Processing and setup times are modelled stochastically using a lognormal distribution, which is governed by the average process/setup times and by a variability coefficient.
- Processing and setup times consist of smaller tasks, which are sufficiently small so that the line balance is not affected by a change in the number of stations.

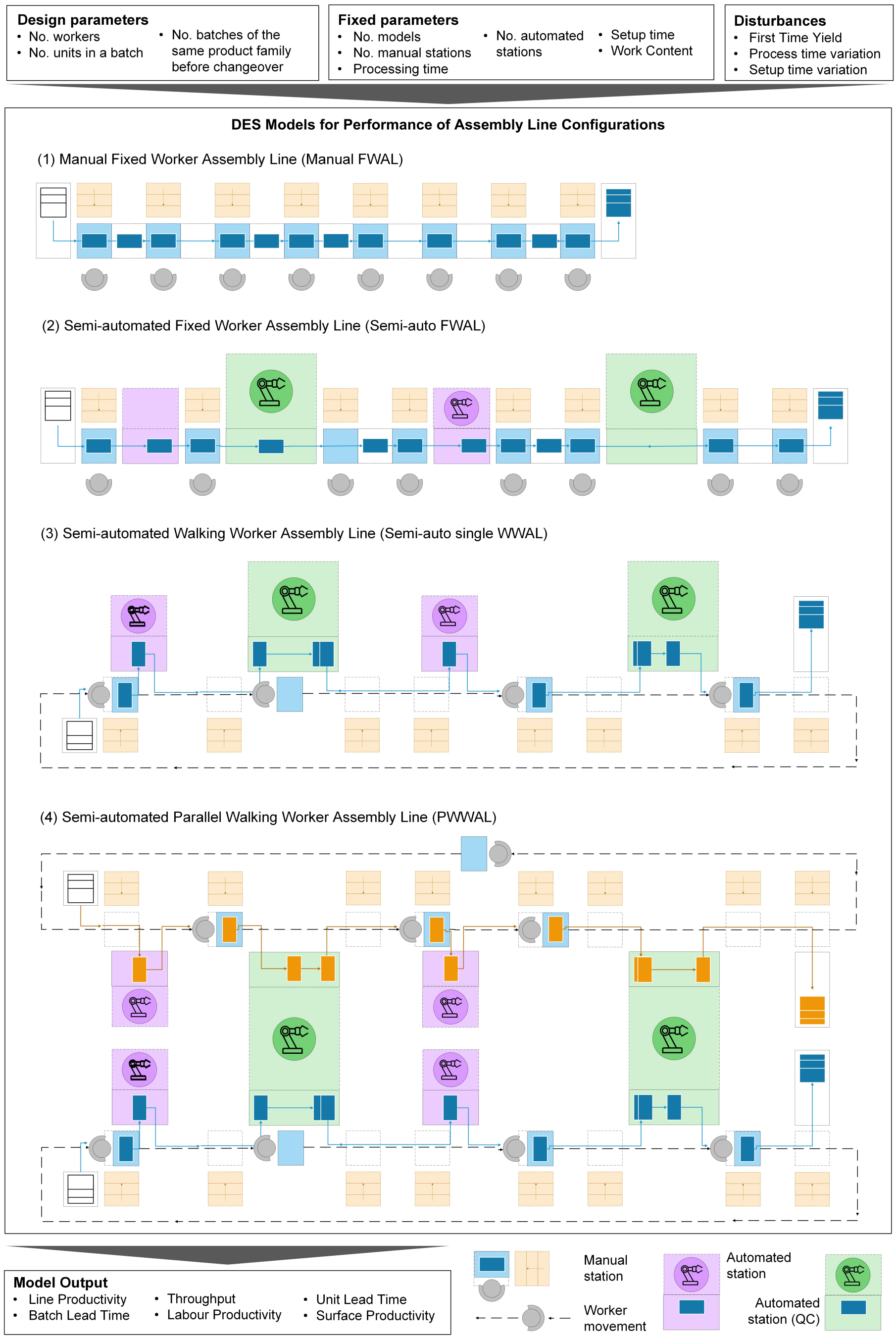


Figure 6.2: DES models for flexible assembly line configurations: (1) manual fixed-worker line (manual FWAL); (2) semiautomatic fixed-worker line (semiauto FWAL); (3) semiautomatic single walking worker line (semiauto single WWAL); (4) parallel walking-worker assembly line (PWWAL). Design parameters are changed when analysing the performance of assembly line configurations. Fixed parameters are based on industrial study case data. Variability of quality, manual assembly, and setup times are considered disturbances. Model output includes relevant KPIs for evaluation.

- When converting manual work content (WC_m) into automated (WC_{auto}), WC_m can be reduced equally from all stations.
- WC_m transformed into WC_{auto} becomes 20% larger due to the inferior assembly speed of the automated stations compared to well-trained human operators.
- Two automated stations perform in-line quality control (QC) in the middle and at the end of the assembly process. Defective units are reworked out of line, which may cause idle time to downstream operators.

Figure 6.2(1) and Figure 6.2(2) depict manual and semiautomated FWALs, which feature the following specific assumptions:

- Fixed workers: the operators are assigned to workstations and they do not leave them.
- Serial layout: the stations form a line, and the work-in-process products travel along them sequentially.
- The line balance depends on the number of operators.
- The manual FWAL features manual stations only, while the semiautomated FWAL includes manual and automated stations.
- Workstation buffers have a maximum capacity of one product.

Figure 6.2(3) shows the semiautomated walking-worker single assembly line, and Figure 6.2(4) shows the proposed parallel walking-worker assembly line. In these line configurations presented here, operators walk along the line and pick the components to assemble for the in-process product on a mobile trolley, while automated stations process units (Figure 6.3a). When arriving at the automated stations, the operators leave their current product in the in buffer and take a processed product from the out buffer of the automated station (Figure 6.3b). The operators then resume their path (Figure 6.3c). When a product is finished, it is placed in the finished products buffer, and then the operator walks back to the starting point to resume production.

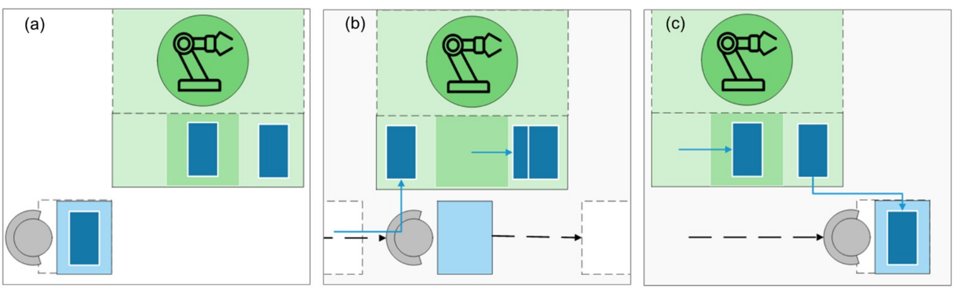


Figure 6.3: Operator–automated station interaction in semiautomated walking-worker assembly line. (a) Operator processes unit in a manual station. (b) Operator leaves unit on the automated station in buffer. (c) Operator takes ready unit from the automated station out buffer and moves to the next manual station to continue assembly.

Thus, both WWAL configurations were modelled under the following specific assumptions:

- The production system includes manual 'stations', which conform to one or two lines, and automated stations, some of which are shared by both lines for PWWAL.
- Despite the assembly being made on mobile trollies, it is the spaces by the picking shelves that are modelled as stations.
- There is a certain number (W) of operators working on the line, with a maximum equal to the number of stations.
- Operators move downstream, cannot overtake other operators, and can wait by a station in case it is not available when they arrive.
- The travelling time of the operators from one station to the next one is simulated considering a constant speed of 1 m/s.
- Automation stations in and out buffers' maximum capacity is one unit.
- Shared automated stations process products following an FIFO rule (first in, first out), and can only place processed units in the out buffer corresponding to the line of origin of the product.

The main objective of the analysis is to maximise line productivity, defined as the number of conforming units produced per operator-hour. In particular, the industry study case sets a line productivity target increase of +25% compared to the initial situation (manual FWAL). Minimising production lead time is also considered important, but less so than line productivity maximisation. The ability to modify throughput with ease is desirable as well. Consequently, a set of three 'main KPIs' (key performance indicators) was composed of line productivity, batch lead time, and throughput. A secondary set of three KPIs was used to understand what drives the main performance measures as well as find potential drawbacks. The 'secondary KPIs' are labour productivity, unit lead time, and surface productivity. Increasing labour productivity and surface productivity and minimising unit lead time is also desirable if possible.

6.3.2 Notation

The following notations are introduced:

Design parameters:

W	Number of workers (index w).
Q	Number of units in a batch.
B_{CO}	Number of batches of the same product family before changeover.

Fixed parameters:

M	Number of models (index m).
K	Number of manual workstations (index k).
J	Number of automated workstations (index j).
T_p	Processing time.
T_s	Setup time.
WC	Work content (i.e., total process time).

Disturbances:

FTY	First time yield.
CV_p	Process time coefficient of variation: $CV_p = \sigma_{Tp}/\mu_{Tp}$.
CV_s	Setup time coefficient of variation: $CV_s = \sigma_{Ts}/\mu_{Ts}$.

Key performance indicators:

P_{Line}	Line productivity (units/operator-h): production rate of conforming units per operator.
LT_B	Batch lead time (min): average time for a batch of units to be finished from the moment the last unit of the previous batch is finished.
Th	Throughput (units/h): production rate of conforming units.
P_{Labour}	Labour productivity (%): percentage of time that operators spend processing units. Setup and walking times are not considered productive.
LT_U	Unit lead time (min): average time for a unit to be finished from the moment it starts being assembled.
P_S	Surface productivity (units/operator-h-m^2): production rate of conforming units per operator and surface unit.

6.3.3 Input Data

The DES models employed data corresponding to the industrial case study. The parameter values are based on the industrial case data, as indicated in Table 6.2. The assembly operations considered in this article deal with three families of similar products. Although all product families share technological principles, core functionalities, and are subjected to the same QC tests, their dimensions, materials, and other secondary features are not the same. Batch sequencing is performed by grouping products of the same family together, which leads to the B_{CO} design parameter.

Table 6.2: Design parameters, fixed parameters, and disturbances considered in the models.

Parameter	**Units**	**Min**	**Max**	**Current State**
Design parameters				
W	Workers	2	10	8
Q	Units	12	48	48
B_{CO}	Batches	1	3	3
Fixed parameters				
M	Models			3
K	Stations			8 (FWAL), 16 (PWWAL)
J	Stations			4
T_p	s			See Tables 6.3 and 6.4
T_s	s			See Table 6.5
WC	s			See Table 6.3
Disturbances				
FTY	%			99
CV_p	%			15
CV_s	%			15

Table 6.2 includes the current state values for the design parameters, which define what are considered standard demand conditions. It also shows the fixed parameters and disturbances included in the models. They remain unchanged for all assembly line configurations on all demand scenarios.

Processing times depend on the model (index m). The average values of manual processing times—for stations $k \in \{1, ..., 8\}$, along with the manual, automated, and walking work contents—are found in Table 6.3.

Note that, based on WC_m for manual FWAL, the automation of ca. 23% of the WC_m means to increase that WC by 20%, under the assumption that well-trained manual operators can assemble faster than a collaborative robot. It was deemed realistic to assume that both FWAL and WWAL process and setup times would have a similar distribution in terms of mean and variability values. It was also assumed that process times can be atomised because the individual (indivisible) tasks considered in the industrial case take, on average, between 7 and 20 seconds, which is significantly lower than the assembly stations process times (cf. Table 6.3).

The average values of automated processing times for stations $j \in \{1, ..., 4\}$ are found in Table 6.4. In theory, none of the automated stations is the AL bottleneck. However, the processing times variability and the incoming units simultaneity calls for additional capacity. In the industrial study case presented here, automated stations $j = 1$ and $j = 3$ are duplicated (cf. Figure 6.2(3),(4)) because they are

Table 6.3: Manual processing times and work content input data.

	Tp_m^{max}	Tp_m^{min}	WC_m	WC_{auto}	WC_{walk}	WC_{total}
Model, m	s	s	s	s	s	s
Manual FWAL						
1	158	146	1179	0	0	1179
2	129	119	962	0	0	962
3	100	92	745	0	0	745
Semiauto FWAL						
1	122	112	908	325	0	1233
2	99	92	740	266	0	1006
3	77	71	572	207	0	779
Semiauto PWWAL						
1	122	112	908	325	33	1266
2	99	92	740	266	33	1039
3	77	71	572	207	33	812

not QC stations, which reduces the investment requirements.

Table 6.4: Automated processing times input data.

	$Tp_{m,j}$ (s)			
Model, m	$j = 1$	$j = 2$	$j = 3$	$j = 4$
1	31	89	105	100
2	28	76	85	77
3	25	53	65	54

The first and second manual stations include tooling and fixtures that require lengthier changeovers than the rest, which consist of picking stations only. Moreover, the T_s base value is also altered depending on the preceding and subsequent model being produced. Table 6.5 shows the setup time average values. Automated stations do not require any setup time as it has been estimated to be of similar magnitude to same-product setup, therefore being included in the processing time.

Table 6.5: Setup time input data.

	T_s (s)	
Station	Product Family Change	Same Product Family
$k \in \{1, 2\}$	480	360
$k \in \{3, ..., 8\}$	48	36

The production sequence depends on the B_{CO} design parameter, as shown in Table 6.6. The sequence is repeated until the end of the simulation time. For semiauto PWWAL, model 1 (m_1) and model 3 (m_3) batches are assigned to one of the parallel lines, and model 2 (m_2) batches are assigned to the other one. In consequence, PWWALs benefit from performing fewer product family changeovers.

Table 6.6: Production sequence input data.

B_{CO}	Sequence (Batches of Q Units)									
1	m_1	m_2	m_3	$\circlearrowleft$						
2	m_1	m_1	m_2	m_2	m_3	m_3	$\circlearrowleft$			
3	m_1	m_1	m_1	m_2	m_2	m_2	m_3	m_3	m_3	$\circlearrowleft$

The DES models consider the inherent variability of manual assembly processes by using a lognormal distribution for process and setup times, based on the recommendations by Banks and Chwif [278]. The mean (μ) for this distribution is the process standard assembly time for each—different for each product family—and the standard deviation (σ) is found as a percentage of the mean given by the parameters CV_p and CV_s. The values for these parameters were estimated from historical data from the industrial partner existing manual assembly lines, and found to be in the range of 15–20% for the assembly lines considered in this study case. To minimise the uncertainty of the results due to the stochastic nature of processing and setup times, each simulation scenario was run 20 times.

To calculate P_S, the surface requirements for each assembly line configuration were measured—manual AL configuration—or estimated from the study case preliminary line designs, resulting in the surface requirements shown in Table 6.7. Note that the greater WWAL lengths, compared to semiautomated FWAL, are due to the increased WIP and operator buffers.

Table 6.7: Shopfloor surface requirements for different assembly line configurations.

Configuration	Depth (m)	Length (m)	Shopfloor Surface (m^2)
Manual FWAL	4	16	64
Semiautomated FWAL	4	23	92
Single WWAL	5	33	165
Parallel WWAL	10	33	330

The simulation time is 60 h, with a 1 h warmup time. At the start, buffers between manual stations are empty (FWAL models), and automated stations are full.

6.3.4 Validation

The manual fixed-worker assembly line configuration (Figure 6.2(1)) was simulated using input parameter values from the industrial study case from a global white goods manufacturer site located in the north of Spain. The simulation output was compared against the company's operational KPIs collected in January 2021. The average relative error of the KPI estimations was 1.8%, and the maximum error was 4.9%. This error magnitude was deemed satisfactory for the scope of this work. Thus, the DES model was validated, and the same simulation methodology was used to build the semiautomated FW and the parallel walking-worker assembly line configurations (Figure 6.2(2)–(4)).

6.3.5 Performance Comparison for Different Demand Scenarios

The performance of the different line configurations was assessed under different demand conditions. The standard demand conditions, *scenario i*, were created by setting the design parameters to 8 operators, a batch size of 48 units, and a product family changeover frequency of 3 batches, as shown in Table 6.8. This scenario represents the performance of the line configurations if the demand remains stable and does not change towards mass customisation. The results from this *scenario i* set the baseline performance of each line configuration.

Table 6.8: Simulation scenarios and design parameters analysed.

Scenario	$\boldsymbol{W}$ **(Operators)**	$\boldsymbol{Q}$ **(Units)**	$\boldsymbol{B_{CO}}$ **(Batches)**
i. Standard demand	8	48	3
ii. High-mix (1)	8	$\{12, 24, 48\}$	3
iii. High-mix (2)	8	48	$\{1, 2, 3\}$
iv. Low-volume	$\{2, 4, 8\}$	48	3
v. High-mix low-volume	8	12	1
vi. Degree of automation	$\{4, 6, 8\}$	$\{12, 48\}$	$\{1, 3\}$

To adapt to increasingly challenging demand conditions, assembly operations flexibility in terms of reduced lead times, smaller batch sizes, and more frequent rotation of product families are critical. To understand the performance of the different assembly line configurations under such conditions, simulation *scenarios ii–v* were set up, as shown in Table 6.8. *Scenarios ii–iv* look into how the performance of each line configuration is affected by the change of the three design parameters individually. *Scenario v* considers the most severe demand conditions at the same time and compares the performance against the base scenario. Finally, *scenario vi* analyses the effect of automation in terms of percentage of work content automated, under either standard or high-mix low-volume demand conditions, and for a varying number of manual operators. On the other hand, the effect of the automation layout structure (i.e., the number of shared automated stations) would be hardly observed and analysed using the industrial study case presented here because none of the automated stations are the AL bottleneck. Therefore, in this particular case, the number of automated stations would not significantly impact the AL operational KPIs. The following section, Section 6.4, includes the outcome of the simulations.

6.4 Results

This section includes the models' outputs (KPIs) for each *scenario i–vi* shown in Table 6.8. The results shown in this section are the average KPI values of 20 simulation runs. The maximum standard deviation of the results, as a percentage of the average value, is 1.1%. This indicates that the results are relatively stable with respect to the models' disturbances. For each scenario, the simulation results are shown in tables including the three AL configurations. The main KPIs (P_{Line}, LT_B, Th) improvements for the semiautomated FWAL and PWWAL configurations are then evaluated compared to the manual FWAL configuration. Note that Th (units/h) and P_{Line} (units/oper-h) variations with respect to manual FWAL are the same because the number of operators remains constant.

6.4.1 Base Scenario: Current-State Demand

The results of simulating the base scenario demand on the four assembly line configurations are shown in Table 6.9. Firstly, P_{Line} increases as a result of automation for semiautomated FWAL and WWAL configurations. It is important to note that the manual work content reduction obtained by introducing automation was ca. −23%.

Table 6.9: Operational KPIs for manual FWAL, semiautomated FWAL, semiautomated single WWAL, and parallel walking-worker assembly line configurations under standard demand conditions (*scenario i*).

	P_{Line} u/oper-h	LT_B min	Th u/h	P_{Labour} %	LT_U min	P_S u/oper-h-m2
Manual FWAL	3.19	132	25.5	87.0	20.5	0.05
Semiauto FWAL	3.98	111	31.9	83.3	23.4	0.043
Semiauto Single WWAL						
$W = 8$	3.48	138	27.9	71.6	25.4	0.021
$W = 7$	3.70	145	25.9	75.7	25.0	0.022
$W = 6$	3.93	156	23.6	79.3	26.3	0.024
$W = 5$	4.03	176	20.1	82.9	20.1	0.024
$W = 4$	4.28	200	17.1	85.6	27.5	0.026
Semiauto PWWAL	4.23	203	33.8	85.6	27.9	0.013

The eight workers semiautomated single WWAL improves the performance compared to the manual FWAL. However, it presents worse performance than semiauto FWAL in terms of each and every one of the KPIs considered because there are not more stations than workers. This means that the single WWAL suffers from both line unbalancing and walking inefficiencies. Progressively reducing the number of workers in this configuration increases P_{Labour}, P_{Line}, and P_S, at the cost of a sharp reduction in Th. Adding a second walking-worker line and sharing some of the existing automated stations leads to increased productivity and throughput, transforming the semiautomated single WWAL into the parallel WWAL shown in Figure 6.2(4). It is very significant that the walking-worker way of working allows duplicating the throughput—from 17.1 to 33.8 units/h—by duplicating the number of workers while maintaining very high labour productivity (85.6%). Since the single WWAL presents no critical productivity advantages over the PWWAL, the following subsections omit the results of the single WWAL and focus on the semiauto FWAL vs. PWWAL comparison.

The semiautomated FWAL configuration achieves a +25% increase in P_{Line} (see Figure 6.4). On the other hand, the PWWAL P_{Line} rises by +33% despite the walking time losses since there are no line balancing losses in this configuration. This is particularly remarkable when considering that WWAL configurations present an additional walking WC of 33 s per unit and 33 s return time to the first station (see Tables 6.3 and 6.7).

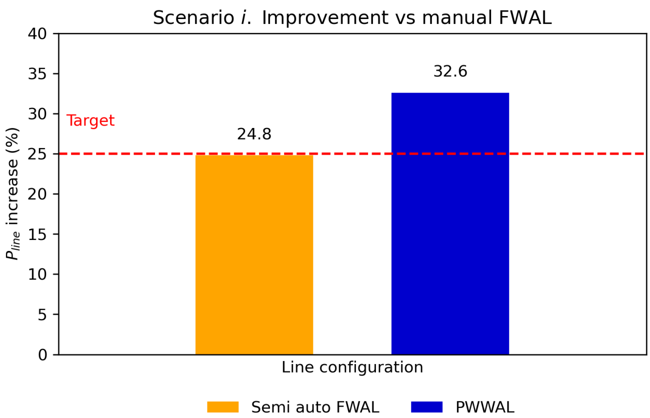


Figure 6.4: Line productivity increase of semiautomated FW and parallel walking-worker with respect to manual FW line configuration under standard demand conditions (*scenario i*).

On the other hand, batch lead time follows different trends: it improves for semiautomated FWAL (−16% LT_B reduction) but it worsens significantly for PWWAL (+54% LT_B increase) compared to manual FWAL. Semiauto FWAL LT_B improves despite the increased line length—eight manual stations plus four automated stations—due to the increased Th (+25%). Contrarily, PWWAL LT_B increases greatly despite its total Th increase (1) due to the walking-worker logic; (2) because each one of the parallel lines consists of only four operators—cf. LT_B for single WWAL with $W = 4$ and LT_B for PWWAL on Table 6.9; and (3) because the total work content increases by ca. 7–9% when taking into account manual, automated, and walking WC (see Table 6.3).

Unit lead time increases as a result of introducing automated stations, but less so for semiauto FWAL (+14% LT_U increase) than for PWWAL (+36% LT_U increase vs. manual FWAL). Once again, note that the LT_U of single WWAL with four operators is approximately the same as the LT_U of PWWAL.

Finally, the surface needed for the PWWAL is much greater than for manual or semiautomated FW lines (see Table 6.7), resulting in a significant P_S decrease.

As shown in Figure 6.4, the main KPI improvements (P_{Line} increase) meet the industrial case study target under standard demand conditions. The next section, Section 6.4.2, analyses how the AL configurations deal with more challenging demand conditions.

6.4.2 High-Mix and Low-Volume Demand Scenarios

Simulation *scenarios ii* to *iv* test the line configurations under tougher demand conditions than *scenario i*. The performance of the assembly systems is expected to deteriorate for all AL configurations, but the focus here is the performance of semiautomated FWAL and PWWAL compared to manual FWAL.

Scenario ii: High-mix presents the necessity of reducing batch sizes due to increasingly atomised demand trends. Table 6.10 shows the KPIs resulting from simulating the different line configurations under a gradually smaller batch size (Q). The PWWAL configuration is best in terms of P_{Line}, Th, and P_{Labour} at all levels of Q, and is the worst in terms of LT_B, LT_U, and P_S. For the three line configurations, all KPIs deteriorate as a result of reducing Q.

Note that line productivity for semiautomated FWAL with $Q = 24$ units is still greater than for manual FWAL with $Q = 48$ units, and that the line productivity for PWWAL with $Q = 12$ units is still significantly superior to manual FWAL with a Q of 48 units. A key driver for this is that setup time losses are smaller for PWWAL than for FWAL because PWWAL employs fewer operators per AL branch.

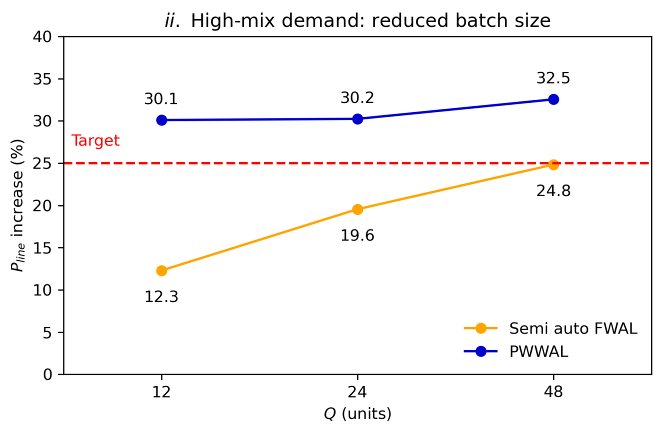


Figure 6.5: Line productivity improvement of semiautomated FW and parallel walking-worker with respect to manual FW line configuration for reduced batch size (Q, *scenario ii*).

Figure 6.5 shows that manual FWAL deals with reduced batch sizes worse than semiautomated AL since the P_{Line} of semiauto FWAL and PWWAL shows

Table 6.10: Operational KPIs of manual FWAL, semiautomatic FWAL, and PWWAL for reduced batch size (Q, *scenario ii*), reduced no. of batches until product family changeovers (B_{CO}, *scenario iii*), and reduced no. of workers (W, *scenario iv*).

		Batch Size, Q (units)			**B_{CO} (batches)**			**W (operators)**		
KPI	**AL Configuration**	12	24	48	1	2	3	2	4	8
P_{Line} (u/oper-h)	Manual FW	2.73	3.04	3.19	3.19	3.20	3.19	3.60	3.45	3.19
	Semiauto. FW	3.07	3.64	3.98	3.91	3.97	3.98	-	-	3.98
	PWW	3.56	3.97	4.23	4.14	4.18	4.23	4.45	4.42	4.23
LT_B (min)	Manual FW	50	77	132	131	131	132	416	225	132
	Semiauto. FW	51	70	111	112	111	111	-	-	111
	PWW	73	124	203	209	206	203	704	366	203
Th (u/h)	Manual FW	21.9	24.4	25.5	25.5	25.6	25.5	7.2	13.8	25.5
	Semiauto. FW	24.5	29.1	31.9	31.3	31.8	31.9	-	-	31.9
	PWW	28.5	31.7	33.8	33.1	33.4	33.8	8.9	17.7	33.8
P_{Labour} (%)	Manual FW	73.2	82.0	87.0	85.8	86.6	87.0	96.2	93.0	87.0
	Semiauto. FW	63.4	75.0	83.3	80.5	82.6	83.3	-	-	83.3
	PWW	72.9	80.9	85.6	85.0	85.6	85.6	90.9	90.2	85.6
LT_U (min)	Manual FW	18.5	19.4	20.5	20.1	20.3	20.5	18.8	19.7	20.5
	semiauto. FW	24.0	23.5	23.4	23.4	23.3	23.4	-	-	23.4
	PWW	33.2	29.7	27.9	28.5	28.2	27.9	66.6	40.1	27.9
P_S (u/oper-h-m^2)	Manual FW	0.043	0.048	0.050	0.050	0.050	0.050	0.056	0.054	0.050
	Semiauto. FW	0.033	0.040	0.043	0.043	0.043	0.043	-	-	0.043
	PWW	0.011	0.012	0.013	0.013	0.013	0.013	0.013	0.013	0.013

improvements for all levels of batch size. It can be seen that PWWAL maintains an improvement of ca. +30 to +33% P_{Line} compared to manual FWAL for all Q levels. On the other hand, semiautomated FWAL improvements vs. manual FWAL decrease as Q decreases. This leads to the conclusion that PWWAL deals with reduced batch sizes better than semiautomated FWAL. This is a key finding since maintaining high line productivity, even when significantly reducing the batch size, is the main goal of the PWWAL.

Scenario iii also considers a high-mix demand situation, in this case by requiring more frequent changeovers, i.e., the number of batches before product family changeover, B_{CO}, decreases. The KPI results of *scenario iii* are shown in Table 6.10. The only performance indicator that is significantly affected is P_{Labour}, which decreases for semiautomated FWAL by ca. 2 percent points. However, this decrease in P_{Labour} is not large enough to drag down P_{Line} significantly, as shown in Figure 6.6.

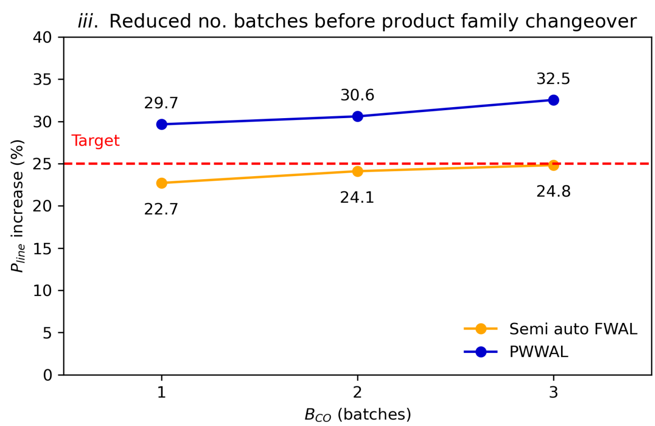


Figure 6.6: Line productivity improvement of semiautomated FW and parallel walking-worker with respect to manual FW line configuration for reduced no. of batches until product family changeovers (B_{CO}, *scenario iii*).

Simulation *scenario iv* considers a situation where the demand levels drop, and the throughput of the AL must be adjusted accordingly. To achieve this, the number of workers, W, is reduced. Note that the semiautomated FWAL is not able to modify this parameter under the constraints presented in Section 6.3. In reality, the production level of the semiautomated line could be adjusted by modifying other factors, such as the number of shifts, which are outside the scope of this work. Table 6.10 shows the simulation results for each line configuration when changing the parameter W.

Firstly, Th decreases as W decreases for manual FWAL and PWWAL configurations, but it does not decrease equally, due to line and labour productivity. P_{Labour} increases significantly for manual FWAL (from 87 to 96.2%) but not so much for PWWAL (from 85.6% to 90.9%) when W is reduced from eight to two workers.

The P_{Labour} increase is due to the better line balance in the case of manual FWAL; and due to the reduction in in-process operator idle time for PWWAL—consistent with the conclusions by Lassalle et al. [288]—and the reduction in automated station saturation caused by the lower Th. Consequently, P_{Line} increases when W decreases.

Lead times, however, behave quite differently. LT_U decreases slightly for manual FWAL but increases sharply for PWWAL because of its production logic, by which operators leave units in the automation queues upon arrival, and then take a unit already processed by the automated stations. Since the number of WIP buffers before automations remains constant regardless of W, when $W << K$, the lead time increases. On the other hand, LT_B increases as W is reduced since its main contributor is the cycle time, which is inversely proportional to W. This trend affects both manual and PWW line configurations.

Finally, P_S increases very slightly when W is reduced, as a consequence of the increased P_{Line}. It is important to note that the PWW line configuration is the only one that allows introducing more operators if needed—until the automations are saturated—which allows increased throughput even further at the cost of reducing productivity.

Figure 6.7 shows that PWWAL performs better than manual FWAL in terms of P_{Line} at all levels of W. However, with $W = 2$ operators it is no longer possible for PWWAL to achieve the target +25% increase in P_{Line} compared to manual FWAL.

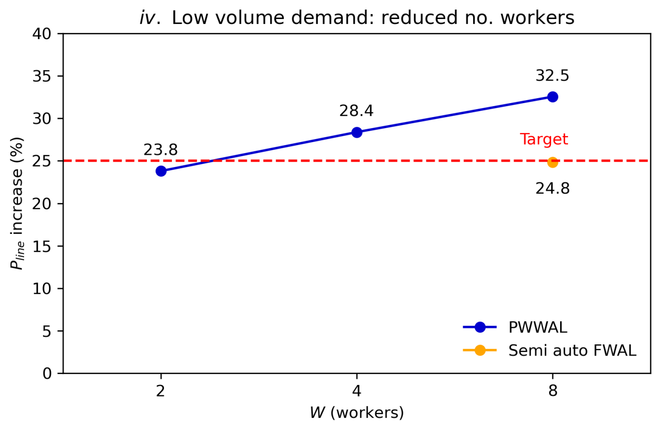


Figure 6.7: Line productivity improvement of semiautomated FW and parallel walking-worker with respect to manual FW line configuration for reduced no. of workers (W, *scenario iv*).

6.4.3 High-Mix Low-Volume Demand Scenario

Simulation *scenario v* considers a combination of *scenarios ii* and *iii* demand conditions: small batch size ($Q = 12$ units) and frequent product family changeovers ($B_{CO} = 1$ batch). Table 6.11 shows the KPIs resulting from *scenario v*.

Table 6.11: Operational KPIs for manual FWAL, semiautomated FWAL, and parallel walking-worker assembly line configurations under high-mix low-demand demand conditions (*scenario v*).

KPI	Units	Manual FWAL	Semiauto FWAL	PWWAL
P_{Line}	u/oper-h	2.63	2.82	3.42
LT_B	min	51	53	88
Th	u/h	21.0	22.6	27.4
P_{Labour}	%	70.3	58.0	70.4
LT_U	min	18.6	24.8	34.5
P_S	u/oper-h-m^2	0.041	0.031	0.010

P_{Line} and Th for semiautomatic FW and PWW lines are greater than those of manual AL configuration. However, only the PWWAL configuration allows a similar P_{Labour} under high-mix low-volume conditions. P_{Labour} decreases sharply under high-mix low-volume demand compared to standard conditions (cf. results of *scenario i* on Table 6.9), which affects semiautomated FWAL more intensely than PWWAL. This explains why P_{Line} improves only by +7% for semiautomated FWAL, compared to +30% for PWWAL, as shown in Figure 6.8.

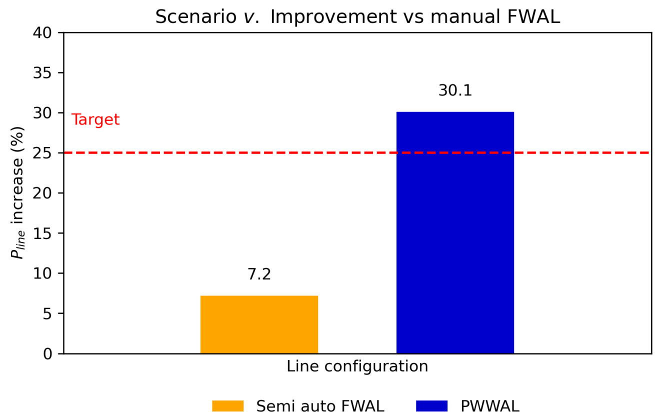


Figure 6.8: Line productivity improvement of semiautomated FW and parallel walking-worker with respect to manual FW line configuration under high-mix low-volume demand conditions (*scenario v*).

On the other hand, LT_B is worse for semiautomated than for manual lines. LT_B for PWWAL is significantly greater than for FWAL. This is deduced from the fact that LT_U almost doubles for PWWAL compared to manual FWAL (34.5 min vs. 18.6 min). This also indicates that the WIP levels of PWWAL must be superior to those of FWAL lines. Finally, P_S shrinks slightly under high-mix low-volume demand conditions compared to *scenario i*.

In summary, under both standard (*scenario i*) and high-mix low-volume demand conditions (*scenario v*), the parallel walking-worker line configuration achieves greater line productivity, which is the main goal of the industrial case presented. However, parallel walking-worker lines suffer from a higher batch lead time than fixed-worker line configurations. The parallel walking-worker configuration allows meeting the target line productivity improvement of +25% even under the most challenging conditions simulated. In contrast, the semiautomated FWAL presents perform better on secondary KPIs, such as lead time and surface productivity.

6.4.4 Degree of Automation

Simulation *scenario vi* tests the performance of semiautomated AL configurations for varying degrees of automation, in terms of the percentage of manual work content that has been assigned to automated stations. *Scenario vi* also considers the influence of demand conditions (Q, B_{co}) and number of manual operators (W). The results of *scenario vi* simulations are shown in Table 6.12 and Table 6.13, with the behaviour of the most significant KPIs depicted in Figure 6.9.

Figure 6.9a shows the assembly line productivity as the degree of automation increases. Note that the *base scenario* corresponds to 23% automated WC. The simulation results show that the productivity is at a maximum for the base scenario with eight manual operators ($W = 8$). This is coherent with the number of manual and automated stations being chosen, aiming for line balance. From this point, decreasing the degree of automation reduces the line productivity, since the manual labour becomes the bottleneck. Increasing the degree of automation while keeping W constant also reduces the line productivity, due to the automated stations becoming the bottleneck. Note that this trend is maintained for both standard demand conditions (solid line series) and high-mix low-volume conditions (dashed line series). Productivity falls because the workers are increasingly idle and the output does not increase. The assumption that manual WC can be automated, increasing the processing time by 20%, plays an important role here. The study case assumes that this is reasonable since a well-trained operator assembles faster than a regular collaborative robot (see Section 6.3.3). Therefore, reducing W should increase the line productivity when the degree of automation is high. Unfortunately, for traditional FWAL lines (yellow), this change cannot be carried out without degrading the line balance. On the other hand, walking-worker lines can reduce the number of manual operators without incurring any penalty. This situation was simulated for $W = 6$ and $W = 4$ total manual operators (medium and light blue series, respectively, in Figure 6.9a. By decreasing W, PWWALs allow to achieve an even greater line productivity with a higher degree of automation. This is due to the fact that the manual and automated process times are being balanced.

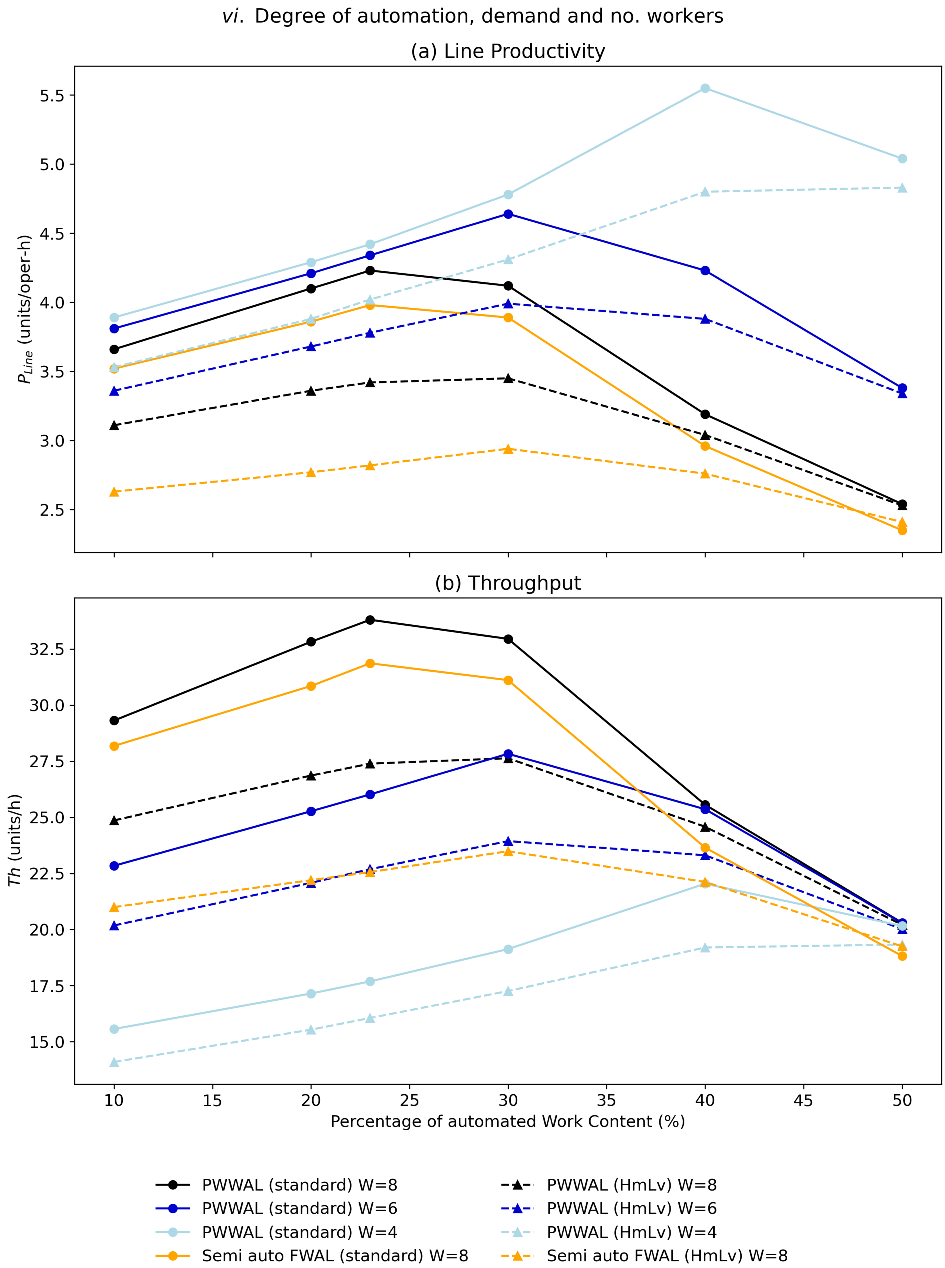


Figure 6.9: Performance of semiautomated FW and parallel walking-worker line configurations, for different number of manual workers, under standard and high-mix low-volume demand conditions (*scenario vi*): (a) line productivity (P_{Line}), (b) throughput (Th).

However, this productivity increase comes at the expense of reducing the throughput of the assembly line, since W has been reduced, as shown in Figure 6.9b. Note how a smaller W results in gradually lower Th for all levels of automation and for all demand conditions. The Th of both line configurations

(PWWAL and semiauto FWAL) for all levels of W tends towards a common point as the degree of automation increases, because Th is governed by the process time of the bottleneck.

In conclusion, PWWALs offer greater flexibility than fixed-worker lines in terms of benefiting from an increased degree of automation because they allow to easily rebalance the manual/automated workload by seamlessly removing operators, thus achieving greater line productivity. On the other hand, this comes at the expense of reducing the throughput and significantly increasing the batch lead time.

Table 6.12: Operational KPIs of semiautomated FWAL and PWWAL for varying degrees of automation and number of workers (W), under base demand conditions (Q, B_{co}).

KPI	**AL Configuration**	**W (oper)**	**Degree of Automation (%)** 10	20	23	30	40	50
		Standard Demand ($Q = 48$ units, $B_{co} = 3$ batches)						
P_{Line} (u/oper-h)	PWWAL	4	3.89	4.29	4.42	4.78	5.55	5.04
		6	3.81	4.21	4.34	4.64	4.23	3.38
		8	3.66	4.10	4.23	4.12	3.19	2.54
	Semiauto FWAL	8	3.52	3.86	3.98	3.89	2.96	2.35
LT_B (min)	PWWAL	4	411	375	366	338	298	320
		6	290	261	254	239	258	321
		8	232	209	203	208	260	327
	Semiauto FWAL	8	122	113	112	121	157	196
Th (u/h)	PWWAL	4	15.6	17.2	17.7	19.1	22.0	20.2
		6	22.8	25.3	26.0	27.8	25.4	20.3
		8	29.3	32.8	33.8	33.0	25.6	20.3
	Semiauto FWAL	8	28.2	30.9	31.9	31.1	23.6	18.8
P_{Labour} (%)	PWWAL	4	84.9	83.1	82.5	80.7	77.0	64.6
		6	80.9	78.6	77.8	74.6	62.3	44.6
		8	74.8	71.7	70.4	64.6	49.3	33.7
	Semiauto FWAL	8	63.2	59.3	58.0	54.9	44.4	32.1
LT_U (min)	PWWAL	4	45.7	41.4	40.1	37.1	32.2	35.2
		6	36.2	32.7	31.7	29.7	32.6	40.9
		8	32.2	28.7	27.9	28.6	37.0	46.8
	Semiauto FWAL	8	23.5	23.4	23.4	29.9	38.4	46.8
P_S (u/ oper-h-m^2)	PWWAL	4	0.012	0.013	0.013	0.014	0.017	0.015
		6	0.012	0.013	0.013	0.014	0.013	0.010
		8	0.011	0.012	0.013	0.012	0.010	0.008
	Semiauto FWAL	8	0.038	0.042	0.043	0.042	0.032	0.026

Table 6.13: Operational KPIs of semiautomated FWAL and PWWAL for varying degrees of automation and number of workers (W), under high-mix low-volume demand conditions (Q, B_{co}).

KPI	**AL Configuration**	W **(oper)**	**Degree of Automation (%)** 10	20	23	30	40	50
	High-Mix Low-Volume Demand ($Q = 12$ units, $B_{co} = 1$ batch)							
P_{Line} (u/oper-h)	PWWAL	4	3.53	3.88	4.02	4.31	4.80	4.83
		6	3.36	3.68	3.78	3.99	3.88	3.34
		8	3.11	3.36	3.42	3.45	3.04	2.53
	Semiauto FWAL	8	2.63	2.77	2.82	2.94	2.76	2.41
LT_B (min)	PWWAL	4	151	137	133	124	112	110
		6	111	102	99	95	96	110
		8	96	89	88	87	96	115
	Semiauto FWAL	8	56	54	54	55	63	75
Th (u/h)	PWWAL	4	14.1	15.5	16.1	17.3	19.2	19.3
		6	20.2	22.1	22.7	23.9	23.3	20.0
		8	24.9	26.9	27.4	27.6	24.6	20.2
	Semiauto FWAL	8	21.0	22.2	22.6	23.5	22.1	19.2
P_{Labour} (%)	PWWAL	4	84.9	83.1	82.5	80.7	77.0	64.6
		6	80.9	78.6	77.8	74.6	62.3	44.6
		8	74.8	71.7	70.4	64.6	49.3	33.7
	Semiauto FWAL	8	63.2	59.3	58.0	54.9	44.4	32.1
LT_U (min)	PWWAL	4	50.5	45.8	44.3	41.2	37.0	36.8
		6	41.1	37.5	36.5	34.6	35.5	41.4
		8	38.1	35.2	34.5	34.2	38.5	47.0
	Semiauto FWAL	8	25.1	24.9	24.8	25.7	30.7	38.7
P_S (u/ oper-h-m^2)	PWWAL	4	0.011	0.012	0.012	0.013	0.015	0.015
		6	0.010	0.011	0.011	0.012	0.012	0.010
		8	0.009	0.010	0.010	0.010	0.009	0.008
	Semiauto FWAL	8	0.029	0.030	0.031	0.032	0.030	0.026

6.5 Discussion

Simulation results indicate that PWWALs have better operational performance than semiautomated or manual FWALs in terms of line productivity, throughput, and labour productivity, especially when facing high-mix low-volume demand, which makes it necessary to perform frequent family product changeovers, use small batch sizes, or use a reduced number of assembly operators. On the other hand, PWWALs present longer batch and unit lead times and require additional WIP stock and shopfloor space.

Automation-driven reduction of the products' manual work content by −23% leads to a productivity increase of +33% for PWWAL (vs. +25% increase for semiautomated FWAL) compared to manual AL configuration under standard demand conditions. Under high-mix demand conditions, PWWAL achieves a +30% productivity increase, significantly superior to the +7% productivity increase for semiautomatic FWAL—compared to manual FWAL, as shown in *scenario v*. In conclusion, the main goal of a +25% line productivity increase when producing small batches of highly mixed products can be achieved by the PWWAL, and not by the FWAL.

The PWWAL configuration suffers less from line unbalance caused by automated stations and product variety, provided that the workers-to-stations ratio remains low and that each worker moves through all the assembly stations. The WWAL cells within a line [294] reintroduce the problems of line balancing, but they reduce the need for operator training. Note that although total WC increases for WWAL compared to FWAL due to operator walking times, these losses are offset by superior labour productivity. PWWAL configuration also suffers less from setup time losses because each AL branch has fewer workers, which minimises the waiting/blocking time losses caused by cycle time differences between the products involved in the changeover.

Introducing automated stations does not improve the average batch lead time, since the increased throughput is offset by the increased total work content and the superior number of workstations. PWWAL configurations present significantly worse batch lead times than semiauto or manual FWALs under any demand situations. It is also important to note that the average unit lead time to complete a unit increases for semiautomated FWAL, and especially for PWWAL configurations, compared to manual FWAL, which means that the WIP stock held at the line at any given moment would be greater. This is caused by the capacity buffers placed before and after the automations, which are required to hold twice as many WIP units in the PWW line since each automated QC station is served by two (slower) assembly lines which could have different cycle times.

Labour productivity decreases due to the introduction of automation and the reduction of batch sizes—which increases the percentage of time dedicated to setups. The PWWAL configuration is less affected than semiautomated FWAL by frequent changeovers since shorter ALs suffer less from operator idle times generated by cycle time differences between incoming and outgoing products. These idle times increase as the number of operators increases. Nonetheless, labour productivity losses are offset by the reduction in work content caused by automation.

Lastly, PWWAL presents high requirements in terms of shopfloor space compared to the fixed-worker assembly lines. PWWAL surface productivity is, under high-mix low-volume conditions, 0.010 units/operator-h-m^2, which is considerably lower than that of manual (0.041) or semiautomated configurations (0.031). The higher surface needs derive from the additional WIP and operator space buffers that the PWWAL needs to operate efficiently.

Increasing the degree of automation creates an imbalance between manual and automated work content that requires adjusting the number of workers. PWWALs offer greater flexibility than fixed-worker lines because they can seamlessly adjust the number of manual operators. However, the increased line productivity resulting from simultaneously increasing the degree of automation and decreasing the number of operators reduces the line throughput and increases significantly the batch lead time.

Besides the KPIs already exposed, PWWAL presents other advantages in terms of flexibility and reconfigurability. Production level changes are made simple by modifying the number of operators working on each AL branch independently—within the limits imposed by the capacity of the automated stations—without changes in the operators work organisation. In fact, the number of workers could be temporarily increased beyond the designated four operators per AL branch at the expense of productivity. A parallel line configuration also brings additional sequencing possibilities, for example, being able to assemble a batch of products in both lines simultaneously to reduce the batch lead time—effectively working with half the batch size—at the cost of line productivity. Finally, the introduction of products to the PWWAL would present fewer drawbacks due to the reduced sensitivity of this line configuration to work content differences and poor line balance.

In conclusion, PWWAL configurations would be particularly beneficial in assembly operation situations where line productivity needs to be maximised under high-mix low-volume demand conditions, and when batch lead times are not a critical factor.

6.6 Conclusions

To address the need for more flexible and more productive assembly operations brought about by mass customisation demand trends, this article presented a concept of a multimodel parallel walking-worker assembly line with shared automations. Based on an industry real-study case, discrete events simulation was utilised to model this assembly line concept, along with manual linear and semiautomated fixed-worker assembly lines. The models were used to compare the performance of the different line configurations under standard demand as well as different scenarios of increasingly challenging conditions in terms of reduced batch sizes and more frequent product changeovers. To evaluate efficiency, a set of six key performance indicators (KPIs) were employed: line productivity, batch lead time, throughput, labour productivity, unit lead time, and surface productivity.

It was found that under high-mix low-volume demand conditions requiring small batch sizes and frequent product family changeovers, the parallel walking-worker line configuration achieves greater line productivity and throughput than the semiautomated or manual fixed-worker line configuration. On the other hand, semiautomated fixed-worker assembly lines present better batch lead time, unit lead time, and surface productivity. Manual fixed-worker configuration productivity is inferior to the semiautomated alternatives according to all KPIs except for surface productivity. Increasing the degree of automation allows to increase the line productivity under all demand conditions, only if the number of workers can be reduced smoothly—which is the case for walking-worker configurations but not for fixed-worker lines. However, this comes at the expense of reducing the line throughput and increasing the lead time.

A key current research limitation lies in considering multiple layouts and shared automation configurations in order to find optimal line configurations or the performance of reconfigurable systems over long periods of time.

Areas for future work include (1) optimising the actual layout of the parallel walking-worker configuration, to minimise the surface footprint; (2) the actual implementation of the parallel walking-worker concept in an industrial setting, which would enable validating the parallel walking-worker assembly line model; (3) expanding the simulation models to include machine breakdowns and quality problems, in terms of rework times and scrap products; and (4) a supply chain simulation layer feeding parts to the assembly lines. Future developments based on current research limitations would include assessing the operational performance of different line configurations in terms of both automation and layout.

6.7 Extended analysis of PWWAL

This section covers four superficial analyses that were carried out after the main six simulation scenarios and therefore were not included in the research article. These simulation *scenarios vii–x* look at several issues regarding the fine-tuning of parallel walking-worker assembly lines, aiming to better understand its behaviour. Therefore, comparison simulations against FWAL models were not set up for these scenarios. Table 6.14 summarises the simulation scenarios and the variables involved.

Table 6.14: Simulation extended scenarios and design parameters analysed.

Design variable	**Range of values**
Scenario vii. Automation layout	
No. shared auto. stations	$\{0, ..., 4\}$
Scenario viii. Operator cognitive support	
CV_p (%)	$\{0, 15\}$
T_s (s)	{0, see Table 6.5}
W (operators)	$\{2, 4, 6, 8\}$
Scenario ix. Auto. station buffer capacity	
BC (units)	$\{0, 1, 2\}$
W (operators)	$\{4, 8\}$
Scenario x. Assembly line length	
Line length (m)	$\{23, ..., 35\}$
W (operators)	$\{4, 8\}$

6.7.1 Automation layout: number of shared stations

Scenario vii was set up by varying the number of shared automated stations, from zero (transforming the PWWAL into two independent WWAL) to four (sharing all automated stations), in order to identify potential operational gains. Said scenario was constructed by duplicating or sharing the automated stations ($j = 1...4$), as shown in Table 6.15.

Table 6.15: *Scenario vii*: PWWAL layout details for a different number of shared automated stations. Stations can be either duplicated (D) or shared between the parallel lines (S).

	Automated station			
No. shared auto. stations	$j = 1$	$j = 2$	$j = 4$	$j = 4$
0: independent WWAL	D	D	D	D
1: only one shared auto.	D	S	D	D
2: standard PWWAL	D	S	D	S
3: only one dedicated auto.	S	S	D	S
4: all auto. stations shared	S	S	S	S

In the particular case under study, the number of shared automated stations seems to have a very limited impact on the AL performance for both standard and high-mix low-volume demand conditions, as shown in Figure 6.10.

These results are coherent with the fact that none of the automated stations are the bottleneck of the PWWAL, even if they are shared (cf. processing times shown on Table 6.3 and Table 6.4). Moreover, the fact that only manual stations incur in setup times reinforces this phenomenon. Note that these results show that the very limited effect of the automation layout on the assembly line performance is due to the particular process and setup times distribution of this industrial study case. Therefore, they cannot be generalised to other PWWAL cases.

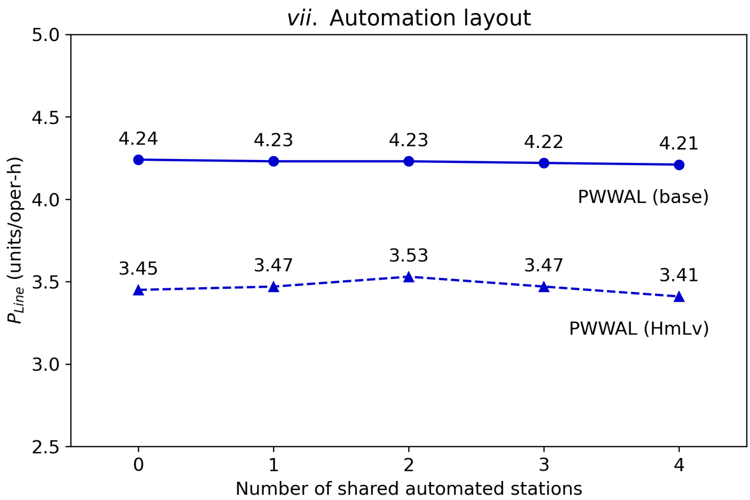


Figure 6.10: *Scenario vii*: automation layout. Effect of the number of shared automated stations on semiautomated parallel walking-worker assembly line (PWWAL) line productivity under standard or high-mix low-volume (HmLv) demand.

6.7.2 Operator cognitive support for production complexity

The systematic literature review and the operator-centred conceptual framework revealed the potential application of augmented or mixed reality (AR/MR) technologies to provide cognitive support to assembly operators to better deal with the complexity brought by the high product variety and variability driven by mass customisation and personalisation demand trends [66, 264, 267].

To gain insight into the order of magnitude of the performance improvements that such technologies could provide to PWWAL lines, *scenario viii* considers that these technologies, combined with traditional Lean tools such as SMED or poke-yoke, would allow to minimise setup time losses and manual assembly process variability. The simulations were performed considering 2 to 8 manual workers to explore the potential impact of these technologies when dealing with low-volume production. The demand conditions used here are equivalent to *scenario i: standard demand*, which corresponds to a batch size (Q) of 48 units and a product family changeover frequency (B_{CO}) of 3 batches. Figure 6.11 shows the results of the simulation scenario.

The results indicate that the potential benefits of reduced setup times (i.e. a mixed-model assembly line instead of multi-model AL) are greater when the number of operators is greater. This is due to the fact that the lines' worker-to-station ratio is larger and there are more frequent lost time incidents (blocking or starved operators). On the other hand, when the lines are manned by just one or two operators per line ($W = 2$ or 4, respectively) there is already a smooth flow and the potential improvement is reduced. Note that for the standard level of production volume ($W = 8$), the labour productivity gap due to process variability and setup

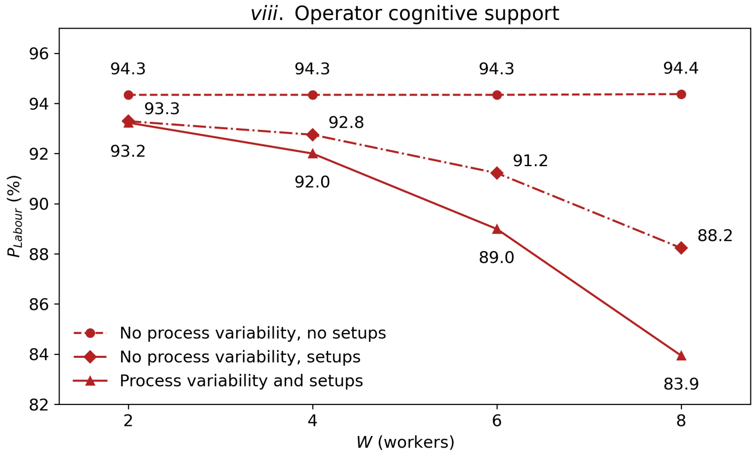


Figure 6.11: *Scenario viii*: operator cognitive support. Effect of process variability and no. of workers on PWWAL labour productivity.

time losses sits in the order of magnitude of 10%, which provides an optimistic, best-case scenario outcome of the investment in operator cognitive support.

6.7.3 Automated stations WIP buffer capacity

In the previously explored *scenarios i–vi*, the automated stations are modelled to include two WIP buffers (before and after the station), with a maximum capacity of one product unit (see assumptions in Section 6.3.1). Although increasing the buffer capacity might provide some advantages because it would mitigate the effects of disturbances, WIP buffers also require floor space, which in turn could increase the length of the assembly lines. This would increase the operator walking time, which would have a negative impact on labour productivity. The extent of such impact will be studied in the next scenario.

This *scenario viii* examines the effect on labour productivity of using larger WIP buffers before and after the automated stations, or no buffers at all. Figure 6.12 shows the simulation results.

The results suggest that there is no significant benefit of duplicating the buffer capacity from 1 unit to 2 units, since the labour productivity change is minimal (below +1% regardless of W). On the other hand, removing the WIP buffers ($BC = 0$) does produce a very noticeable decrease in labour productivity, in the order of magnitude of −20% (−22% for $W = 8$, −18% for $W = 4$). These considerations persist independently of the number of workers. In light of these results, maintaining a buffer capacity of one unit (before and after the automated stations) appears to be optimal in view of labour productivity and layout issues previously mentioned.

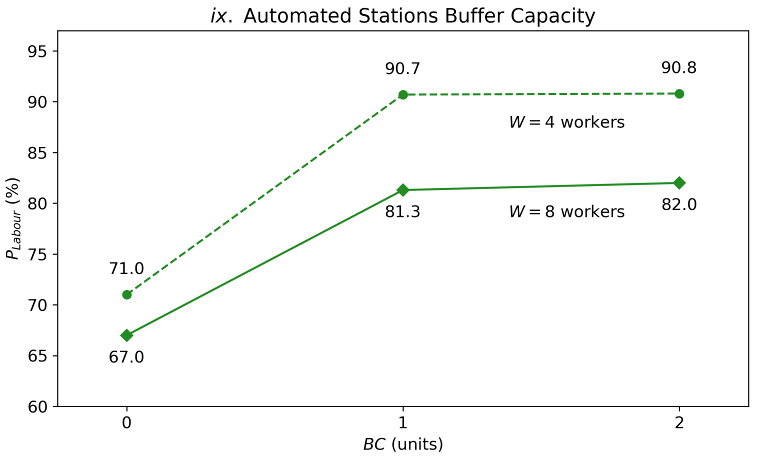


Figure 6.12: *Scenario ix*: effect of automated station buffer capacity on PWWAL labour productivity.

6.7.4 Assembly line length

An assembly line design consideration that would seem particularly relevant for PWWAL is the line length because the walking operators need to go across the line twice for every product unit they assemble. Therefore, this *scenario x* looks into the effect that shortening or extending the assembly line would have on its labour productivity. As a reference, the assembly line length considered so far is 33 m (see Table 6.7). This scenario considers a significant reduction in line length (down to 23 m) that could result from an assembly design focused on optimising this parameter, at the expense of other factors, such as operator ergonomic risks or WIP buffer capacity. The simulation results, displayed in Figure 6.13, show the effect of line length for standard ($W = 8$) and low production volume ($W = 4$).

First of all, the results indicate that the number of workers does not interact with the line length. Secondly, despite the increase in labour productivity as a result of reducing the line length, even a very significant reduction in line length (from 35 m down to 23 m) only increases the labour productivity by less than +1%. These superficial simulation results hint that the PWWAL performance is not very sensitive to line length, and therefore should not be considered a key factor for PWWAL design. Also, this conclusion is consistent with previous studies on this matter by Al-Zuheri et al., which analysed the effect of walking speed of manual walking-worker lines [293], and found that higher walking speed does not improve the assembly line productivity.

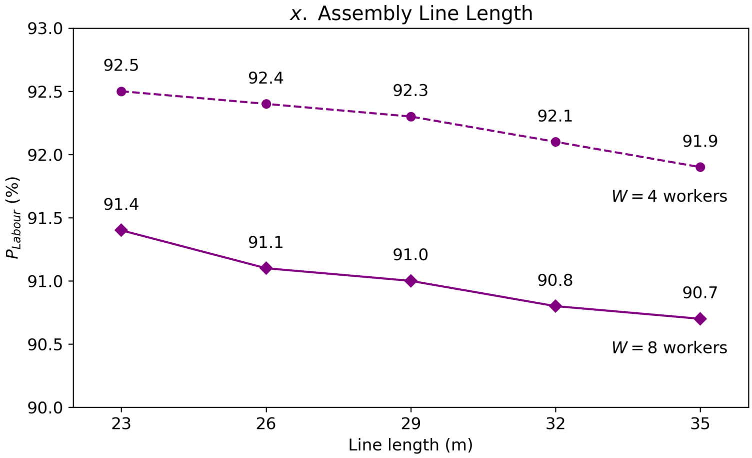


Figure 6.13: *Scenario x*: effect of parallel walking-worker assembly line length on labour productivity.

6.8 Summary

This chapter addresses the principal aim of the thesis: finding methodologies to increase the productivity of flexible assembly operations under challenging high-mix low-volume demand conditions. The simulation tools built and verified in previous Chapter 5 were employed to study the possibilities brought by joining formerly separated low-volume assembly lines and introducing automated assembly stations in addition to the walking-worker system. Parallel walking-worker lines maintain high productivity despite frequent changeovers or different product cycle times. Moreover, they enable seamlessly changing the number of operators without suffering from the line unbalance losses encountered by equivalent fixed-worker assembly lines. A set of six key performance indicators was used to obtain insight into these assembly systems from different angles.

The simulation results shown in Section 6.4 revealed that under mass customisation demand conditions requiring small batch sizes and frequent product family changeovers, the parallel walking-worker line configuration achieves greater line productivity and throughput than the semiautomated or manual fixed-worker line configuration. The results estimated a large improvement in line productivity as a result of introducing automation in parallel walking-worker assembly lines (+30%), significantly greater than the productivity improvement of fixed-worker assembly lines (+7%), under high-mix low-volume demand conditions.

Specifically, this chapter makes three key contributions:

1. A multimodel parallel walking-worker assembly line design was presented. This assembly line design is estimated to achieve a +30% productivity increase (greater than the initial goal of +25%) while maintaining high flexibility in terms of line throughput, enabling a quick adaptation to demand

variations.

2. A comprehensive set of operational KPIs was used to estimate the performance of fixed and walking-worker assembly lines from different angles. Under any demand conditions, parallel walking-worker lines present higher productivity and throughput than traditional fixed-worker lines. This chapter's results highlighted the trade-off between productivity and lead time experimented by parallel walking-worker lines.
3. Simulation results show that increasing the degree of automation allows incrementing the line productivity under all demand conditions, but only if the number of workers can be reduced smoothly—which is the case for walking-worker configurations but not for fixed-worker lines. However, this comes at the expense of reducing the line throughput and increasing the lead time.

The main limitations to the research presented in this chapter are (1) that the DES models only allowed analysing a particular assembly line configuration—in terms of the number of manual stations, automated stations, and their layout—, which may not be optimal; and (2) that the models' scope is limited to assembly operations, and does not include the supporting departments—e.g., maintenance or in-plant logistics—which could also introduce additional constraints.

The work expounded in this chapter led the way to expand the simulation models to include a key supporting department: in-plant logistics. In particular, Chapter 7 studies the use of a classic Lean logistics tool, milkrun trains, to feed multi-model assembly lines under disturbances.

CHAPTER 7

Milkruns for in-plant logistics under disturbances

The operator-centred conceptual model presented in Chapter 3 located several production support departments—such as maintenance, quality control, logistics and planning—in the outer layers of the model. One of the limitations of the assembly system performance evaluation models presented in Chapters 4–6 is that they do not take into account the potential constraints introduced by said supporting departments. From the point of view of The Cooktop Company industrial study case, it was considered that the restrictions imposed by the maintenance or quality control departments would be less critical for multi-model parallel assembly lines than in-plant logistics.

Previous research projects carried out at the University of Zaragoza Department of Design and Manufacturing Engineering [297–299] focused on the analysis of a classic Lean tool for in-plant logistics: milkrun trains. Due to the milkrun's inherent ability to deal with different production cycle times, a study was conducted to understand the ability of milkrun logistics to feed parallel multi-model assembly lines under disturbances. Once again, the DES modelling methodology described and verified in Chapter 5 was employed to model the milkrun and assembly systems, as shown in Figure 7.1.

The research presented in this chapter was published in the Special Issue "Lean Manufacturing and Industry 4.0" of the journal *Machines* [300]. In consequence, each section of the chapter corresponds to an article section: Introduction (7.1), Literature review (7.2), Materials and Methods (7.3), Results (7.4), Discussion (7.5) and Conclusion (7.6). Finally, Section 7.7 summarises the key findings and contributions of the chapter.

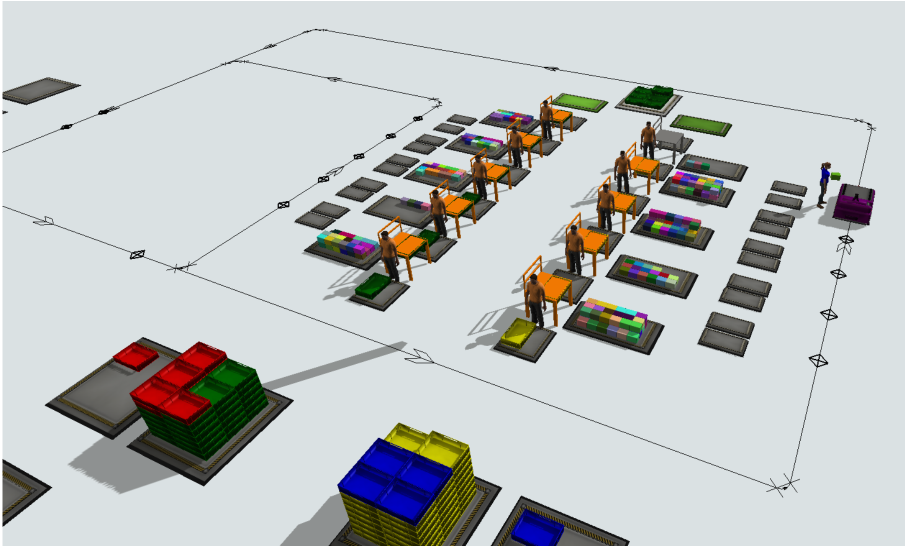


Figure 7.1: DES model FlexSim® screenshot of parallel assembly lines in-plant logistics using milkrun.

Article title:

Multi-Model In-Plant Logistics Using Milkruns for Flexible Assembly Systems under Disturbances: An Industry Study Case

Article abstract:

Mass customisation demand requires increasingly flexible assembly operations. For the in-plant logistics of such systems, milkrun trains could present advantages under high variability conditions. This article uses an industrial study case from a global white goods manufacturing company. A discrete events simulation model was developed to explore the performance of multi-model assembly lines using a set of operational and logistics Key Performance Indicators. Four simulation scenarios analyse the separate effects of an increased number of product models and three different sources of variability. The results show that milkruns can protect the assembly lines from upstream process disturbances.

7.1 Introduction

Since the end of the 20th century, it is considered that demand trends are shifting from mass production towards mass customisation [6] and mass personalisation [28]. To address this situation, manufacturing companies need to produce an increasing number of different products, in smaller quantities each, without compromising on quality or price [2]. For consumer goods manufacturers, this means shifting from large batches of very similar products towards high-mix low-volume production. To gain an advantage or simply remain competitive, production flexibility, reconfigurability and resilience are key [284].

In a typical discrete production process—e.g., automobiles, white goods, home electronics, furniture, toys—the assembly stage taking place after manufacturing is also of capital importance [13]. Traditional assembly operations are performed in manual or semi-automated lines or cells, which are usually dedicated to one product or a small family of products closely related [268]. These products are assembled in batches to minimise the losses incurred due to product changeovers [48, 53]. Looking at existing assembly operations approaches to build upon, Lean Manufacturing [5] proposes a methodology inherently oriented towards reduced batch sizes, frequent product changeovers, multi-product assembly cells and cross-functional operator teams [145, 301]. In this context, it seems clear that traditional assembly lines face serious threats when confronted with the high-mix low-volume demand brought by the mass customisation paradigm. The main challenges include dealing with complexity, uncertainty and disturbances, successfully deploying disruptive digital technologies [61]—i.e., Industry4.0 [8] or smart manufacturing [22]—and further integrating the sub-systems related to assembly: supporting functions such as internal logistics [58], maintenance [64] or quality control [57].

Internal logistics is the supply chain function most closely related to the assembly operations since it is tasked with feeding components to the assembly line or cell without introducing production constraints [297, 302]. Flexible assembly lines driven by mass customisation and featuring mixed- or multi-model production pose additional challenges to internal logistics [43], which impact directly on the classic Lean supply performance indicators [118]. In-plant milkruns [303] (*misuzumashi* [304], *tow-train* [302]) are one of the best available Lean tools for efficiently supplying parts to flexible multi-model assembly lines [156].

The brief literature review that will be presented in Section 7.2 shows that despite an increasing research depth on the topic of milkrun logistic systems for flexible assembly lines, there are still limited published works which include variability. Two papers are very closely related to our research topic: Korytkowski et al.'s [305] is great but features a single-model assembly line, while Faccio et al.'s [306] article considers mixed-model assembly lines, but the sources of variability considered there are limited to milkrun train capacity and refilling interval. This connects with the key avenues for future work identified by Gil-Vilda et al. [297], which point to including variability and disturbances to the study of milkrun systems.

In consequence, the goal of this article is to continue exploring the use of milkrun trains for the internal logistics of flexible assembly operations featuring multiple manual assembly lines. In particular, we aim to look at scenarios where demand presents mass customisation characteristics (i.e., high-mix low-volume). The work presented here aims to evaluate the performance of milkrun trains and assembly lines in this demand context by focusing on two main aspects, following the lines for further investigation detected by Gil-Vilda et al. [297], namely the product mix (multi-model in opposition to single-model assembly) and the impact of variability and stochastic disturbances.

To address the aforementioned objectives, the following research questions are formulated:

1. What is the effect on the operational and logistics Key Performance Indicators (KPIs) of producing multiple models in an assembly line compared to single-model production? Are there significant differences between mixed-model and multi-model production from the milkrun internal logistics point of view?
2. How is the milkrun-assembly lines system affected by variability? In particular, to what extent is it impacted by assembly process variability and supply chain disturbances?

To carry out this research, Discrete Events Simulation (DES) was the chosen tool. A real industrial study case from a global white goods manufacturer site located in northern Spain is presented and used to provide the foundations of the different simulation scenarios analysed to address the research questions.

The structure of this article is the following: Section 7.2 presents a brief literature review on the topic, highlighting the key findings made by previous research and the open lines of research derived from them. Section 7.3 Methodology introduces the assumptions used to build the simulation model, details the study case data and the parameters as well as the performance indicators selected to define and assess the simulation scenarios. Section 7.4 Results presents the outcome of the simulation, which is then discussed in Section 7.5.

7.2 Literature Review

Feeding the components to assembly lines requires complex in-plant logistics to do so in an efficient, flexible and responsive manner. Although many feeding policies could be used [307], some have clear advantages when facing a demand situation of mass customisation or mass personalisation.

In the context of Lean logistics, milkruns (also named 'tow-trains' or shuttles) are defined as '*pickups and deliveries at fixed times along fixed routes*' [302]. Inbound and outbound milkrun delivery systems work analogously, sharing a key aspect: '*milkruns are round tours on which full and empty returnable containers are exchanged in a 1:1 ratio*' [303].

Several authors have proposed different approaches for classifying milkrun systems. For instance, Kilic et al. [308] proposed that the main problem for milkrun design is to determine the routes and time periods aiming to minimise total cost, which are composed of transportation and Work In Process (WIP) holding costs. Their framework classifies milkrun problems depending on the need to determine the time periods, the routes or both; for one- or multiple-routed milkruns; and considering either equally or differently timed routes. On the other hand, Mácsay et al. [309] described four milkrun-based material supply strategies, while Klenk et al. [310] modelled milkrun systems using Methods-Time Measurement (MTM) parameters and explored six major milkrun concepts.

Alnahhal et al. conducted a literature review in 2014 [311] that found a scarcity of studies looking at in-plant milkrun systems as a whole, and that there was a research tendency to drift away from Lean goals to look for optimality based on restrictive objectives in its stead. Later articles, however, addressed in-plant milkruns from multiple angles; in particular, for mixed-model assembly systems closely related to multi-model systems, which are the focus of this article. A plethora of study cases have also been published in recent years, helping to illustrate the benefits of milkruns and the production challenges they help to overcome. The following subsections look into some of them in further detail.

7.2.1 In-Plant Milkruns for Mixed-Model Assembly Lines

Alnahhal et al. [312] looked into using milkruns for mixed-model assembly lines from decentralised supermarkets. Variables such as train routing, scheduling and loading problems were considered, aiming to minimise the number of trains, loading variability route length variability and assembly line inventory costs. Different analysis tools were employed: analytical equations, dynamic programming and Mixed-Integer Programming (MIP). On the other hand, Golz et al. [313] used a heuristic solution in two stages to minimise the number of shuttle drivers, focusing on the automotive sector.

This sector was also the focal point of Faccio et al.'s work [306], in which they proposed a general framework using short-term (dynamic) and long-term (static) sets of decisions allowing to size up the feeding systems for mixed-model assembly lines composed of supermarkets, kanbans and tow-trains. In another article [314], Faccio et al. dived deeper into the subject by investigating kanban number optimisation. It was highlighted that traditional kanban calculation methods fell short under a multi-line mixed-model assembly systems.

Emde et al. also looked at optimising some aspects of mixed-model assembly lines, namely (1) the location of in-house logistics zones [315] and (2) the loading of tow-trains to minimise the inventory at the assembly and to avoid material shortages, using an exact polynomial procedure [316]. Discrete Events Simulation was used by Vieira et al. [317] in an automated way (using a tailored API on top of a DES commercial software) to model and analyse the costs of mixed-model supermarkets.

7.2.2 Other Aspects of in-Plant Milkruns

A few articles examined the performance evaluation of milkrun systems. Klenk et al. [318]evaluated milkruns in terms of cost, lead time and service level. Their article used real data from the automotive industry with a focus on dealing with demand peaks. Bozer et al. [319] presented a performance evaluation model used to estimate the probability of (1) exceeding the physical capacity of the milkrun train and (2) exceeding the prescribed cycle time. This model assumed a basic, single-train system and that assembly lines are never starved of components. It highlighted some of the milkrun advantages: low lead times, low variability and low line-side inventory levels. Other articles describe milkrun systems evaluation methods which employ cost efficiency [309] or the required number of tow-trains [320]. Many authors used discrete event simulation to evaluate the potential performance of milkrun systems as a tool for milkrun design [321], evaluating dynamic scheduling strategies [322] or digital twin verification and validation [323].

The Association of German Engineers (VDI—*Verein Deutscher Ingenierure*) proposed the standardisation guidelines VDI 5586 [324] for in-plant milkrun systems design and dimensioning. Schmid et al. [325] discussed the draft VDI norm and found several drawbacks. Their article states that algorithms can support the milkrun design process; however, this system's design cannot be formulated as a regular optimisation problem. In a later article, Urru et al. [326] highlighted that VDI 5586 was the only norm for milkrun logistics systems design and that it is only applicable under severe restrictions. A methodology was then proposed to complement the VDI guideline. Kluska et al. proposed a milkrun design methodology which includes the use of simulation as supporting tool [321].

Gyulai et al. [327] provided an overview of models and algorithms for treating milkrun systems as a Vehicle Routing Problem (VRP). This article introduced a new approach with initial solution generation heuristics and a local search method to solve the VRP.

Gil-Vilda et al. [297] focused on studying the surface productivity and milkrun work time of U-shaped assembly lines fed by a milkrun train using a mathematical model. This article established promising avenues for future research: (1) assessing the impact of the number of parts per container and (2) analysing the impact of variability.

On the topic of variability, two articles stand out. Korytkowski [305] posed the research question about *'how disturbances in the production environment and managerial decisions affect the milkrun efficiency'*. This work analyses a single-model assembly line by employing discrete events simulation including three variability parameters—assembly process coefficient of variability, probability of a delayed milkrun cycle start and the magnitude of such delay—in addition to other three parameters: WIP buffer capacity, TAKT time synchronisation, and the milkrun cycle time. The KPIs used were throughput, WIP stock, milkrun utilisation and workstation starvation. The key conclusions were that TAKT sync does not affect the KPIs, even in conjunction with limited WIP buffer capacity. It was also found that a higher milkrun cycle time decreases the milkrun utilisation and increases the assembly line stock. Finally, this article concluded that milkrun systems mitigate

Table 7.1: Key aspects of selected research articles on in-plant milkrun systems which include study cases.

Article	Analysis Tool	Objective	No. Lines	No. Vehicles	Product Mix	Variability	Real Ind. Case	Sector
Aksoy [328]	MILP and heuristics	MR route optimisation	Multi	Multi	Single	No	Yes	Automotive
Alfonso [329]	Simulation	Ergonomy and material flow improvement	Multi	Single	Single	No	Yes	Automotive
Alnahhal [312]	MIP, DP and math modelling	Min WIP, variability, handling cost	**Multi**	Multi	**Mixed**	No	No	NS [1]
Coelho [323]	Simulation	Verify & validate digital twin for in-plant logistics	Multi	NS	NS	**Yes**	Yes	Automotive
Costa [330]	Simulation	Train loading	Multi	Single	Single	No	Yes	Electronics
Emde [331]	MIP and heuristics	Min WIP	**Single**	Single	**Mixed**	No	No	Automotive
Faccio [306]	Math model	Min no vehicles and WIP	**Multi**	Multi	**Mixed**	**Yes**	Yes	Automotive
Faccio [314]	Math model	Optimal no. kanbans	**Multi**	Multi	**Mixed**	**Yes**	Yes	Automotive
Gil-Vilda [297]	Math model	Max surface productivity	Single	Single	Single	No	Yes	Unknown
Golz [313]	MILP and heuristics	Min no. trains	**Multi**	Single	**Mixed**	**Yes**	No	Automotive
Gyulai [327]	Heuristics and local search method	Min no. vehicles	Multi	Multi	NS	No	NS	Automotive
Kilic [308]	Mixed Integer Programming (MIP)	Min cost (no vehicles $\times$ distance travelled)	Multi	Multi	NS	No	Yes	Automotive
Klenk [318]	Math model	Handling demand peaks	Multi	Single	NS	**Yes**	Yes	Automotive
Korytkowski [305]	Simulation	Effect of disturbances and management decisions	Single	Single	Single	**Yes**	No	NS
Pekarcikova [332]	Simulation	Improve logistic flows	Single	Single	Single	No	NS	Automotive
Rao [322]	Simulation	Improve material flow, reduce no. vehicles	Multi	Multi	Single	No	NS	NS
Satoglu [333]	Math model and heuristics	MR route to minimise handling and stock costs	Multi	Single	Single	No	Yes	Electronics
Simic [334]	Particle swarm optimisation	Min stock costs	Single	Single	Single	No	No	Automotive

[1] NS: Not Specified.

the impact of production variations, which implies that they do not require large safety times built into them. Faccio et al. [306] also introduced variability sources in their dynamic milkrun framework for mixed-model assembly lines. In particular, this article includes tow-train capacity variability (related to the number of parts per kanban container, which is linked to the stochastic demand considered) and refilling interval variability.

7.2.3 In-Plant Milkrun Study Cases

There is no scarcity of published articles featuring study cases of in-plant milkrun systems. However, there are not so many articles specifically focusing on milkruns feeding multi-model assembly lines, and only a few articles consider stochastic variables. It is also noteworthy that the majority of study cases on the topic belong to the automotive industry. Table 7.1 summarises the study case articles found in this brief review, which includes the articles mentioned previously as well as a few additional documents [328, 330, 331, 333, 334] which specifically present milkrun study cases.

Table 7.1 shows some noteworthy points. First of all, no article specifically shows study cases of multi-model assembly lines, although there are some articles on mixed-model systems. Secondly, very few articles present real industrial study cases outside of the automotive sector. Finally, variability has not been commonly considered by research articles on the topic so far. The work presented here aims to cover the three highlighted shortcomings.

7.3 Materials and Methods

In this article, the operational performance of two assembly lines and the milkrun train that feeds them is evaluated under different conditions. The system consisting of assembly lines and internal logistics was studied by considering a set of inputs, a Discrete Events Simulation model and a set of output KPIs, as depicted in Figure 7.2. The model consists of two main parts: the assembly lines and the supply chain feeding the components to the Assembly Line (AL) in containers using a milkrun train. Simulation was chosen for building this model because it allows the introduction of stochastic elements [270], such as process or logistics variability, which is necessary to achieve this work's goals. The simulation tool employed was FlexSim® (2022.0, FlexSim Software Products, Inc., Orem, UT, USA). Several simulation scenarios are created by modifying different parameters and disturbances values to analyse desired aspects of the system behaviour. Section 7.3.1 details the modelling assumptions. Section 7.3.2 includes the notation and definitions employed, and Section 7.3.3 includes the input data used in the models, which are used for validation (Section 7.3.4) and the experiment design (Section 7.3.5).

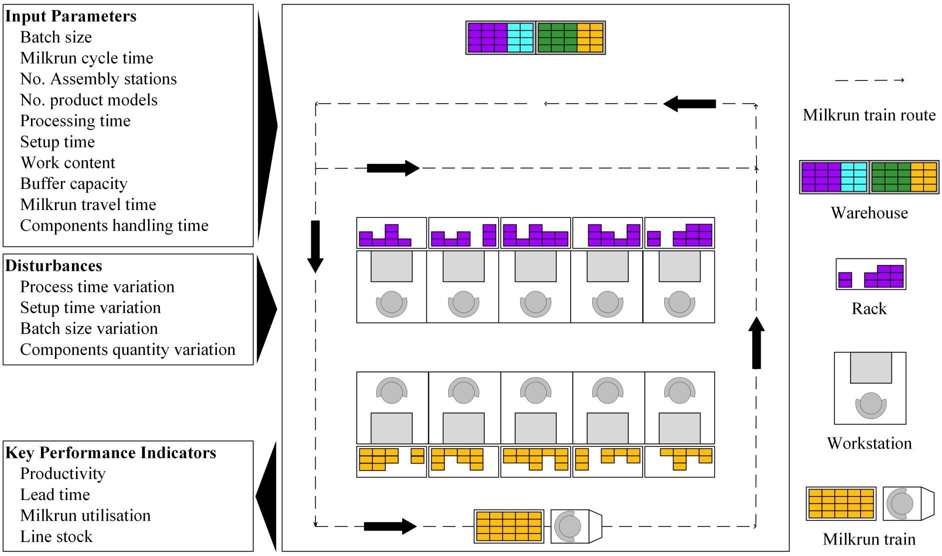


Figure 7.2: In-plant milkrun for multi-model assembly lines. Input parameters and disturbances are changed when analysing the performance of the system using simulation. Model output includes relevant operational and logistics Key Performance Indicators (KPIs) for evaluation.

7.3.1 Assumptions

The simulation model depicted in Figure 7.2 is made of two main subsystems: (1) two manual assembly lines, which feature operators, workstations, product buffers and components racks; and (2) internal logistics, which include a milkrun train, the components Points Of Use (POUs), a warehouse and the information flow necessary to ensure the assembly line receives the required components on time; see Figure 7.3.

Assembly lines: Figure 7.3a,b show the elements of the assembly lines used in this model, which feature the following assumptions following the classification of assembly systems by Boysen et al. [268]:

- The assembly systems are unpaced, buffered lines.
- These are fixed-worker assembly lines: operators are assigned to stations.
- There is manual assembly only (no semi- or fully automated work content).
- The number of workstations is constant. Each station can process only one product unit at a time.
- Operators need to gather all components specified by the Bill of Materials (BOM) to proceed to assemble at their stations; see Figure 7.3a.
- The demand mix is known and it continues for the whole simulation horizon.
- The assembly lines can be single-model, mixed-model or multi-model. Single-model lines only produce one product variant per AL. Mixed-model lines can produce more than one model, but there is no setup time between products. Multi-model lines are similar to mixed-model lines but they do incur setup

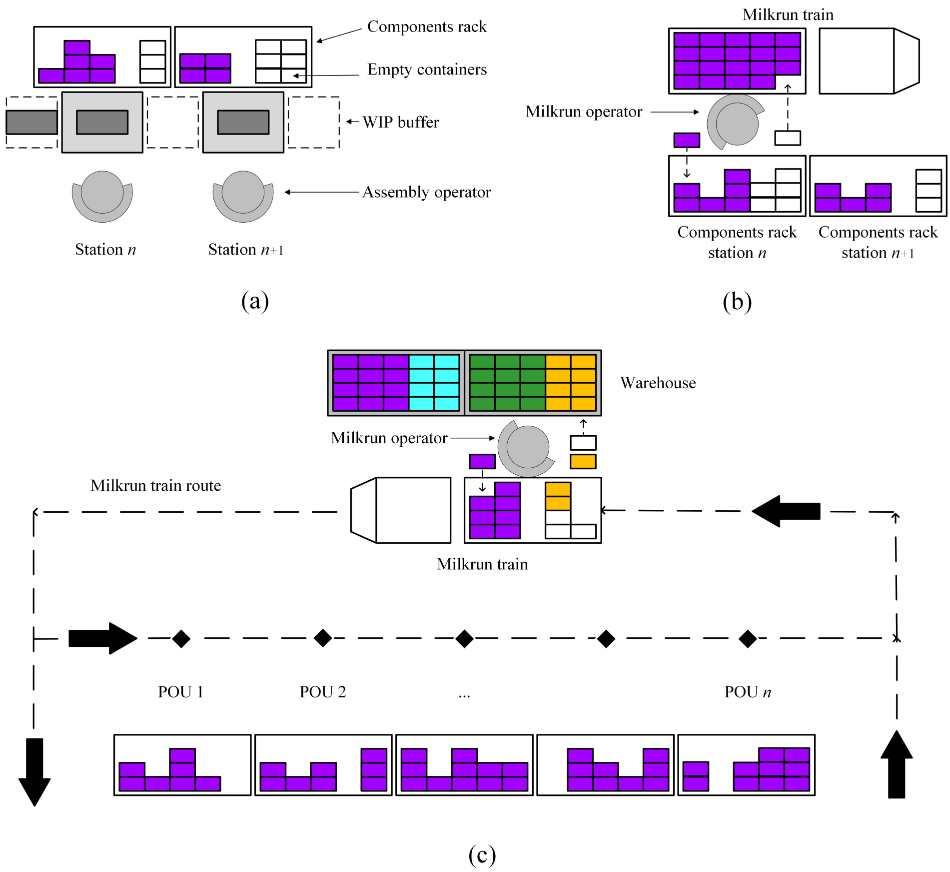


Figure 7.3: Simulation model subsystems interaction. (**a**) Assembly line stations; (**b**) Milkrun operator loading and unloading containers to assembly station; (**c**) Milkrun train picking at the warehouse, followed by the components replenishment cycle across all Points Of Use (POUs) of the route.

time losses when changing over from one product model to another.

- Setup times, where present, are not dependent on the product sequence.
- The product sequence consists of an alternating pattern of batches of products. The batch size is stochastic, based on a discrete uniform distribution to represent the probability of a batch being released to the assembly line with fewer units than standard. This represents the disturbances caused by upstream manufacturing processes. The probability distribution is governed by the batch size coefficient of variability (CV_q).
- Processing and setup times are stochastic. They follow a lognormal distribution based on mean values and standard deviations, which are expressed by the coefficients of variability (CV_p, CV_s).
- Slightly different processing times on each station mean that these are unbalanced assembly lines, as shown in the 'Input' subsection.

Internal Logistics: Figure 7.3 shows the main components of the internal logistics, which consists of four subsystems:

- Information flow between the assembly lines and the milkrun train, so that the milkrun picks up the right components for the product models that will be needed in the AL. This includes the calculations of the number of containers of each component N_i. This is worked out based on the expected consumption over the milkrun cycle time (d), the no. of pieces of component i per product unit (n_i) and the no. of pieces per container (q_i), with a minimum of 2, as shown in Equation 7.1. This minimum of 2 containers is required to prevent assembly line starvation, which could occur otherwise since the milkrun logic implies taking empty containers and replacing them with full ones on the next cycle.
$$N_i = \max\left(\left\lceil \frac{d_i \cdot n_i}{q_i} \right\rceil, 2\right) \tag{7.1}$$
- The number of pieces in each component container is stochastic, based on the standard number of pieces per container and a coefficient of variability (CV_c). A discrete uniform distribution is employed, which uses CV_c as the lower limit and the standard no. of pieces as the upper limit. This represents the probability of a certain number of pieces being non-conforming due to quality problems, inaccurate counting at the external suppliers' production site or incorrect re-packing at the in-plant warehouse, especially for components packed in bulk, such as nuts and bolts.
- Milkrun train picking at the warehouse (see Figure 7.3c) is modelled as a single POU. The milkrun train is emptied upon arrival, and it is thereafter filled again with the required containers for the next supply cycle.
- The milkrun transportation time from/to all POUs (Figure 7.3c) is based on historical time measurements from the industrial study case. Since the data show very little variability, the model assumes a deterministic transportation time given by the input parameter T_t.
- Supply chain operator loading and unloading of component containers to the assembly lines at each POU, as shown in Figure 7.3b. There are two possible situations: (1) Regular cycle (same product model): the operator replaces the empty boxes in the 'returns rack' with full boxes of the same component. The handling time is different for full and empty containers; see the input subsection. (2) Product changeover cycle (before the assembly line changeover): in which the milkrun operator firstly replaces any current product empty container to ensure that the current batch can be finished and then loads the next containers of the next product components so that they are available to the assembly operators when they finish the stations' changeover.

7.3.2 Notation

The following notations are introduced:

Input: Parameters

Q	Batch size.
CT	Assembly cycle time.
CT_{MR}	Milkrun cycle time.
L	No. of assembly lines, index l.
K	No. of assembly workstations (no. POUs) per assembly line, index k.
M	No. of product models, index m.
T_p	Processing time.
T_s	Setup time.
WC	Work content (i.e., total process time).
BC	No. of work in progress units between workstations.
T_t	Milkrun transportation time to/from assembly line.
T_h^e	Milkrun operator container handling time, empty container.
T_h^f	Milkrun operator container handling time, full container.

Input: Disturbances

CV_p	Process time coefficient of variation: $CV_p = \sigma_{Tp}/\mu_{Tp}$.
CV_s	Setup time coefficient of variation: $CV_s = \sigma_{Ts}/\mu_{Ts}$.
CV_c	Conforming units per container coefficient of variation.
CV_q	Batch size coefficient of variation.

Output: Key Performance Indicators

P_{Line}	Line Productivity (units/operator-h): production rate of conforming units per assembly operator.
LT_B	Lead Time (min): average time for a batch of units to be finished from the moment the last unit of the previous batch is finished.
U	Milkrun Utilisation (%): fraction of total available time that the supply chain operator is busy (picking components at the warehouse, driving the milkrun train and handling containers to load/unload the components at the POUs).
S	Stock in the assembly line (units): average stock of components held in the assembly line measured in equivalent finished product units.

7.3.3 Input Data

The simulation model uses data provided by the industrial study case, which presents a common situation faced by plenty of manufacturing businesses globally. Table 7.2 shows the model parameters base, min and max values.

Table 7.2: Input parameters and disturbances base and range values.

Parameter	Units	Min	Max	Base Value
Input parameters				
Q	units			48
CT	s			see Table 7.3
CT_{MR}	min			140
L	lines			2
K	stations			5
M	models	2	4	4
T_p	s			see Table 7.3
T_s	s			480
WC	s			see Table 7.3
BC	units			1
T_t	min			4
T_h^e	s			1
T_h^f	s			2
Disturbances				
CV_p		0	0.50	0.15
CV_s		0	0.50	0.15
CV_q		0	0.50	0.10
CV_c		0	0.20	0.00

The operations considered in this model include two manual assembly lines which assemble four product models, two on each line. The mean processing times for each model and station along with work content and cycle time is summarised in Table 7.3. These processing times were obtained from the industrial company standard operating procedures, which in turn are calculated using MTM.

Table 7.3: Product processing time input data.

		T_p (s)						
Line	m	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	CT (s)	WC (s)
1	*1*	192.8	187.5	185.5	188.2	190.1	192.8	944.1
	2	214.3	210.2	215.4	212.0	210.7	215.4	1062.6
2	*3*	237.6	238.5	236.7	233.0	232.1	238.5	1177.9
	4	176.1	176.1	175.1	173.2	173.0	176.1	873.5

The products within a line share materials, technological features and general purposes, but they require different components, assembly fixtures and tooling. This calls for changeovers to adjust the workstations when a batch of a different product model is required. The parameter governing setup times is T_s, which takes each operator approximately 6 min (see Table 7.2), independently of the product sequencing.

Each product unit consists of many different components, as shown in Table 7.4. Most components are required only once per finished product unit, although some components, especially the smaller ones, may be required in larger numbers.

Table 7.4: Bill Of Materials summary data.

	No. Components					**Total No.**	**Total**
m	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	**Components**	**Pieces**
1	16	6	10	11	4	47	62
2	28	4	14	13	13	72	132
3	20	7	20	18	21	86	160
4	16	9	9	24	14	72	105

Components are transported to the POUs and then presented to the assembly operators in containers, i.e., boxes, trays or small trolleys. Each container carries a certain number of pieces of one component, typically a few dozens for middle- and large-size components, and about one hundred pieces for small components, such as bolts, screws and washers.

In this particular study case, an important number of components are packed in very large quantities per container compared to the number of pieces needed to feed the assembly line for the duration of the milkrun cycle. Note that the the milkrun cycle time is approximately similar to the time required to complete a production batch. To illustrate this fact, Table 7.5 shows the number of components of each product model that are packed in *large quantities*. Here, *large quantities* refers to the case in which one single container includes a number of pieces allowing to assemble more than two full batches of products—i.e., it is equivalent to the assembly line consumption of two milkrun cycles.

Table 7.5: Details of the high number of components served in large quantities [2] to the assembly lines.

	Product Model				**Avg**
Number of Components	$m=1$	$m=2$	$m=3$	$m=4$	
Total no. components	47	72	86	72	69
Packed in large quantities [2]					
No. components	13	25	29	37	26
Percentage components	28%	35%	34%	51%	28%

[2] Containers including a no. of pieces equivalent to the consumption of more than two milkrun cycles.

When the milkrun operator arrives at each POU, the containers are handled between the train and the back side of the POU racks. Based on measurements at the industrial partner facility, one second was estimated for handling empty containers and two seconds for containers full of components, as shown in Table 7.2. When walking from the milkrun train to the POU, the milkrun operator's speed was considered 1 m/s. The milkrun train speed in the assembly line area was found to be around 1 m/s, and the POU positions are separated approximately 2 m from each other, resulting in a 12 m long assembly line. Regarding the milkrun train travel from the warehouse to either assembly line, the industrial partner measurements showed little variability for an average travel time of approximately 4 min each way. The milkrun preparation time at the warehouse (picking time) was simulated considering the warehouse as a single picking point and treated as any POU of the assembly line.

The DES model takes into account the inherent variability of manual assembly operations by using lognormal distributions for processing and setup times, following the recommendations of [278]. The lognormal distribution is generated using the mean (μ) values of T_p and T_s—see Table 7.3—and the standard deviation (σ), which is given as a percentage of the mean by the coefficients of variation CV_p and CV_s. The base values for the coefficients were estimated from historical data provided by the industrial partner of this study case. The data allowed estimating CV_p and CV_s to be in the range of 0.15–0.20 for manual assembly lines. Note that since one of the goals of this work is to analyse the influence of processing and setup times variability on the internal logistics performance, CV_p and CV_s will take a range of values in certain simulation scenarios. Another two sources of variability, introduced in Section 7.3.1, are considered: the conforming units per container variability (CV_c) and the batch size quantity variability (CV_q). They are relevant along with the processing and setup variability because the logistic performance of the milkrun system is directly related to them.

7.3.4 Verification and Validation

The validation and verification of the simulation models were performed separately for assembly operations and internal logistics.

For the assembly operations section, historical production KPIs data were gathered and compared against the results of a simple parametric model and a discrete events simulation model. The results presented by the authors in [279] allowed the validation of both models by comparison against real industry study case data. It was also possible to verify the parametric model against the simulation model (considering no variability) because their results difference was smaller than 3.5% for any considered performance metric. In summary, the results indicated that both parametric and simulation models slightly underestimate total output and that they overestimate the production rate, labour productivity and line productivity. Both models were found to be reliable for the context considered here since the mean relative error was 1.63% and the max relative error was 4.9%.

Regarding the internal logistics part of the simulation model, the validation was carried out using measurements at the industrial partner assembly lines from June 2022. A total of 18 milkrun cycle measurements were registered, finding an average milkrun utilisation of 78.4%. This was compared with the equivalent simulation model results ($U = 71.6\%$) to calculate a relative error of 8.7%, slightly below 10%, which was considered satisfactory for the scope of this work.

7.3.5 Experiment Design

To address the research questions laid out in Section 7.1, several simulation scenarios were designed and then implemented on the simulation model by modifying the model's parameters. Table 7.6 summarises the parameters and range of values used to set up the simulation scenarios.

Table 7.6: Simulation scenarios.

Scenario	**Parameter**	**Units**	**Range**
i. Product mix	M	models	$\{2, 4\}$
	T_s	s	$\{0, 480\}$
ii. Process variability	CV_p, CV_s	per unit	$[0, 0.50]$
iii. Batch size variability	CV_q	per unit	$[0, 0.50]$
iv. Components quantity var.	CV_c	per unit	$[0, 0.20]$

The first research question—*'(1) What is the effect on the operational and logistics KPIs of producing multiple models in an assembly line compared to single-model production? Are there significant differences between mixed-model and multi-model production from the milkrun internal logistics point of view?'*—is examined by changing the number of product models under demand (one model per assembly line for single-model, $M = 2$; two models per assembly line per mixed- and multi-model, $M = 4$) and the setup time duration parameter (T_s set to 0 s for mixed-model, 480 s for multi-model). For this *scenario i.*, process and batch quantity coefficients of variability take their base values (T_p and T_s 0.15, CV_q 0.10), and the conforming units per container coefficient of variability is set to 0, as stated in Table 7.2.

The second research question—*'(2) How is the milkrun-assembly lines system affected by variability? In particular, to what extent is it impacted by assembly process variability and supply chain disturbances?'*—will be decomposed into the three variability sources considered in the simulation model. Firstly, process variability is governed by parameters CV_p (assembly processing time variability) and CV_s (setup time variability). These parameters will take values ranging from 0 (no variability at all) up to 0.50 (high variability), making up *scenario ii.* Secondly, the batch size variability coefficient will be used to represent in-plant manufacturing issues leading to smaller-than-standard batches of products being released for assembly. Similarly to the previous scenario, in *scenario iii.* CV_q values will range from 0 to 0.50, covering from no disturbances up to half of the batches having fewer units than it was intended. Finally, *scenario iv.* looks into external supplier perturbations which are simulated using the components quantity coefficient of variability. CV_c will take values in the range of 0 to 0.20, meaning that each components container can have up to 20% fewer valid pieces in the less favourable case. The effect of the interactions between the variability parameters was not analysed because a preliminary two-level full factorial design of experiments showed that two-factor interactions were not significant for the KPIs under study in comparison to the effects of the variability parameters by themselves.

The following Section 7.4 Results shows the outcome of the simulation scenarios introduced here.

7.4 Results

This section includes the outcome of the simulations corresponding to *scenarios i.-iv.* Section 7.4.1 addresses the first research question, and Section 7.4.2 includes *scenarios ii.-iv.*, which jointly address the second research question.

The results shown here are obtained with a simulation horizon of 74 h with a warm-up time of 2 h (i.e., nine production shifts after the warm-up is finished). To account for the stochastic nature of the results, each simulation scenario is run 20 times. This number was chosen because it was found that using a larger number of runs did not affect the resulting output in a statistically significant manner. At the start of each simulation run, all assembly stations and buffers between them are empty as well as all the components racks and the milkrun train.

The results shown in this section are presented in boxplots where the upper and lower limit of the boxes corresponds to the first and third quartiles. The coloured line is the mean and the whiskers limits are set to 1.5 times the interquartile range. Outlier data points (beyond the whiskers) are marked by a circle. The charts scale has been kept constant across all simulation scenarios to facilitate comparison.

7.4.1 Single-Model vs. Mixed-, Multi-Model Assembly

The selected operational KPIs comparing the performance of the assembly lines under *scenario i.* demand conditions are shown in Figure 7.4 and summarised in Table 7.7.

Table 7.7: *Scenario i*: Mean and standard deviation (SD) of main KPIs for single-, mixed- and multi-model assembly lines.

	P_{Line} (u/oper-h)		LT_B (min)		U (%)		S (u)	
Product Mix	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Single-model	3.33	0.015	188.9	1.5	50.60	0.82	181.7	1.9
Mixed-model	3.31	0.006	192.0	1.4	72.05	1.23	222.8	6.2
Multi-model	3.19	0.013	191.4	1.1	71.50	1.24	223.2	8.4

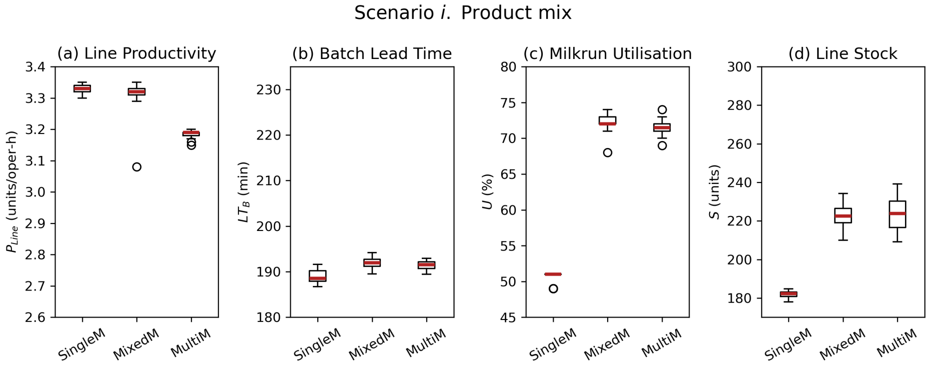


Figure 7.4: *Scenario i.*: Mean and deviation values of KPIs for single-, mixed- and multi-model assembly lines. (a) Line productivity, (b) batch lead time, (c) milkrun utilisation and (d) assembly line stock levels.

The productivity of single- and mixed-model lines is significantly superior to multi-model lines, as is expected considering that the setup time becomes zero (from 480 s per batch of 48 units, which represents just below 5% of the time needed to complete the batch on average). The difference in productivity between single- and mixed-model lines is related to operator idle and blocked times following product model changeovers as a result of cycle time differences between the incoming and outgoing products. Said difference does not account for significant productivity results in this case. Batch lead time, as expected, is slightly larger for mixed- and multi-model lines compared to single-model lines.

On the internal logistics KPIs side, milkrun utilisation and assembly line stock show a clear differentiation between single-model assembly lines and the other two. Incorporating multiple product models increases greatly the utilisation (from 51% to 72%, a +44% increment). Note that this steep increase could be linked to the high percentage of components packed in large quantities. This will be examined in the next Section 7.5 Discussion.

The component stock in the assembly line also suffers an increase for mixed- and multi-model lines driven by the same reason: single-model assembly lines see their average component stock decrease as the containers with very large quantities of pieces are consumed over time. Contrarily, mixed- and multi-model lines are constantly fed with small component boxes full of pieces. In the case shown here, the difference is significant but not dramatic, at an approx. +22% increase (from 182 to 223 units). In summary, increasing product mix negatively affects operational KPIs (reduces productivity, increases batch lead time), which was expected. It also increases greatly supply chain operator utilisation (+44% rise), although the magnitude of this sharp increase could be attributed to the high percentage of components packed in large quantities.

7.4.2 Variability and Disturbances

This subsection looks at how increasing levels of variability affect the operational (P_{Line}, LT_B) and internal logistics KPIs (U, S). As described in Section 7.3.5, simulation experiments were set up to independently analyse the influence of assembly line process variability (CV_p and CV_s, *scenario ii.*), batch size variability (CV_q, *scenario iii.*) and conforming components variability (CV_c, *scenario iv.*).

Process Variability

To analyse the impact of the assembly line process and setup variability, the respective coefficients were modified increasingly from 0 up to 0.50 (the base value for the industrial case study is 0.15; see Table 7.2). Figure 7.5 shows the results of this simulation scenario, and Table 7.8 includes the results' numeric values for average and standard deviation.

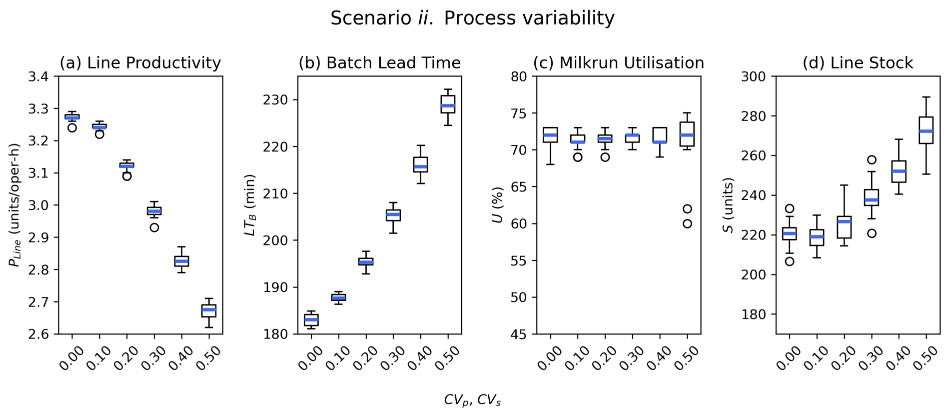


Figure 7.5: *Scenario ii.*: Mean and deviation values of KPIs for varying levels of process and setup coefficients of variation. (a) Productivity, (b) batch lead time, (c) milkrun utilisation, and (d) assembly line stock level.

In terms of operational KPIs, Figure 7.5a,b show that, as expected, an increase in process variability negatively the performance of the assembly line, especially considering that this lines' number of work-in-process units is limited to one. In particular, it can be seen that the productivity deteriorates greatly when CV_p and CV_s are greater than 0.20 both in terms of mean and standard deviation. Batch lead time follows the same trend.

Figure 7.5c shows that U does not suffer any changes, although its standard deviation increases slightly. On the other hand, the assembly line components' stock levels are severely impacted, rising from approx. 220 units for none or very small variability (CV_p and CV_s at 0–0.10) up to an average of approx. 270 units for CV_p, CV_s 0.50, which represents a noticeable +23% increase. Standard deviation also rises, but it remains small compared to the mean values of S, as shown in Figure 7.5d. In summary, only AL stock levels are affected by in-process variability, while the milkrun driver's workload remains unaffected.

Table 7.8: *Scenario ii.*: Mean and standard deviation of main KPIs for increasing values of process variability.

	P_{Line} (u/oper-h)		LT_B (min)		U (%)		S (u)	
CV_p, CV_s	Mean	SD	Mean	SD	Mean	SD	Mean	SD
0.00	3.27	0.012	183.0	1.2	71.75	1.33	220.4	4.9
0.10	3.24	0.011	187.8	0.8	71.25	1.16	218.7	5.8
0.20	3.12	0.015	195.4	1.1	71.45	1.05	238.5	7.6
0.30	2.98	0.019	205.2	1.8	71.30	0.99	238.1	8.8
0.40	2.83	0.021	216.0	2.2	71.45	1.23	252.6	7.8
0.50	2.67	0.025	228.7	2.3	71.28	4.06	272.1	10.7

Batch Size Variability

To understand the impact that upstream manufacturing process issues would have on the assembly operational and internal logistics performance, *scenario iii.* was set up by changing the value of CV_q, which determines the probability of an assembly production batch smaller than standard. CV_q takes values between 0 (no disruption) and 0.50 (meaning that on average, half the batches released to the assembly lines have between 36 and 48 units. The simulation results of *scenario iii.* are summarised in Figure 7.6, and average and standard deviation data are shown in Table 7.9.

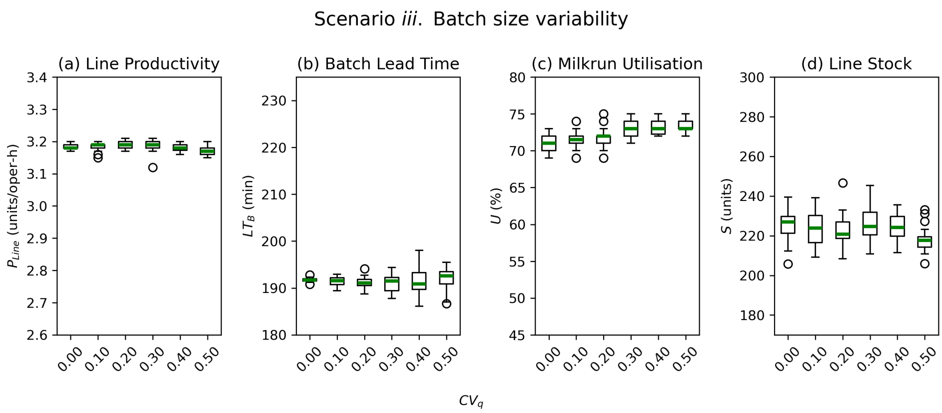


Figure 7.6: *Scenario iii.*: Mean and average values of KPIs for varying levels of batch size coefficients of variation. (a) Productivity, (b) batch lead time, (c) milkrun utilisation, and (d) assembly line stock.

Figure 7.6a,b shows that the average of both line productivity and lead time remains constant despite changes in CV_q. Although P_{Line} standard deviation increases slightly, it remains very low at about 0.25–0.43% of the average value. The lead time SD, on the other hand, does increase more than five-fold while remaining very low compared to average values (SD of 0.24–1.39%). Therefore, the data show that batch size variability has no significant impact on the operational KPIs. Although variability rises as CV_q grows, it remains at very low levels in relative terms.

Figure 7.6c,d show very little impact on internal logistics KPIs as a result of an important rise in batch size variability. The milkrun utilisation average does increase slightly (from 71 to 73%, c.+4% rise), but the SD reduction (from 1.25% to 0.82%) is not statistically significant. In a similar fashion, assembly line components stock decreases slightly in both average and standard deviation values, but none of these changes are statistically significant.

Table 7.9: *Scenario iii.*: Mean and standard deviation of main KPIs for increasing values of batch size variability.

	P_{Line} (u/oper-h)		LT_B (min)		U (%)		S (u)	
CV_q	Mean	SD	Mean	SD	Mean	SD	Mean	SD
0.00	3.18	0.008	191.7	0.5	70.68	1.25	225.6	8.0
0.10	3.19	0.013	191.4	1.1	71.50	1.24	223.2	8.4
0.20	3.19	0.012	191.1	1.2	71.74	1.37	222.6	9.1
0.30	3.19	0.019	191.0	2.0	72.84	1.07	225.8	8.5
0.40	3.18	0.011	191.1	2.8	73.17	0.92	224.7	6.7
0.50	3.17	0.014	191.9	2.7	73.32	0.82	218.1	6.8

Components Quantity Variability

The goal of this subsection is to analyse the impact of the components quantity coefficient of variability CV_c. This coefficient is employed to represent disturbances within in-house or external suppliers' processes, resulting in a lower-than-standard number of conforming pieces in each component container. As explained in Section 7.3, the number of conforming pieces per container is simulated using a discrete uniform distribution which has the inferior limit set to CV_c percent of the nominal value. *Scenario iv.* considers CV_c values from 0 to 0.20, as shown in Table 7.10.

Figure 7.7a shows that productivity is affected negatively by an increase in CV_c, although the magnitude of the impact is very limited: only a -2.2% reduction from the base scenario when components containers have up to 20% less conforming pieces than expected. Similarly, lead time is impacted negatively by CV_c increase, as depicted in Figure 7.7b. The LT_B average rises slightly (c.+2%) and suffers a greater dispersion of results (SD increases by +54%). All in all, even a substantial increase in components quantity variability does not affect the assembly lines' operational KPIs severely.

Regarding internal logistics KPIs, Figure 7.7c,d show that an increase of CV_c has no significant impact on either milkrun utilisation or assembly line component stock levels.

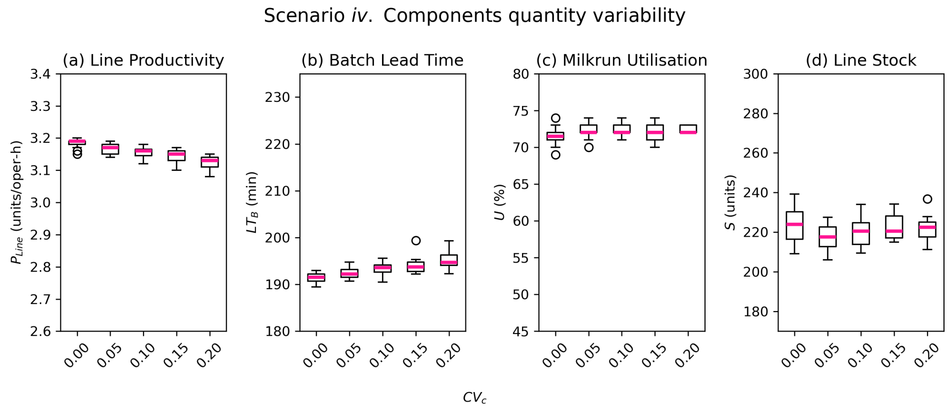


Figure 7.7: *Scenario iv.*: Mean and deviation values of KPIs for varying levels of components quantity coefficients of variation. (a) Productivity, (b) batch lead time, (c) milkrun utilisation, (d) assembly line stock.

Table 7.10: *Scenario iv.*: Mean and standard deviation of main KPIs for increasing values of component quantity variability.

	P_{Line} (u/oper-h)		LT_B (min)		U (%)		S (u)	
CV_c	Mean	SD	Mean	SD	Mean	SD	Mean	SD
0.00	3.19	0.013	191.4	1.1	71.50	1.24	223.2	8.4
0.05	3.17	0.015	192.4	1.2	72.17	0.99	217.5	6.2
0.10	3.16	0.016	193.5	1.2	72.26	0.81	220.0	6.8
0.15	3.15	0.019	194.0	1.6	72.00	1.05	222.0	5.6
0.20	3.12	0.019	195.2	1.7	72.40	0.50	221.9	5.9

7.5 Discussion

The results shown in the previous section have been summarised in Table 7.11.

Table 7.11: Summary of KPI change trends resulting from each scenario considered.

Scenario	**Productivity**	**Lead Time**	**Milkrun Utilisation**	**Line Stock**
Goal	$\uparrow$	$\downarrow$	$\downarrow$	$\downarrow$
i. Product mix	$\searrow$	$\nearrow$	$\upuparrows$	$\upuparrows$
ii. Process variability: CV_p, CV_s $\uparrow$	$\downdownarrows$	$\upuparrows$	$=$	$\upuparrows$
iii. Batch size variability: CV_q $\uparrow$	$=$	$=$	$\approx$	$\approx$
iv. Components qty. variability: CV_c $\uparrow$	$\searrow$	$\nearrow$	$\approx$	$\approx$

Increasing the product mix from single- to mixed- and multi-model assembly lines results in a moderate impact on operational performance (P_{Line}, LT_B) but a very significant negative effect on internal logistics KPIs, which could have further implications. For instance, the rise of assembly line component stock would increase the required floor space and decrease the assembly line surface productivity.

It is important to note that according to the results shown in Section 7.3.1, the greatest factor affecting U is the product mix, with a remarkable +44% increase resulting from changing from single- to multi-model assembly.

This sharp increase in U is caused by the rising number of containers that need to be handled, which is due to two main reasons.

(1) First of all, the number of component containers to be handled is larger every time there is a product changeover, which is the case for almost every milkrun cycle under the assumption that the milkrun cycle time is approximately similar to the time required to complete a batch of products (cf. CT_{MR}, Q in Table 7.2 and CT in Table 7.3). The increased number of containers to be handled is due to the fact that the supply chain operator needs to take all the containers of the outgoing model from the POU racks regardless of how many component pieces are left and replace them with components for the incoming product model. During regular supply cycles, on the other hand, containers are only replaced if needed (empty boxes work as kanban signals).

(2) The second reason is related with the compound effects of the first reason and the fact that in this particular study case, we find a large number of components packed in large quantities (see Table 7.5). This fact means that for a significant percentage of the components, each milkrun train carries enough pieces to assemble more than four times the required amount of pieces. Furthermore, the milkrun train will need to take back to the warehouse a full container and a half-empty container every time a changeover is needed.

Thus, it seems reasonable to conclude that milkrun utilisation is higher on mixed- and multi-model lines compared to single-model assembly lines. However, the magnitude of the increase shown in the Results must be considered carefully, since it it would be strongly related to the container quantities of this particular industrial study case.

As a closing remark on this subject, two aspects could be looked at in order to reduce the milkrun utilisation for multi-model assembly lines. Firstly, if enough shop-floor space is available, small components packed in large quantities could be left by the workstations, forming an assembly line supermarket, independent of the regular milkrun cycles. For larger components, relaxing the rule of minimum two containers (see Equation 7.1) could be considered. Secondly, packing components in smaller quantities (so that two containers cover approximately the consumption of a milkrun cycle) could also reduce the milkrun workload so that it is only slightly higher than for single-model assembly lines.

Production variability (CV_p, CV_s) is the most important disturbance factor affecting productivity, lead time and assembly line components stock. However, it does not affect supply chain operator utilisation because the productivity reduction implies a reduction of output rate (which slows down components consumption). The reason behind this is that the milkrun work logic establishes a fixed replenishment frequency (milkrun cycle time), resulting in a supply chain operator workload effectively unaffected by several minor variations over the course of a full replenishment cycle.

Despite the previous expectation that variability would always impact performance negatively, results from Sections 7.4.2 and 7.4.2 show that the internal logistics KPIs are not sensitive to disturbances originated by batch size and components quantity variability (CV_q and CV_c respectively). This implies that employing milkruns for the internal logistics of flexible multi-model assembly lines under high-mix low-volume demand is a way to shield this part of the supply chain from upstream disturbances, arriving from either external or internal processes.

It was also found that variability regarding batch size (CV_q) does not have any noticeable negative impact on operational performance, as shown in Figure 7.6c.

Note that as mentioned in Section 7.2, this article addresses a gap in the literature by specifically addressing in-plan logistics for multi-model assembly operations, including variability, and using a real study case—specially from an industry sector other than automotive.

The fact that the simulation model used in this work is based on a real industry study case provides valuable insight into the behaviour of similar assembly operations—internal logistics systems under increasingly hard conditions in terms of variability and product mix. However, it is important to note that this also limits the generalisation extent of the results obtained due to certain aspects listed below.

First of all, the case employed here considers only a relatively small product variation within each assembly line (ΔWC 13% and 34% for AL no. 1 and AL no. 2, respectively) and almost no difference in terms of average WC per model when comparing both lines (ΔWC c.2%). Understanding how much product variability affects the operational and internal logistics KPIs could be a potential avenue for further research to understand the extent of the potential benefits of employing milkruns for high-mix low-volume assembly.

Secondly, it could be argued that the number of conforming components coefficient of variability (CV_c) only modifies the number of pieces per container available to the assembly operator, but it does not realistically capture the possibility of components actually arriving at the assembly line and then causing quality control failures or unexpected assembly process time increases, which would imply additional productivity losses due to reasons such as product rework and idle/blocked assembly operators.

Thirdly, milkrun transportation time was considered deterministic because the industry case measurements indicated this time were consistent. However, for multi-train production sites, variability caused by occasional milkrun train traffic jams could be considered.

Finally, modelling the milkrun train as a single wagon could be slightly underestimating its utilisation despite the satisfactory validation results. Specifically, in potential scenarios featuring longer milkrun cycle times—note that the CT_{MR} parameter was unchanged through scenarios *i.* to *iv.*—this would entail a greater number of component containers and therefore potentially a greater number of required wagons leading to an increased walking time for the supply chain operator, which the current simulation model would not capture.

7.6 Conclusions

To address a mass customisation demand context that drives high-mix low-volume assembly operations, this article studied the implications of using milkrun trains for the internal logistics of multi-model assembly lines. Based on a real industrial study case from the white goods sector, a discrete events simulation model was employed to set up four different scenarios which evaluate the effect of product mix and three different sources of variability. To measure such impact, a set of four Key Performance Indicators (KPIs) were used, two corresponding to assembly operations and two corresponding to supply chain efficiency.

It was found that multi-model lines increase significantly the milkrun utilisation and the assembly line components stock compared to single-model lines. However, the magnitude of this large increase could be partially attributed to particularities of the study case. Operational KPIs were also affected negatively but to a much lesser extent. Internal logistics performance is greatly affected by the variability of assembly line processing time, especially in terms of component stock. Other sources of variability, such as the ones affecting the number of units per production batch or the components quantity per container, have very limited impact on the selected KPIs. This would imply that employing milkruns for the internal logistics of flexible multi-model assembly lines under high-mix low-volume demand is a way to shield this part of the supply chain from upstream disturbances, arriving from either external or internal processes.

Two key limitations of this work are the relatively low product variability in terms of work content and the milkrun train physical features simplification.

Further research paths include exploring the implications of much greater product work content variability, incorporating more detailed physical models of the milkrun train and expanding the simulation model to include adjacent layers that could constrain the performance of the assembly system as a whole, such as quality (defects, reworks, quality controls) or breakdowns and maintenance.

7.7 Summary

This chapter aims to provide further insight into multi-model parallel assembly lines by exploring the use of milkrun trains for their in-plant logistics. To do so, the research presented here builds on previously developed conceptual frameworks (Chapter 3) and simulation tools (Chapter 5), while focusing on the mass customisation demand context. Four different simulation scenarios were used to assess the effect of product mix and three sources of variability (assembly processes, other in-plant processes and external suppliers) on a set of four key performance indicators consisting of two operational and two logistics performance measures.

This chapter makes three specific contributions:

1. It addresses a gap in the literature by investigating in-plant logistics for multi-model assembly under variability disturbances.
2. It was found that internal logistics performance is very sensitive to the assembly line processing time variability, especially regarding components stock.
3. The results showed that employing milkruns for in-plant logistics is a way of shielding multi-model assembly lines from upstream disturbances.

Although the results of the simulations presented in this chapter are heavily influenced by the particularities of the industrial study case (see Section 7.5), the DES modelling methodology and the simulation models developed as part of this study can be reused to analyse other similar situations, either industrial or conceptual study cases.

Future avenues for this research line could focus on increasing the internal logistics simulation level of detail, for example by incorporating milkrun train and containers dimensions, weight and other physical aspects to the models. Further research could also concentrate on increasing the product variety range, or adding other supporting departments' constraints, such as maintenance, quality control and rework policies.

CHAPTER 8

Summary, conclusions and outlook

This chapter will conclude the thesis with a brief summary of the key research findings and how they contribute to answering the research aims, as well as the limitations of this study and an outlook of potential avenues for further research.

8.1 Summary of key findings

The overarching research aim of this thesis was to *understand and define how to design semiautomatic assembly systems to improve flexibility and productivity under high-mix low-volume demand.* To guide the research, three main research objectives were stated, which have been answered sequentially along the chapters of this thesis.

(1) The first research objective was to *understand the state of the art of Industry 4.0 assembly.* To do so, Chapter 2 presented a systematic literature review focusing on six key concepts: assembly, Lean, key performance indicators, mass customisation, Industry 4.0 and operators. The key findings of the review were that there is a lack of methodologies for implementing Industry 4.0 technologies so that they deliver all their potential benefits. It was also found that the mass customisation and personalisation demand trends drive the assembly systems increasing complexity. To address this issue, a holistic view of the systems would be required, along with the use of multiple performance measures which enable a perspective of the implications of Industry 4.0 technologies from different angles. Finally, in Chapter 3 an operator-centred conceptual framework was presented, allowing to clear classification of the Industry 4.0 digital technologies according to

their relationship with assembly operators.

(2) The second research objective was to *develop a methodology and the tools for the performance evaluation of flexible assembly systems.* Firstly, Chapter 3 introduced the general definitions and the industrial study case to be used in the rest of the thesis. In Chapter 4, a simplistic yet effective mathematical model was presented. This model, which focuses on calculating changeover losses to estimate the performance of multi-model assembly lines, was then used along design of experiments techniques to identify the most critical factors affecting these assembly lines. To evaluate the assembly lines' performance, several KPIs were used: labour productivity, line throughput and lead time, among others, which allowed us to gain insight into the relationships between them under different circumstances.

When answering the specific research question *What are the key drivers for multi-model assembly line performance?*, the results showed that the number of stations and the batch size are key to labour productivity and lead time, an important measure of the system's capability to deliver quickly to customer orders. The results also highlighted the trade-off between these two KPIs, so that they cannot be optimised simultaneously.

To overcome the limitations of the mathematical model –namely, its lack of stochastic parameters and the difficulty to integrate different ways of operator-workstation interaction– Chapter 5 presented discrete events simulation models and their verification against empirical data from the industrial study case.

(3) The third research objective was to *find assembly line configurations with at least +25% productivity increase by introducing partial automation.* Walking-worker assembly lines can leverage the productivity advantages of assembly lines with fewer stations, which results from reduced line balancing and changeover time losses. This assembly line configuration can avoid the disadvantages in terms of maximum line throughput derived from employing shorter lines by sharing the automated stations between two parallel lines.

Thus, Chapter 6 presents a study of semiautomatic parallel walking-worker assembly lines (PWWAL) in comparison to traditional fixed-worker lines (FWAL). The simulation modelling methodology developed previously was used to analyse six simulation scenarios of increasingly challenging high-mix low-demand conditions, which are expressed in terms of progressively smaller batch sizes and increasingly more frequent product family changeovers.

The simulation results showed that PWWALs can outperform FWALs in terms of productivity in all demand scenarios, achieving the +25% productivity increase goal. A key advantage of PWWALs is that they can seamlessly reduce the number of manual workers without compromising the line balance, therefore enabling efficient low-volume production. PWWALs also present advantages over FWAL regarding their capability to incorporate different degrees of automation without reducing their productivity; however the maximum line throughput becomes limited. On the other hand, PWWALs present significantly superior lead times and shopfloor surface requirements.

Finally, Chapter 7 expanded the scope of analysis of previous studies by incorporating outer layers of the operator-centred conceptual framework. In particular, the in-plant logistics function was analysed to better understand the implications of using milkrun trains to feed multi-model parallel assembly lines under severe disturbances. The simulation results showed that milkruns can be a great way to protect assembly lines from disturbances originating in upstream processes.

8.2 Contributions

This thesis made several contributions that have been listed at the end of each chapter, and which are summarised here grouped by stage.

Regarding the *Problem definition* stage:

(1) The systematic literature review evidences a lack of specific methodologies for the implementation of Industry 4.0 digital technologies on assembly systems. Key literature on the topic shows that mass customisation and personalisation demand trends lead to more complex assembly systems. These systems include many different layers that need to be addressed holistically. To gain perspective from multiple angles of how the several layers affect one another, sets of performance measures ought to be used. The literature review was published as a journal article in *Applied Sciences* [27].

(2) This thesis developed an operator-centred Industry 4.0 conceptual framework specific to manual assembly operations. Based on this framework, a clear classification between Industry 4.0 digital technologies according to their relationship with assembly operators. Hardware technologies (e.g. collaborative robots, augmented/mixed reality) are located in direct contact with the operators, as opposed to software technologies (e.g. big data, machine learning, cloud computing), which are employed by supporting departments and only affect assembly operators in an indirect way. The conceptual model was published as a conference article in *Procedia CIRP* [256].

In relation to the *Tool development* stage:

(3) This thesis proposed a simple analytic model for the performance evaluation of multi-model assembly lines which is easy to implement and sufficiently capable for preliminary analysis. Design of experiments results show that the two most critical factors for the operational performance of multi-model assembly lines are the number of stations and the batch size. Considering the mass customisation demand trends, there are—and will be—strategic advantages to further reducing the production batch sizes. This led to the conclusion that looking at designing flexible assembly lines with a reduced

number of stations would be a way to enhance productivity and mitigate the negative effect of frequent product changeovers. Since reducing the number of working stations implies a reduction of maximum line capacity, an apparent way to maintain production capacity flexibility would be to consider shorter parallel assembly lines. Further study of the influence of the relationship between total setup time and the number of stations led to the conclusion that this modelling assumption does not affect the results of the previous analysis. The mathematical model and the design of experiments analysis of critical factors to manual assembly line performance were published as a conference article in *IOP Conference Series: Materials Science and Engineering* [274].

(4) Several discrete events simulation models were developed to analyse flexible assembly operations with a focus on realistic product model changeovers, suitable for studying high-mix low-volume assembly. They were later verified and validated them using the previously developed parametric model and an industrial study case from a global white goods manufacturer. This work was published as a conference article in *Procedia CIRP* [279].

Finally, regarding the *Improvement* stage:

(5) A multi-model parallel walking-worker assembly line design was presented. This assembly line design is estimated to achieve a significant productivity increase while maintaining high flexibility in terms of line throughput, enabling a quick adaptation to demand variations. A comprehensive set of operational KPIs was used to estimate the performance of fixed and walking-worker assembly lines from different angles. Under any demand conditions, parallel walking-worker lines present higher productivity and throughput than traditional fixed-worker lines. These results highlighted the trade-off between productivity and lead time experimented by parallel walking-worker lines. The results also showed that increasing the degree of automation allows incrementing the line productivity under all demand conditions, but only if the number of workers can be reduced smoothly, which is the case for walking-worker configurations but not for fixed-worker lines. However, this comes at the expense of reducing the line throughput and increasing the lead time. This assembly line concept and the results of the analysis were published as a journal article in *Processes* [283].

(6) This thesis addresses a gap in the literature by investigating in-plant logistics for multi-model assembly under variability disturbances. It was found that internal logistics performance is very sensitive to the assembly line processing time variability, especially regarding components stock. The simulation results showed that employing milkruns for in-plant logistics is a way of shielding multi-model assembly lines from upstream disturbances. This analysis was published as a journal article in *Machines* [300].

8.3 Further research

Further research following the results obtained in this thesis can be structured around three main lines towards the implementation of Industry 4.0 technologies to improve assembly operations under high-mix low-volume demand conditions: analysis methodology, parallel walking-worker assembly lines, and milkruns for in-plant logistics.

8.3.1 Analysis methodology

The simulation models already developed could be expanded, following the same modelling methodology, to include supporting departments that were out of the scope of this thesis. For example, the inclusion of maintenance problems (automated station breakdowns or minor stops) or different rework policies for defective units (e.g. in-line or out-of-line, done by operators or by team leaders) would be fair starting points to cover the fourth layer of the operator-centred model.

The simulation modelling approach developed here could be used to implement a Digital Twin, one of the Industry 4.0 key enabling technologies. Along with the Internet of Things, it would be possible to deploy sensors in the assembly lines to gather data directly from the real system. Analysing short and medium-term scenarios using simulation would allow early detection of performance risks, such as transient bottlenecks caused by highly variable demand mixes.

Another avenue for research would be the use of simulation together with other tools, such as mixed-integer programming or scheduling techniques, that would allow the optimisation of the assembly line layouts.

8.3.2 Parallel walking-worker assembly lines

To continue the research on semiautomatic PWWALs, three areas stand out. First of all, the study of PWWALs by simulation tools would need to use more study cases, since some of the analyses already carried out were limited by the industrial case considered here. The investigation could be deepened by looking into aspects such as assembly line layout configuration, the effects of the number of automated stations, and the human operator's training, to cite just a few. The assembly workstation's detailed design could be another area of interest, especially regarding ergonomic risks. Additional sources of disturbances—the current model considers processing and setup times variability—such as stochastic breakdowns or different types of quality issues, would also constitute valuable avenes for future research.

Secondly, evaluating the incorporation of Industry 4.0 technologies could be explored, such as the use of collaborative robots for assembly or quality control tasks, or to provide support during product changeovers. Operator cognitive support provided by augmented/ mixed reality and cyber-physical systems could be beneficial to address the increased requirements in terms of human operator training that walking-worker lines require compared to fixed-worker ALs.

Finally, the actual industrial implementation of semiautomated PWWALs would allow us to verify the simulation results obtained here and detect further issues and opportunities of this assembly line configurations to deal with high-mix low-volume demand.

8.3.3 Milkruns for in-plant logistics

Regarding the use of milkrun trains for in-plant logistics, once again having a wealth of case studies would allow the in-depth evaluation of some of the questions already investigated. For example, the effect of mixed- and multi-model assembly lines on the milkrun utilisation, which depends heavily on the products' bills of materials and the number of parts per container being fed to the assembly lines.

Expanding the scope of the milkrun system models could be done in two directions. The system could grow to include more detailed operations of the in-plant warehouse and more milkrun trains serving other assembly lines. This way it would be possible to analyse the potential resource conflicts caused by disturbances, such as milkrun trains traffic jams or warehouse operators saturation. The simulation model could also be expanded by including physics considerations, such as the containers' weight and dimensions, and the milkrun train number of wagons and their available volume. This level of detail would enable a more accurate evaluation of the milkrun operator workload.

Finally, the digitalisation of milkrun systems could be explored. In this regard, artificial intelligence, the internet of things and autonomous guided vehicles could present synergies. For example, artificial intelligence algorithms could be used along with simulation models to optimise milkrun loading thanks to real-time data gathered from the assembly line racks.

8.4 Publications

The following were published as a result of this thesis:

Journals

- A. Miqueo, M. Torralba, and J. A. Yagüe-Fabra. "Lean Manual Assembly 4.0: A Systematic Review". In: *Applied Sciences* 10.23 (2020), p. 8555. DOI: 10.3390/app10238555.

- A. Miqueo, J. A. Yagüe-Fabra, M. Torralba, M. J. Oliveros, and G. Tosello. "Parallel Walking-Worker Flexible Assembly Lines for High-Mix Low-Volume Demand". In: *Processes* 11.1 (2023), p.172. DOI: 10.3390/pr11010172.

- A. Miqueo, M. Gracia-Cadarso, M. Torralba, F. Gil-Vilda, and J. A. Yagüe-Fabra. "Multi-Model In-Plant Logistics Using Milkruns for Flexible Assembly Systems under Disturbances: An Industry Study Case". In: *Machines* 11.1 (2023), p.66. DOI: 10.3390/machines11010066.

Conference (peer-reviewed)

- A. Miqueo, M. Torralba, and J. A. Yagüe-Fabra. "Operator-centred Lean 4.0 framework for flexible assembly lines". In: *Procedia CIRP* 104 (2021), pp. 440–445. DOI: 10.1016/j.procir.2021.11.074.

- A. Miqueo, M. Martín, M. Torralba, and J. A. Yagüe-Fabra. "Labour productivity in mixed-model manual assembly 4.0". In: *IOP Conference Series: Materials Science and Engineering* 1193.1 (2021), p.012104. DOI: 10.1088/1757-899X/1193/1/012104.

- A. Miqueo, M. Torralba and J. A. Yagüe-Fabra. 'Models to evaluate the performance of high-mix low-volume manual or semi-automatic assembly lines'. In: *Procedia CIRP* 107 (2022), pp. 1461–1466. DOI: 10.1016/j.procir.2022.05.175

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APPENDIX A

Resumen en castellano

A.1 Resumen

Las tendencias globales de la personalización e individualización en masa impulsan la producción industrial en serie corta y variada; y por tanto una gran variedad de productos en pequeñas cantidades. Por ello, la customización en masa precisa de sistemas de ensamblaje que sean a la vez altamente productivos y flexibles, a diferencia de la tradicional oposición entre ambas características. La llamada cuarta revolución industrial trae diversas tecnologías habilitadoras que podrían ser útiles para abordar este problema. Sin embargo, las metodologías para implementar el ensamblaje 4.0 todavía no han sido resueltas. De hecho, para aprovechar todas las ventajas potenciales de la Industria 4.0, es necesario contar con un nivel previo de excelencia operacional y un análisis holístico de los sistemas productivos. Esta tesis tiene como objetivo entender y definir cómo mejorar la productividad y la flexibilidad de las operaciones de montaje en serie corta y variada.

Esta meta se ha dividido en tres objetivos. El primer objetivo consiste en comprender las relaciones entre la Industria 4.0 y las operaciones de ensamblaje, así como sus implicaciones para los operarios. El segundo objetivo consiste en desarrollar una metodología y las herramientas necesarias para evaluar el rendimiento de diferentes configuraciones de cadenas de ensamblaje. El último objetivo consiste en el diseño de sistemas de ensamblaje que permitan incrementar su productividad al menos un 25 %, produciendo en serie corta y variada, mediante la combinación de puestos de montaje manual y estaciones automatizadas.

Para abordar la fase de comprensión y definición del problema, se llevó a cabo una revisión bibliográfica sistemática y se desarrolló un marco conceptual para el Ensamblaje 4.0. Se desarrollaron, verificaron y validaron dos herramientas de evaluación del rendimiento: un modelo matemático analítico y varios modelos de simulación por eventos discretos. Para la verificación, y como punto de partida para los análisis, se ha utilizado un caso de estudio industrial de un fabricante global de electrodomésticos. Se han empleado múltiples escenarios de simulación y técnicas de diseño de experimentos para investigar tres cuestiones clave.

En primer lugar, se identificaron los factores más críticos para el rendimiento de líneas de montaje manuales multi-modelo. En segundo lugar, se analizó el rendimiento de líneas de montaje semiautomáticas paralelas con operarios móviles en comparación con líneas semiautomáticas o manuales con operarios fijos, empleando diversos escenarios de demanda en serie corta y variada. Por último, se investigó el uso de trenes milkrun para la logística interna de líneas de ensamblaje multi-modelo bajo la influencia de perturbaciones.

Los resultados de las simulaciones muestran que las líneas paralelas con operarios móviles pueden superar a las de operarios fijos en cualquier escenario de demanda, alcanzando como mínimo el objetivo de mejorar la productividad en un 25 % o más. También permiten reducir cómodamente el número de operarios trabajando en la línea sin afectar negativamente al equilibrado de la misma, posibilitando la producción eficiente de bajo volumen. Los resultados de las simulaciones de logística interna indican que los milkrun pueden proteger las líneas de ensamblaje de las perturbaciones originadas en procesos aguas arriba.

Futuras líneas de investigación en base a los resultados obtenidos en esta tesis podrían incluir la expansión e integración de los modelos de simulación actuales para analizar las cadenas de montaje paralelas con operarios móviles incorporando logística, averías y mantenimiento, problemas de control de calidad y políticas de gestión de los retrabajos. Otra línea podría ser el uso de diferentes herramientas para el análisis del desempeño como, por ejemplo, técnicas de programación de la producción que permitan evaluar el desempeño operacional de diferentes configuraciones de cadenas de montaje con operarios móviles, tanto en términos de automatización como de organización en planta. Podrían incorporarse tecnologías de la Industria 4.0 a los modelos de simulación para evaluar su impacto operacional global –como cobots para ensamblaje o para la manipulación de materiales, realidad aumentada para el apoyo cognitivo a los operarios, o AGVs para la conducción de los trenes milkrun. Por último, el trabajo presentado en esta tesis acerca las líneas de ensamblaje semiautomáticas con operarios móviles a su implementación industrial.

A.2 Introducción

Las operaciones de ensamblaje se enfrentan a una tradicional oposición entre la alta productividad de la automatización y la flexibilidad superior de las líneas de montaje manuales. El contexto global de la producción de electrodomésticos se caracteriza por las tendencias de demanda de gran personalización de los productos y por las nuevas posibilidades que ofrecen las nuevas tecnologías inteligentes.

A pesar del potencial casi ilimitado que se atribuye a la introducción de tecnologías digitales disruptivas, las metodologías para su implementación real, así como la madurez operacional requerida para una digitalización exitosa de las operaciones de ensamblaje, son todavía cuestiones sin resolver.

El objetivo de esta tesis es comprender y definir líneas de ensamblaje capaces de lidiar de manera flexible con productos altamente personalizados alcanzando una gran productividad y, por tanto, preparando dichas líneas para la llegada de la llamada cuarta revolución industrial: la Industria 4.0.

Este capítulo presenta el contexto y la motivación de la tesis, el problema de la investigación, los objetivos y preguntas de la investigación, el alcance y, finalmente, resume la estructura del documento.

A.2.1 Contexto y motivación

La primera revolución industrial tuvo lugar durante los siglos XVIII y XIX en los países de Occidente. Fue posible gracias a la máquina de vapor y la mecanización del trabajo, y permitió un fuerte aumento de la producción de bienes manufacturados. En un paradigma de *mercado simple*, donde la demanda de productos industriales superaba ampliamente a la oferta, había una fuerza impulsora estable para el aumento de la producción [1, p.17–20].

La segunda revolución industrial ocurrió en diferentes regiones a lo largo de finales del siglo XIX o principios del XX. Vino impulsada por avances tecnológicos (como las piezas intercambiables, la electricidad o el proceso Bessemer para la producción de acero, entre otros), e innovaciones organizativas como la gestión científica de la producción y las cadenas de montaje. Apareció así la producción en masa, que se convertiría en el paradigma dominante de los sistemas de producción hasta la década de 1980. La producción en masa permitió la fabricación de grandes volúmenes a bajo coste mediante la estandarización (es decir, reduciendo la variedad de productos) para poder beneficiarse de las economías de escala y la especialización de la mano de obra. Esto hizo que cada vez más personas pudieran permitirse comprar productos industriales elaborados, lo que impulsó un ciclo virtuoso de aumento del volumen de producción y una mayor reducción de los costes unitarios [1, p.21–32].

En la segunda mitad del siglo XX, el desarrollo de la electrónica y los ordenadores trajo consigo la automatización y la robotización de la producción, así como una velocidad de transmisión de la información mucho mayor. Los productos estandarizados de bajo coste dejaron de ser suficientes: las tendencias de demanda cambiaron y dieron paso al *mercado volátil*. Como resultado, el nuevo objetivo de los sistemas de producción era tener una mayor variedad de productos y tiempos de entrega lo más cortos posible [2]. El Sistema de Producción Toyota (TPS, por sus siglas en inglés [3]) surgió en Japón en las décadas de 1950 y 1960, y se convirtió en la mejor forma de lograr dichos objetivos [4]. Su expansión global en la década de 1980 bajo el nombre de *Producción Lean* [5] coincidió con la aparición de otro desarrollo clave: los sistemas de fabricación flexible (*Flexible Manufacturing Systems*, FMS), que integran ordenadores, máquinas de control numérico y sistemas automáticos para el manejo de materiales [6, p.158]. Tanto Lean como FMS, que no son mutuamente excluyentes, tienen como objetivo la producción de volúmenes intermedios de productos con un cierto grado de variedad. Este paradigma productivo, que abarca aproximadamente desde la década de 1980 hasta la actualidad, se caracteriza por la volatilidad del mercado, la generalización de las tecnologías y sistemas de la información (IT/IS), la producción Lean y los FSM. Se le ha denominado Industria 3.0 [2, 7] para referirse a lo que se considera que será el próximo paradigma de la producción: la cuarta revolución industrial, o Industria 4.0, hecha posible por una serie de tecnologías digitales [8].

Para comprender mejor el impacto potencial que esta cuarta revolución industrial podría tener en los sistemas de ensamblaje, es necesario ahondar en varios conceptos básicos: el ensamblaje industrial, la automatización, la productividad y la flexibilidad y la evolución de la demanda hacia la personalización y la individualización en masa.

El montaje o ensamblaje es la parte de un proceso productivo donde se unen varios componentes y subconjuntos hasta que el producto adquiere su forma final, convirtiéndose en un producto acabado. El *montaje industrial* es, siguiendo la definición de Nof et al., «la suma de todos los procesos mediante los cuales varios componentes y subconjuntos se ensamblan para formar un conjunto diseñado geométricamente o producto completo (como una máquina o un circuito electrónico) ya sea mediante un proceso unidad a unidad, por lotes o continuo» [9, p.2]. El sistema de ensamblaje utilizado es crítico, ya que determina en gran medida la productividad, la calidad del producto y su coste final.

La cadena de montaje, introducida por Henry Ford, se considera el primer sistema de ensamblaje moderno y demostró ser muy eficaz para producir grandes cantidades de un único producto estándar. Las cadenas de montaje se pueden definir como «una disposición de trabajadores, máquinas y equipos en los que el producto a ensamblar pasa consecutivamente de una operación especializada a la siguiente hasta que se completa. También se las denomina líneas de producción» [9, p.2].

En cuanto al agente que ejecuta el ensamblaje, «las operaciones de manipulación pueden ser realizadas por robots, personas, o combinaciones de ambos» [6, p.148]. En función del grado de automatización hay tres tipos básicos de ensamblaje:

> Los sistemas de montaje se utilizan prácticamente en todos los tipos de fabricación de bienes duraderos. Hay tres tipos básicos de sistemas

> de ensamblaje: (1) ensamblaje manual, llevado a cabo por operarios humanos, generalmente con la ayuda de herramientas simples . . . (2) sistemas de montaje que combinan operarios humanos y mecanismos automatizados . . . (3) sistemas de montaje totalmente automatizados para piezas producidas en serie, especialmente en condiciones peligrosas para las personas [6, p.167].

Los sistemas automáticos e híbridos emplean robots industriales para llevar a cabo partes, o todo, el proceso de ensamblaje, lo cual aumenta la productividad y reduce los costes de mano de obra. Una de las tecnologías habilitadoras clave para la cuarta revolución industrial es la robótica colaborativa, que presenta ventajas significativas respecto a los robots de ensamblaje convencionales en términos de seguridad, coste y facilidad de implementación y reconfiguración [10, 11]. Este enfoque en la reconfigurabilidad de los sistemas automatizados está estrechamente relacionado con la tradicional oposición entre productividad y flexibilidad.

La productividad, es decir, la eficiencia, la cantidad de recursos necesarios para producir un determinado producto, no puede expresar por sí sola la capacidad real de un sistema de producción para responder a la demanda del mercado y adaptarse a los sucesivos cambios [12]. El creciente énfasis sobre la variedad y personalización de los productos hace necesario que los sistemas de ensamblaje se diseñen y operen teniendo en cuenta la flexibilidad [13]. Este enfoque, sin embargo, puede dificultar el aprovechamiento de las ventajas de productividad resultantes de las economías de escala y la especialización de los procesos. Los sistemas tradicionales de montaje dedicados aprovechan los ordenadores y la maquinaria automatizada para lograr costes de producción muy bajos en productos estándar, no personalizados. Requieren, no obstante, grandes inversiones de capital y, por lo tanto, grandes volúmenes de producción para ser rentables. Por su parte, los sistemas de ensamblaje totalmente manuales siguen existiendo, a pesar de su baja productividad, debido a su gran flexibilidad. Esto los hace viables para satisfacer la demanda de nichos de mercado y productos especializados (Figura A.1).

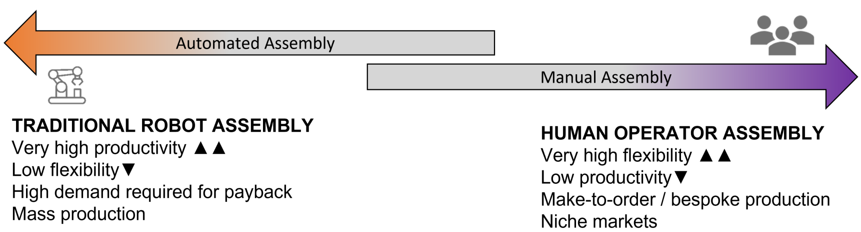

Figura A.1: Dicotomía tradicional entre sistemas automatizados muy productivos, pero poco flexibles, y cadenas de montaje manuales muy flexibles, pero menos productivas.

Ocupando un término medio entre ambos, los sistemas de ensamblaje flexibles son capaces de integrar puestos de montaje manuales y automáticos para producir cierta variedad de productos de manera eficiente, incluso en volúmenes de producción medianos.

La *flexibilidad* de los sistemas de ensamblaje «puede verse como la capacidad de un sistema para cambiar y asumir diferentes posiciones o estados en respuesta a cambios en la demanda, incurriendo en pequeñas pérdidas de tiempo, esfuerzo, coste o rendimiento» [14, p.262] (basado en [15]). De los diez tipos de flexibilidad identificados por ElMaraghy et al. [14, p.263] (basado en Browne et al. [16] y Sethi y Sethi [17]), esta tesis se centra en los siguientes cuatro aspectos:

- Flexibilidad del *producto*: «facilidad (en tiempo y coste) de incorporar nuevos productos a un mix de productos existente. Contribuye a la agilidad».
- Flexibilidad de *volumen*: «la capacidad para variar el volumen de producción dentro de la capacidad de producción máxima, manteniendo la rentabilidad».
- Flexibilidad de *expansión*: «facilidad (en tiempo y coste) de aumentar la capacidad de producción máxima y/o los tipos de productos a producir, a través de cambios físicos en el sistema».
- Flexibilidad de *producción*: «El rango de todos los tipos de componentes que se pueden producir sin añadir grandes inversiones en equipos».

La creciente atención a la flexibilidad está estrechamente relacionada con la evolución de las tendencias de demanda globales. A pesar de que tradicionalmente existía una clara segmentación entre los bienes producidos en serie y los productos fabricados por pedido (o bajo demanda), los mercados se han ido desplazando hacia la personalización de artículos producidos en masa. Aunque esto no era económicamente viable en el pasado, los avances tecnológicos lo han hecho posible. En un futuro cercano, la personalización en masa podría volverse no solo deseable, sino un requisito a cumplir por cualquier empresa manufacturera que quiera seguir siendo competitiva [2].

La *personalización en masa* (en inglés, *mass customisation*) es una tendencia desde la década de 1980, caracterizándose por los cambios en la variedad y el volumen demandado por cada referencia de producto. «En comparación con la producción en masa (que alcanzó su punto álgido en 1955), la variedad de cada producto en la personalización en masa es grande, y el volumen de producción de cada variante del producto es relativamente pequeño» [6, p.6].

El cambio industrial de la producción en masa a la personalización en masa ya fue pronosticado en 1987. La capacidad de producir productos personalizados que cumplan con los requisitos de cada consumidor con costes de producción cercanos a los de la fabricación en masa es el objetivo de la personalización en masa. Brindar la oportunidad de tener un producto en el lugar, forma y momento que deseen, resuena bien en los clientes. La cantidad de productos personalizados en masa aumenta gradualmente, al igual que los servicios personalizados. Este tipo de paradigma productivo se denomina *individualización en masa* (en inglés, *mass personalisation*) [18, p.313].

La personalización e individualización en masa llevan a una situación de demanda particularmente desafiante: gran variedad y bajo volumen de producción (en inglés, *high-mix low-volume*) [19]. Este tipo de producción, también llamada en serie corta y variada, se caracteriza por la demanda de una gran cantidad de artículos, en pequeñas cantidades por artículo y con variaciones que no siguen patrones estacionales, lo que hace que su pronóstico sea difícil e ineficiente.

Los tamaños de lote de producción cada vez más pequeños y los productos individuales completamente personalizados enfatizan la necesidad de que los fabricantes diseñen y utilicen los sistemas de producción, y las operaciones de ensamblaje en particular –ya que son la última parte de la cadena de producción–, con el objetivo claro de ser capaces de enfrentarse a, y prosperar en, un contexto de demanda para el que la flexibilidad es una característica clave. Para seguir siendo competitivas en este contexto, las empresas manufactureras tendrán que aumentar su productividad al tiempo que se vuelven más flexibles. Afortunadamente para ellas, son numerosas las nuevas tecnologías digitales que se espera sean útiles para lograrlo [8].

En las últimas décadas, los avances tecnológicos digitales han abierto nuevas posibilidades para diversos sectores económicos. Los proveedores de servicios fueron los primeros en beneficiarse de ellos. Más tarde, el gobierno alemán reconoció las posibles ventajas de implementar tales soluciones en el sector manufacturero europeo, y acuñó el término «Industria 4.0» [20] para conceptualizar la esperada cuarta revolución industrial: un cambio en el paradigma de fabricación que aprovecharía tecnologías digitales disruptivas, permitiendo a Alemania –y Europa– mantener una posición de liderazgo industrial haciéndose más ágiles y eficientes y centrándose en la fabricación avanzada y de alto valor añadido [21]. Otros países líderes en fabricación, como Estados Unidos, China, Japón e India también han establecido planes estratégicos similares que subrayan la importancia de aprovechar las nuevas tecnologías digitales para impulsar sus industrias [22].

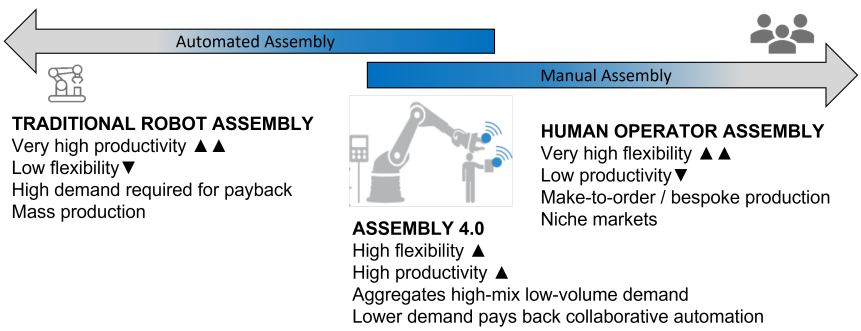

Figura A.2: Las tecnologías de la Industria 4.0 podrían ayudar a resolver la dicotomía entre productividad y flexibilidad de las cadenas de montaje.

Industria 4.0, *industria inteligente*, *fabricación inteligente* o *fábricas inteligentes*, entre otros [22], son términos utilizados para describir la misma visión: mayor flexibilidad y automatización; flujos de datos e información entre procesos, funciones y compañías; mejora de la calidad para lograr una producción sin defectos; aprovechamiento del *big data*, las redes neuronales, el aprendizaje automático y la inteligencia artificial, entre otras tecnologías, para maximizar la eficiencia y la capacidad de reacción [23]. Sin embargo, el camino para materializar la cuarta revolución industrial en las operaciones de ensamblaje –el *Ensamblaje 4.0* [24], representado en la Figura A.2– dista mucho de estar establecido. De hecho, para aprovechar los potenciales beneficios de las tecnologías inteligentes sería necesario desarrollar sistemas de ensamblaje con un nivel de excelencia operativa y madurez Lean que rara vez se encuentra en la mayor parte de las industrias.

Como ilustra la Figura A.3, parece claro que la aplicación de nuevas tecnologías para digitalizar las operaciones de montaje solo puede causar una ventaja disruptiva si el rendimiento operativo de todos los sistemas subyacentes –incluidos elementos convencionales como la maquinaria, el hardware, las personas o las políticas organizativas– tiene una base sólida. Como indican Rüttiman y Stöcki, «si el sistema de fabricación está mal concebido, la digitalización sólo podrá optimizar un mal diseño» [25].

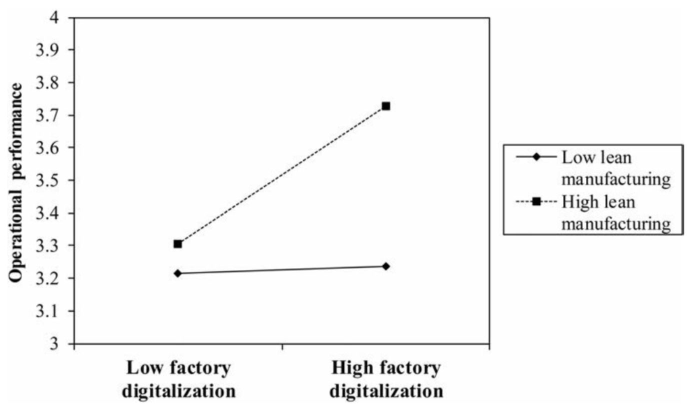

Figura A.3: Interacción entre la digitalización de la fábrica y la producción Lean.
Figura: Buer et al. [26], CC BY 4.0.

Hasta la fecha, la búsqueda de metodologías eficaces para la implantación de las tecnologías de la Industria 4.0 en las operaciones de montaje con una visión sistémica –en oposición a los proyectos pequeños y aislados con efectos limitados en la mejora de productividad– sigue siendo una cuestión pendiente. Sin embargo, la recompensa de cubrir este vacío podría ser la materialización de sistemas verdaderamente flexibles y productivos que puedan hacer frente, e incluso prosperar, en los mercados más cambiantes y exigentes.

A.2.2 Finalidad, objetivos y cuestiones de la investigación

El objetivo central de esta tesis es comprender y definir cómo diseñar operaciones de montaje en serie corta y variada para mejorar su flexibilidad y productividad.

Para ello, se definieron tres objetivos de investigación principales, cada uno de los cuales sienta las bases del siguiente:

1. Comprender el estado del arte de las operaciones de ensamblaje de la cuarta revolución industrial.
   - ¿Cómo se relacionan el ensamblaje y la personalización en masa, la producción Lean y la Industria 4.0?
   - ¿Cómo podrían las tecnologías de la Industria 4.0 mejorar la flexibilidad y la productividad de las operaciones de montaje?
   - ¿Cuál es el papel de los operarios en relación con las tecnologías digitales de la Industria 4.0?
2. Desarrollar un método y las herramientas necesarias para caracterizar y evaluar el rendimiento de diferentes configuraciones de cadenas de montaje flexible.
   - ¿Cómo se puede evaluar el rendimiento de las operaciones de montaje flexible semiautomatizado?
   - ¿Qué combinación de parámetros de entrada, perturbaciones e indicadores clave del desempeño deben utilizarse para dicha evaluación?
   - ¿Cuáles son los factores clave para el rendimiento de una línea de ensamblaje multi-modelo para la producción en serie corta y variada?
3. Diseñar sistemas de montaje que aumenten su productividad en al menos un 25 % cuando hacen frente a una demanda de gran variedad y bajo volumen, incorporando una combinación de puestos de trabajo automatizados y manuales.
   - ¿Cómo pueden configurarse las líneas de montaje semiautomáticas para lograr importantes incrementos de productividad y a la vez mantener una gran flexibilidad cuando producen en serie corta y variada?
   - ¿Qué factores clave deben tenerse en cuenta a la hora de diseñar estas líneas para que las iniciativas de digitalización puedan mejorar aún más su rendimiento?
   - ¿Qué tecnologías podrían aplicarse a este caso de estudio concreto?

A.2.3 Alcance

Esta tesis se estructura en tres etapas, cada una de las cuales se centra en un objetivo de investigación, tal y como se muestra en la Figura A.4.

La primera etapa, Definición del problema, define y delimita el problema, permitiendo comprender mejor las cadenas de montaje manuales y semiautomáticas. También establece el marco conceptual sobre el que se construyen las etapas siguientes.

La segunda etapa, Herramientas de análisis, introduce, valida y verifica dos herramientas de evaluación del rendimiento de las líneas de montaje flexibles, y las utiliza en un estudio preliminar para identificar sus factores más críticos.

En la tercera etapa, Mejora, se estudia el rendimiento de las cadenas de montaje paralelas con operarios móviles, estableciendo una comparación con las líneas tradicionales con operarios fijos. A continuación, esta etapa amplía los modelos de simulación para estudiar el uso de *milkrun* para la logística interna de las cadenas de montaje multiproducto como medio para hacer frente a las perturbaciones.

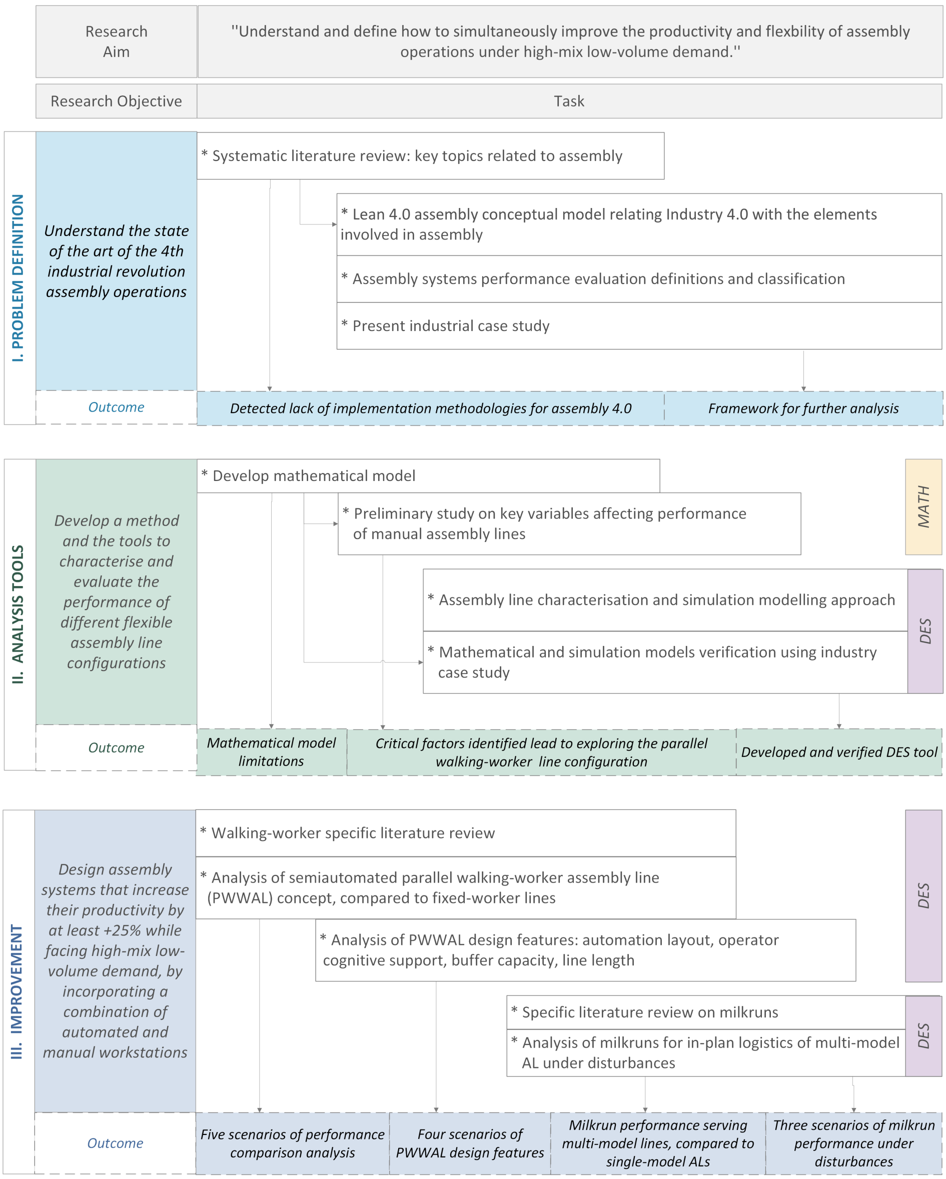

Figura A.4: Finalidad, objetivos, alcance y capítulos.

Definición del problema

La primera etapa de esta tesis, *Definición del problema*, se deriva de la finalidad general de esta investigación: comprender y definir cómo diseñar las operaciones de montaje para mejorar la flexibilidad y la productividad bajo una demanda de gran variedad y bajo volumen . En primer lugar, se investiga el estado del arte de las operaciones de ensamblaje en relación con cinco áreas clave: las tendencias de demanda de personalización e individualización en masa; las nuevas posibilidades que brindan las tecnologías digitales de la Industria 4.0; los indicadores a utilizar para evaluar el impacto de las nuevas tecnologías; la relación de la Industria 4.0 con el paradigma de la producción Lean; y el papel de las personas en esta transformación. Metodológicamente, se emplea una revisión sistemática de la bibliografía para identificar la falta de metodologías de implantación del Ensamblaje 4.0.

A partir de las principales conclusiones de la revisión bibliográfica, se plantea un marco conceptual centrado en las personas que organiza las distintas capas que intervienen en las operaciones de ensamblaje y subraya sus relaciones, revelando qué tecnologías digitales de la Industria 4.0 podrían implementarse y qué capas del modelo conceptual se verían afectadas. La implantación metódica de nuevas tecnologías digitales disruptivas para mejorar las operaciones de ensamblaje requiere una evaluación cuidadosa de su impacto potencial en el rendimiento del sistema. Esto permitiría que los proyectos de digitalización transformaran realmente el rendimiento operativo de todo el sistema y evitaran obtener únicamente ganancias parciales o menores.

Para sentar las bases de dicho análisis, se introducen las definiciones y conceptos básicos de la evaluación del rendimiento de los sistemas de ensamblaje y se presenta un caso de estudio industrial real, que se utilizará en las etapas siguientes. En base al objetivo general de la investigación, el ámbito de dicha evaluación del rendimiento se enfoca específicamente a los sistemas de montaje manuales y semiautomáticos. Las métricas de rendimiento se centran en la medición de la productividad y el plazo de entrega, mientras que la flexibilidad se evalúa mediante la respuesta del sistema a las perturbaciones y a las exigentes condiciones impuestas por producción en serie corta y variada. Productividad y flexibilidad contribuyen conjuntamente a introducir el paradigma de la personalización en masa en el ámbito del análisis. Así, este paradigma subraya la importancia de dos elementos clave: los cambios de modelo de producto y la variabilidad asociada a los procesos estocásticos, que se integrarán posteriormente en las herramientas de evaluación del rendimiento.

Herramientas de análisis

La segunda etapa, *Herramientas de análisis*, está directamente relacionada con el segundo objetivo de investigación de esta tesis: desarrollar una metodología y las herramientas para caracterizar y evaluar las operaciones de montaje para la producción en serie corta y variada. Para ello, se desarrollan dos herramientas de análisis. En primer lugar, se presenta un modelo matemático simplificado. A pesar de sus limitaciones, relacionadas con la dificultad para integrar variables estocásticas, el bajo coste computacional de este modelo paramétrico permite realizar estimaciones preliminares con rapidez. Se emplea para encontrar los factores más importantes que afectan al rendimiento de los sistemas de ensamblaje del caso de estudio industrial, reduciendo así el número de variables a considerar. Para superar las limitaciones del modelo matemático, se introducen a continuación modelos de simulación por eventos discretos. Para garantizar que esta metodología de modelado es adecuada para llevar a cabo análisis posteriores y para respaldar las conclusiones del análisis preliminar, ambos modelos (paramétrico y de simulación) se validan y verifican usando datos empíricos procedentes del caso de estudio industrial. Por lo tanto, esta etapa proporciona dos herramientas de análisis adecuadas para evaluar el rendimiento de las cadenas de montaje en serie corta y variada, incluido el impacto potencial de las tecnologías de la Industria 4.0, puesto que el marco presentado en la etapa anterior ya identificaba dónde se situaría cada tecnología digital y qué elementos del sistema se verían afectados.

Mejora

Una vez desarrolladas y probadas las herramientas de análisis, la tercera fase, *Mejora*, aborda el último objetivo clave de la investigación: diseñar sistemas de ensamblaje que aumenten su productividad en al menos un 25 % en producción de serie corta y variada mediante la introducción de una combinación de estaciones de montaje automáticas y manuales. En base a los resultados del análisis preliminar, se presentan líneas de montaje paralelas con operarios a pie.

Para comprobar los posibles beneficios de esta configuración de las cadenas de montaje, especialmente en términos de la dupla productividad-flexibilidad, se realiza una comparación entre líneas semiautomatizadas de operario fijo y operario móvil, evaluando su rendimiento frente al de una configuración de línea manual convencional de operario fijo. Para ampliar el alcance del análisis a otras capas del modelo conceptual, se lleva a cabo otra simulación para analizar el uso de una herramienta Lean de probada eficacia para alimentar de componentes las líneas de montaje multimodelo: los trenes *milkrun*. El objetivo de este estudio es evaluar si la logística interna añadiría restricciones al rendimiento de las cadenas paralelas de ensamblaje multimodelo, especialmente cuando se enfrentan a la producción en serie corta y variada, y están sujetas a perturbaciones de diferentes fuentes.

A.2.4 Estructura del documento

De acuerdo con el esquema presentado, esta tesis se organiza de la siguiente manera:

En el Capítulo 1 se han explicado los antecedentes y la motivación de la tesis. Se han detallado los objetivos, las metas y las preguntas de la investigación, y se ha esbozado el alcance de la tesis.

El Capítulo 2 presenta el estado de la cuestión a través de una revisión bibliográfica sistemática para comprender la relación entre la productividad, la flexibilidad y las nuevas tecnologías digitales para operaciones de ensamblaje. En concreto, la revisión examina cuatro aspectos estrechamente relacionados: el ensamblaje para la personalización en masa; la Industria 4.0 y la evaluación del rendimiento; la producción Lean como punto de partida para las fábricas inteligentes; y las implicaciones de la Industria 4.0 para las personas que trabajan en las operaciones de ensamblaje.

El Capítulo 3 establece el marco teórico de la investigación. En primer lugar, se propone un modelo conceptual de Ensamblaje 4.0 centrado en el operario. Dicho modelo ordena los componentes del sistema de operaciones de montaje junto con sus interacciones entre sí y con las nuevas tecnologías de la Industria 4.0. A continuación, se explican las definiciones y conceptos básicos de la evaluación del rendimiento de los sistemas de ensamblaje flexible. Por último, este capítulo presenta el caso de estudio industrial de The Cooktop Company, que se utilizará en los capítulos sucesivos.

En el Capítulo 4 se presenta un modelo matemático analítico centrado en los cambios de serie de las cadenas de montaje. A continuación, se emplea el modelo junto con técnicas de diseño de experimentos para analizar los factores más críticos para el rendimiento de los sistemas de montaje flexible. Por último, se valida uno de los supuestos clave del modelo.

En el Capítulo 5 se desarrollan modelos de simulación por eventos discretos para superar las limitaciones de la herramienta analítica del capítulo anterior. En este capítulo se exponen las principales características de los diferentes modelos de simulación utilizados en la tesis, el método empleado para la obtención de datos de The Cooktop Company, y la validación y verificación de los modelos frente a los datos empíricos del caso de estudio industrial.

En el Capítulo 6, los resultados previos sobre las cadenas de montaje flexibles y las herramientas de simulación ya desarrolladas se utilizan para estudiar las líneas de montaje paralelas con operarios móviles, que presentan varias ventajas clave con respecto a las tradicionales cadenas semiautomáticas. Este capítulo incluye una revisión bibliográfica específica y exhaustiva sobre las cadenas de montaje paralelas y con operarios móviles, seguida de los supuestos de modelado y la descripción del modelo de simulación. Se emplean seis escenarios para explorar el efecto de diversas condiciones de demanda en un contexto de personalización en masa, así como el grado de automatización introducido en las diferentes configuraciones de línea. Cuatro escenarios de simulación adicionales estudian distintos elementos para el ajuste fino del diseño de las líneas paralelas de operarios móviles.

El Capítulo 7 amplía el alcance del análisis al estudiar la logística interna de las cadenas de montaje mediante trenes milkrun. Este capítulo también incluye una revisión bibliográfica específica del uso de milkrun para logística interna. Se detalla el modelado del milkrun y se utilizan cuatro escenarios de simulación para analizar el efecto del mix de productos y de tres fuentes distintas de perturbaciones sobre los indicadores clave del desempeño.

Por último, el Capítulo 8 resume las principales conclusiones y aportaciones de la tesis. También analiza las principales líneas para continuar la investigación.

A.3 Resumen, conclusiones y perspectivas futuras

Este capítulo concluirá la tesis con un breve resumen de los principales resultados de la investigación y de cómo contribuyen a los objetivos de la misma; así como las limitaciones de este estudio y una perspectiva de posibles vías de investigación futura.

A.3.1 Resumen de las conclusiones principales

El objetivo general de investigación de esta tesis era «comprender y definir cómo diseñar sistemas de ensamblaje semiautomáticos para mejorar la flexibilidad y la productividad en serie corta y variada». Para orientar la investigación, se plantearon tres objetivos de investigación principales, que se han ido respondiendo secuencialmente a lo largo de los capítulos de esta tesis.

(1) El primer objetivo de la investigación era «comprender el estado del arte del ensamblaje de la Industria 4.0». Para ello, el Capítulo 2 expuso una revisión bibliográfica sistemática centrada en seis conceptos clave: el ensamblaje, la producción Lean, los indicadores clave del desempeño (KPIs), la personalización en masa, la Industria 4.0 y los operarios. Las principales conclusiones de la revisión fueron que faltan metodologías para implantar las tecnologías de la Industria 4.0 de modo que aporten todos sus beneficios potenciales. También se detectó que las tendencias de demanda de personalización y customización en masa hacen que los sistemas de ensamblaje sean cada vez más complejos. Para abordar esta cuestión, sería necesaria una visión holística de los sistemas, junto con el uso de múltiples medidas del rendimiento que permitan obtener una perspectiva desde diferentes ángulos de las implicaciones de las tecnologías de la Industria 4.0. Por último, en el Capítulo 3 se presentó un marco conceptual centrado en la persona, que permite clasificar claramente las tecnologías digitales de la Industria 4.0 en función de su relación con los operarios de montaje.

(2) El segundo objetivo de la investigación era «desarrollar una metodología y las herramientas para la evaluación del rendimiento de los sistemas de ensamblaje flexible». En primer lugar, el Capítulo 3 introdujo las definiciones generales y el caso de estudio industrial que se utilizaría en el resto de la tesis. En el Capítulo 4, se presentó un modelo matemático simple pero eficaz. Este modelo, que se centra en el cálculo de las pérdidas de productividad debidas al cambio de serie para estimar el

rendimiento de las líneas de montaje multimodelo, se empleó a continuación junto con técnicas de diseño de experimentos para identificar los factores más críticos que afectan a estas líneas de montaje. Para evaluar el rendimiento de las líneas de montaje, se utilizaron varios KPIs: productividad de los operarios, productividad de la línea y *lead time*, entre otros, lo que permitió conocer las relaciones entre ellos en distintas circunstancias.

De cara a responder de forma específica a la pregunta de investigación «¿Cuáles son los factores clave del rendimiento de una cadena de montaje multimodelo?», los resultados mostraron que el número de puestos y el tamaño de lote son fundamentales para la productividad de los operarios y el lead time. Este último es una medida importante de la capacidad del sistema para responder rápidamente a los pedidos de los clientes. Los resultados también subrayaron el carácter contrapuesto de estos dos indicadores, de tal forma que no pueden optimizarse simultáneamente.

Para superar las limitaciones del modelo matemático –a saber, su falta de parámetros estocásticos y la dificultad de integrar distintas formas de interacción operador-estación de trabajo–, en el Capítulo 5 se presentó una metodología de modelado para la simulación por eventos discretos y la verificación de dichos modelos con datos empíricos del caso de estudio industrial.

(3) El tercer objetivo de la investigación era «encontrar configuraciones de líneas de montaje que permitan un aumento de la productividad de al menos un 25 % gracias a la introducción de la automatización parcial». Las líneas de montaje con operarios móviles pueden aprovechar las ventajas de productividad de las cadenas de montaje con un menor número de operarios, que son consecuencia de la reducción de las pérdidas de tiempo por el equilibrado de línea y los cambios de serie. La configuración de línea con operarios móviles puede evitar las desventajas derivadas del empleo de líneas más cortas, como una menor tasa máxima de producción, compartiendo las estaciones de montaje automático entre dos líneas paralelas.

Así pues, el Capítulo 6 presenta un estudio de las líneas de montaje semiautomáticas paralelas con operarios móviles (en inglés, *parallel walking worker assembly lines*, PWWAL) en comparación con las líneas convencionales de operarios fijos (*fixed worker assembly lines*, FWAL). La metodología de modelado desarrollada anteriormente se utilizó en este capítulo para analizar seis escenarios de simulación de condiciones de demanda cada vez más desafiantes, que se expresan en términos de tamaños de lote progresivamente más pequeños y cambios de familia de productos cada vez más frecuentes, necesarios para producir una gran variedad de artículos en pequeñas cantidades.

Los resultados de la simulación mostraron que las PWWAL pueden superar a las FWAL en términos de productividad en todos los escenarios de demanda, alcanzando el objetivo de incrementar la productividad en un 25 % o más. Una ventaja clave de las PWWAL es que pueden reducir sin problemas el número de operarios sin afectar negativamente al equilibrado de la línea, lo que permite una producción eficiente para bajo volumen. Las PWWAL también presentan ventajas sobre las FWAL en cuanto a su capacidad para incorporar distintos grados de automatización sin reducir su productividad, aunque la tasa de producción máxima de la línea se vea limitada. Por otra parte, las PWWAL presentan un lead time significativamente superior y requieren una mayor superficie en planta.

Por último, el Capítulo 7 amplió el alcance de los estudios anteriores incorporando capas externas del modelo conceptual centrado en el operario. En concreto, se analizó la función de la logística interna para comprender mejor las implicaciones del uso de trenes milkrun para alimentar cadenas de montaje paralelas multimodelo bajo el efecto de perturbaciones severas. Los resultados de las simulaciones mostraron que los milkrun pueden ser una excelente forma de proteger las cadenas de montaje de las perturbaciones originadas en los procesos aguas arriba.

A.3.2 Contribuciones

En esta tesis se han realizado varias contribuciones, que se han ido enumerado al final de cada capítulo, y que se resumen aquí agrupadas por etapas.

Respecto a la etapa de *Definición del problema*:

(1) La revisión sistemática de la literatura pone de manifiesto la falta de metodologías específicas para la implementación de las tecnologías digitales de la Industria 4.0 en los sistemas de ensamblaje. La bibliografía clave sobre el tema muestra que las tendencias de demanda de personalización e individualización en masa implican una mayor complejidad en los sistemas de ensamblaje. Dichos sistemas incluyen muchas capas diferentes que deben abordarse de forma holística. Para obtener una perspectiva desde múltiples puntos de vista de cómo las distintas capas se afectan mutuamente, han de utilizarse conjuntamente varios indicadores del desempeño. La revisión bibliográfica sistemática fue publicada por la revista *Applied Sciences* [27].

(2) Esta tesis ha desarrollado un marco conceptual centrado en la persona para las operaciones de montaje manual en el contexto de la Industria 4.0. Sobre la base de este marco, se ha establecido una clasificación clara entre las tecnologías digitales 4.0 en función de su relación con los operarios de montaje. Las tecnologías de hardware (por ejemplo, los robots colaborativos o la realidad aumentada/mixta) se encuentran en contacto directo con los operarios, a diferencia de las tecnologías de software (por ejemplo, el *big data*, la inteligencia artificial o la computación en la nube), que son empleadas por departamentos que apoyan al ensamblaje, y que solo afectan a los operarios de montaje de forma indirecta. El modelo conceptual fue publicado como artículo de congreso en la revista *Procedia CIRP* [256].

En relación con la etapa de *Desarrollo de la herramienta*:

(3) En esta tesis se propone un modelo analítico sencillo para la evaluación del rendimiento de las cadenas de montaje multimodelo, de fácil implementación y con capacidad suficiente para realizar análisis preliminares. Los resultados obtenidos con técnicas de diseño de experimentos muestran que los dos factores más críticos para el rendimiento operativo de las líneas de montaje multimodelo son el número de puestos de montaje y el tamaño de lote. Teniendo en cuenta las tendencias de la demanda de personalización en masa, reducir aún más el tamaño de los lotes de producción genera (y generará) ventajas estratégicas a quienes sean capaces de hacerlo sin dañar la productividad. Esto llevó a la conclusión de que estudiar el diseño de líneas de montaje flexibles con un número reducido de estaciones sería una forma de mejorar la productividad y mitigar el efecto negativo de los cambios de serie frecuentes. Dado que la reducción del número de puestos de trabajo implica una reducción de la tasa de producción máxima de la línea, una forma obvia de mantener la flexibilidad en cuanto a capacidad de producción sería plantear cadenas de montaje paralelas más cortas. Un estudio más detallado sobre la influencia de la relación entre el tiempo total de cambio de serie y el número de puestos permitió concluir que los resultados del análisis anterior no se ven afectados por esta hipótesis de modelado. La descripción del modelo matemático y el diseño de experimentos de los factores críticos para el rendimiento de las líneas de montaje manual se publicaron como artículo de congreso en la revista *IOP Conference Series: Materials Science and Engineering* [274].

(4) Se desarrollaron varios modelos de simulación de eventos discretos para analizar operaciones de ensamblaje flexible, enfocadas a un modelado realista de los cambios de modelo, de tal manera que fueran adecuados para estudiar el ensamblaje en serie corta y variada. Posteriormente se verificaron y validaron dichos modelos utilizando el modelo paramétrico ya desarrollado previamente y un caso de estudio industrial de un fabricante internacional de electrodomésticos. Este trabajo fue publicado como artículo de congreso en la revista *Procedia CIRP* [279].

Finalmente, respecto a la etapa de *Mejora*:

(5) Se ha presentado un diseño de líneas de ensamblaje multimodelo paralelas con operarios móviles. Se estima que este diseño de línea de montaje puede lograr un aumento significativo de la productividad, al tiempo que mantiene una alta flexibilidad en términos de tasa de producción, lo que permite una rápida adaptación a las variaciones de la demanda. Se empleó un extenso conjunto de KPIs operacionales para estimar el rendimiento de las líneas de montaje fijas y con operarios móviles desde distintos puntos de vista. Bajo cualesquiera condiciones de demanda, las líneas paralelas con operarios móviles presentan mayor productividad y mayor tasa de producción que las líneas tradicionales con operarios fijos. Estos resultados resaltan la contraposición

entre productividad y lead time que experimentan las líneas paralelas de operarios móviles. Los resultados también mostraron que un aumento del grado de automatización permite incrementar la productividad de la línea en todas las condiciones de demanda, pero solo si el número de trabajadores puede reducirse sin problemas, lo que ocurre en las configuraciones de operarios móviles, pero no en las líneas de operarios fijos. Sin embargo, esto se consigue a costa de reducir la tasa de producción de la línea y aumentar el lead time. Este concepto de línea de montaje y los resultados del análisis se publicaron como artículo de investigación en la revista *Processes* [283].

(6) Esta tesis aborda un vacío en la literatura investigando la logística interna para el ensamblaje multimodelo bajo perturbaciones estocásticas. Se determinó que el desempeño de la logística interna es muy sensible a la variabilidad del tiempo de proceso de la cadena de montaje, especialmente en lo relativo al stock de componentes. Los resultados de la simulación mostraron que el empleo de milkrun para la logística interna es una forma de proteger las líneas de ensamblaje multimodelo de las perturbaciones aguas arriba. Este análisis se publicó como artículo de investigación en la revista *Machines* [300].

A.3.3 Líneas futuras de investigación

La investigación futura en base a los resultados obtenidos en esta tesis puede estructurarse en torno a tres líneas principales encaminadas hacia la implementación de tecnologías digitales de la Industria 4.0 para mejorar las operaciones de ensamblaje para serie corta y variada: las metodologías de análisis, las líneas de ensamblaje paralelas de operarios móviles y el uso de sistemas milkrun para la logística interna.

Metodologías de análisis

Los modelos de simulación ya desarrollados podrían ampliarse, siguiendo la misma metodología de modelado, para incluir departamentos anejos que quedaron fuera del alcance de esta tesis. Por ejemplo, un punto de partida interesante para la inclusión de la cuarta capa del modelo conceptual centrado en el operario sería la inclusión de problemas de mantenimiento (como las averías en los puestos de montaje automáticos, o las microparadas) o diferentes políticas de retrabajo de unidades defectuosas (verbigracia, en línea o fuera de línea, realizado por los propios operarios de montaje o por los jefes de equipo).

El enfoque de modelado de simulación desarrollado aquí podría utilizarse para implementar un gemelo digital, una de las tecnologías habilitadoras clave de la Industria 4.0. Junto con el internet de las cosas, sería posible desplegar sensores en las cadenas de montaje para recopilar datos directamente del sistema real. En base a esos datos, el análisis de escenarios a corto y medio plazo mediante simulación permitiría detectar con antelación los riesgos para el rendimiento, como los cuellos de botella transitorios causados por un mix de demanda muy variable.

Otra vía de investigación sería el uso de la simulación junto con otras herramientas, como la programación mixta-entera o técnicas de programación de la producción, que permitirían optimizar la disposición en planta de las cadenas de montaje.

Líneas de ensamblaje paralelas con operarios móviles

Tres áreas destacan de cara a proseguir la investigación sobre las líneas semiautomáticas paralelas de operarios móviles (PWWAL). En primer lugar, el estudio de las PWWAL mediante herramientas de simulación se beneficiaría de utilizar más casos de estudio, ya que algunos de los análisis ya realizados estaban limitados por las particularidades del caso industrial aquí considerado. Se podría profundizar en la investigación estudiando aspectos como la disposición en planta de la cadena de montaje, los efectos del número de estaciones automáticas y la formación de los operarios, por citar solo algunos. El diseño en detalle de los puestos de trabajo de los operarios podría ser otra cuestión de interés, especialmente en lo que respecta a los riesgos ergonómicos. Otras vías interesantes para investigaciones futuras son otras fuentes de perturbaciones (el modelo actual tiene en cuenta la variabilidad de los tiempos de montaje y de cambio de serie) como las averías estocásticas o los distintos tipos de problemas de calidad.

En segundo lugar, podría estudiarse la incorporación de tecnologías de la Industria 4.0, como el uso de robots colaborativos para tareas de ensamblaje o control de calidad, o para prestar apoyo durante los cambios de serie. El apoyo cognitivo al operario, proporcionado por la realidad aumentada/mixta y los sistemas ciberfísicos, podría ser beneficioso para ayudar a superar los mayores requisitos en términos de formación de operarios humanos que precisan las líneas de operarios móviles en comparación con las de operarios fijos.

Por último, la implementación industrial de las cadenas semiautomáticas paralelas de operarios móviles permitiría verificar los resultados de simulación obtenidos en esta tesis y detectar problemas y oportunidades adicionales de esta tipología de línea de ensamblaje para hacer frente a la producción en serie corta y variada.

Milkrun para logística interna

Respecto a la utilización de los trenes milkrun para la logística interna, disponer de numerosos casos de estudio permitiría una vez más evaluar en profundidad algunas de las cuestiones ya investigadas. Por ejemplo, el efecto del tipo de cadena de montaje (modelo único, modelo mixto o multimodelo) en la utilización del milkrun, que depende en gran medida de la lista de materiales de los productos y del número de piezas por caja de los componentes que se presentan en las cadenas de montaje.

La ampliación del alcance de modelos de simulación del milkrun podría hacerse en dos direcciones. El sistema podría ampliarse para incluir más detalles de las operaciones en almacén interno de la planta y podrían incluirse más trenes milkrun que presten servicio a otras cadenas de montaje. De este modo, sería posible analizar los posibles conflictos de recursos causados por las perturbaciones estocásticas, que podrían derivar en problemas como embotellamientos de los trenes milkrun o la saturación de los operarios del almacén. El modelo de simulación también podría ampliarse incluyendo consideraciones físicas, como el peso y las dimensiones de las cajas, el número de vagones del tren y su volumen disponible. Este nivel de detalle permitiría una evaluación más precisa de la carga de trabajo de los operarios del milkrun.

Por último, podría explorarse la digitalización de los sistemas milkrun. En este sentido, la inteligencia artificial, el internet de las cosas y los vehículos de guiado automático (AGV) podrían presentar sinergias. Por ejemplo, se podrían utilizar algoritmos de inteligencia artificial junto con modelos de simulación para optimizar la carga de los trenes milkrun gracias a datos recogidos en tiempo real en los propios puestos de la cadena de montaje.

A.4 Publicaciones

Como resultado de esta tesis, se han publicado los siguientes artículos:

Artículos de investigación

- A. Miqueo, M. Torralba, and J. A. Yagüe-Fabra. “Lean Manual Assembly 4.0: A Systematic Review”. In: *Applied Sciences* 10.23 (2020), p. 8555. DOI: 10.3390/app10238555.

- A. Miqueo, J. A. Yagüe-Fabra, M. Torralba, M. J. Oliveros, and G. Tosello. “Parallel Walking-Worker Flexible Assembly Lines for High-Mix Low-Volume Demand”. In: *Processes* 11.1 (2023), p.172. DOI: 10.3390/pr11010172.

- A. Miqueo, M. Gracia-Cadarso, M. Torralba, F. Gil-Vilda, and J. A. Yagüe-Fabra. “Multi-Model In-Plant Logistics Using Milkruns for Flexible Assembly Systems under Disturbances: An Industry Study Case”. In: *Machines* 11.1 (2023), p.66. DOI: 10.3390/machines11010066.

Artículos de Congreso (revisados por pares)

- A. Miqueo, M. Torralba, and J. A. Yagüe-Fabra. “Operator-centred Lean 4.0 framework for flexible assembly lines”. In: *Procedia CIRP* 104 (2021), pp. 440–445. DOI: 10.1016/j.procir.2021.11.074.

- A. Miqueo, M. Martín, M. Torralba, and J. A. Yagüe-Fabra. “Labour productivity in mixed-model manual assembly 4.0”. In: *IOP Conference Series: Materials Science and Engineering* 1193.1 (2021), p.012104. DOI: 10.1088/1757-899X/1193/1/012104.

- A. Miqueo, M. Torralba and J. A. Yagüe-Fabra. ‘Models to evaluate the performance of high-mix low-volume manual or semi-automatic assembly lines’. In: *Procedia CIRP* 107 (2022), pp. 1461–1466. DOI: 10.1016/j.procir.2022.05.175

APPENDIX B

Publications

B.1 A. Miqueo, M. Torralba, and J. A. Yagüe-Fabra. "Lean Manual Assembly 4.0: A Systematic Review". In: *Applied Sciences* 10.23 (2020), p. 8555.

B.2 A. Miqueo, M. Torralba, and J. A. Yagüe-Fabra. "Operator-centred Lean 4.0 framework for flexible assembly lines". In: *Procedia CIRP* 104 (2021), pp. 440–445.

B.3 A. Miqueo, M. Martín, M. Torralba, and J. A. Yagüe-Fabra. "Labour productivity in mixed-model manual assembly 4.0". In: *IOP Conference Series: Materials Science and Engineering* 1193.1 (2021), p.012104.

B.4 A. Miqueo, M. Torralba, and J. A. Yagüe-Fabra. "Models to evaluate the performance of high-mix low-volume manual or semiautomatic assembly lines". In: *Procedia CIRP* 107 (2022), pp. 1461–1466.

B.5 A. Miqueo, J. A. Yagüe-Fabra, M. Torralba, M. J. Oliveros, and G. Tosello. "Parallel Walking-Worker Flexible Assembly Lines for High-Mix Low-Volume Demand". In: *Processes* 11.1 (2023), p.172.

B.6 A. Miqueo, M. Gracia-Cadarso, M. Torralba, F. Gil-Vilda, and J. A. Yagüe-Fabra. "Multi-Model In-Plant Logistics Using Milkruns for Flexible Assembly Systems under Disturbances: An Industry Study Case". In: *Machines* 11.1 (2023), p.66.

B.1 Review Article: Applied Sciences (2020)

applied sciences

MDPI

Review

Lean Manual Assembly 4.0: A Systematic Review

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Abstract: In a demand context of mass customization, shifting towards the mass personalization of products, assembly operations face the trade-off between highly productive automated systems and flexible manual operators. Novel digital technologies—conceptualized as Industry 4.0—suggest the possibility of simultaneously achieving superior productivity and flexibility. This article aims to address how Industry 4.0 technologies could improve the productivity, flexibility and quality of assembly operations. A systematic literature review was carried out, including 234 peer-reviewed articles from 2010–2020. As a result, the analysis was structured addressing four sets of research questions regarding (1) assembly for mass customization; (2) Industry 4.0 and performance evaluation; (3) Lean production as a starting point for smart factories, and (4) the implications of Industry 4.0 for people in assembly operations. It was found that mass customization brings great complexity that needs to be addressed at different levels from a holistic point of view; that Industry 4.0 offers powerful tools to achieve superior productivity and flexibility in assembly; that Lean is a great starting point for implementing such changes; and that people need to be considered central to Assembly 4.0. Developing methodologies for implementing Industry 4.0 to achieve specific business goals remains an open research topic.

Keywords: assembly; lean; Industry 4.0; human-centered; operator 4.0

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1. Introduction

The current situation of assembly operations is characterized by an increasingly varied demand (mass customization) while the production faces a trade-off between the superior productivity of automated assembly systems and the absolute flexibility and adaptability of manual assembly. Therefore, high-volume production of discrete goods received heavy investments for automation, while low volume, made-to-order or engineer-to-order products were typically assembled manually [1,2]. In this context, Lean production (a generalization of the Toyota Production System) expanded from its origin—automotive—to many other sectors and was adapted as necessary to the particularities of each industry or company [3]. Lean production typically focuses on value as perceived from the customer's point of view. Thus it considers that the flexibility to quickly adapt to market demand is critical. For Lean, rigid automation can be seen as a hindrance rather than an advantage, and seeks to incorporate the human factor to automation: *jidoka*, or "automation with a human touch" [4].

The term Industry 4.0, initially adopted by a German strategic program [5], is used nowadays to express the relationship between different elements of the current manufacturing sector and the new digital technologies. These Key Enabling Technologies are, according to [6]: Big data and analytics, Autonomous robots, Simulation, Horizontal and vertical system integration, the Industrial Internet of Things (IoT), Cybersecurity, The cloud, Additive manufacturing, and Augmented Reality. Recent research on Industry 4.0 tends to focus on the possibilities brought by a certain new digital technology or develops a framework to understand what would be the effect of incorporating such new technologies [7]. The arrival of the new digital technologies could address the aforementioned dichotomy of highly productive yet rigid automation vs. flexible but less-productive manual assembly. The quickly developing fields of human–robot collaboration, virtual/augmented reality and Automated quality control, to cite some examples, show promise in bringing forward actually flexible and adaptable automation that has the best of both worlds.

Scarcely explored is the development of implementation methodologies that bridge Industry 4.0 conceptual frameworks with the current state of industrial environments and the process to successfully deploy new digital technologies that bring the expected returns of investment. Additionally, if the Lean production approach and its techniques are also related to this implementation, the concept of Lean 4.0 could be used, as shown in the literature [8]. Since Lean production and Industry 4.0 certainly have some commonalities [9], Lean could prove useful in providing a starting point for the implementation of Industry 4.0 technologies that improve assembly operations in a mass customization demand context.

In order to assess the impact of any changes, careful evaluation systems are needed to ensure that technology investments are implemented to solve the problems and address business goals, and not just because they are available or they bring some cosmetic advantage.

The 4th Industrial Revolution is expected to transform the role of the people, but to what extent will assembly operators be affected—are humans to be replaced by machines or empowered by new technology?

The issue that this literature review aims to address is: *How could Industry 4.0 technologies improve the flexibility, productivity and quality of assembly operations?* To look into it, we aim to answer the following questions:

1. What are the characteristics and implications of mass customization for assembly operations?
2. What new Industry 4.0 digital technologies are relevant to assembly operations?How to make the most out of their potential, and how to measure the improvement?
3. Is Lean production the best starting ground for implementing Industry 4.0 assembly operations?
4. How would Industry 4.0 affect people in assembly? How to support people transitioning to Assembly 4.0?

To answer these questions, a systematic literature review was carried out. From these four sets of questions, six key concepts are extracted, as shown in Figure 1: The scope of this article is limited to *assembly* operations, particularly focusing on *mass customization* demand. Neither fully automated systems nor manual assembly deal comfortably with mass customization demand since one lacks flexibility and the other's productivity falls short. *Industry 4.0* aims to address this gap by providing superior connectivity between machines and people. *Lean production* may serve as a foundation for Assembly 4.0, transversally providing a framework to analyze and conceptualize the new role of *human operators*. Finally, to evaluate the efficiency of assembly systems, *Key Performance Indicators* are commonly used.

This article is structured in the following manner: Section 2—Materials and Methods—describes the methodology used for the review, which focuses on the six key concepts related to the issue being addressed. This section also includes a brief bibliometric analysis of the references used for the analysis. Section 3—Results—includes an analysis of literature, grouped into four main subsections: (3.1) Assembly operations, (3.2) Industry 4.0, (3.3) Lean, and (3.4) People. Each subsection focuses on one of the questions that this article aims to answer. Section 4—Discussion—gathers the main conclusions found in the previous analysis and addresses the main issue stated before.

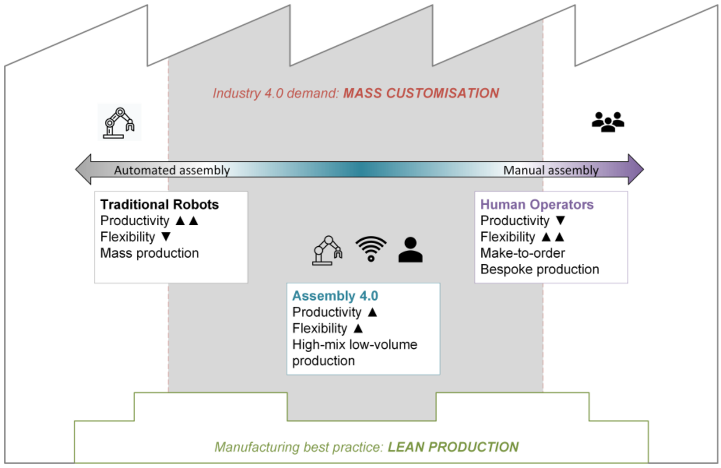

Figure 1. Key concepts used for the systematic literature review.

2. Materials and Methods

In order to address the issue introduced in the previous section and to answer the aforementioned questions, a systematic literature review was conducted. This section firstly describes the methodology employed in such a review, and secondly, offers a brief bibliometric analysis of the results.

The literature review was carried out in four stages—see Figure 2: database search, screening, eligibility and literature analysis.

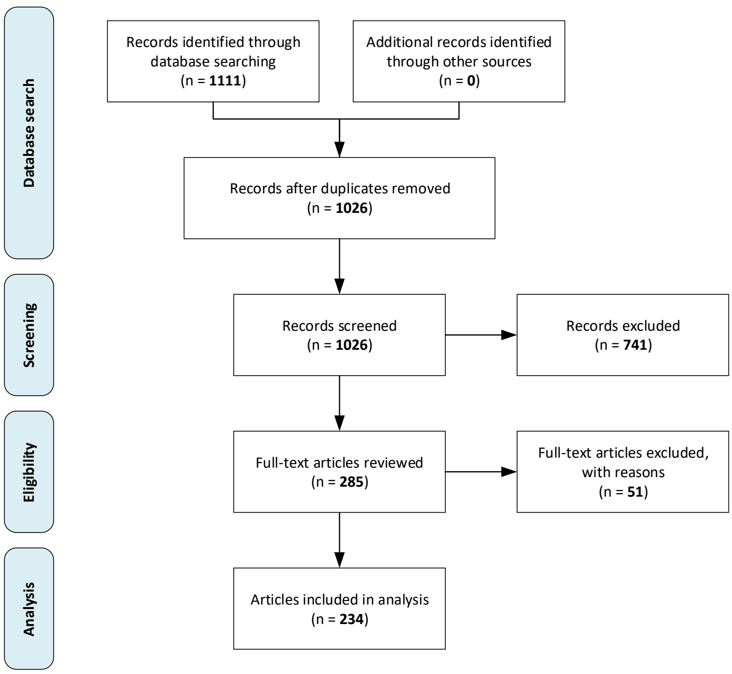

Figure 2. Search process and results, adapted from PRISMA [10].

The databases used for the initial stage were SCOPUS (Elsevier) and Web of Science, and only included relevant publications belonging to the following fields: Manufacturing engineering, Industrial engineering, Generalist engineering, Operations and management science. Since the topic under study is the conjunction of several broad subjects, we decided to conduct a systematic literature review that specifically targets their intersections. The six key concepts that were used are Assembly, Mass customization, Key Performance Indicator (KPI), Lean manufacturing, Industry 4.0 and Operator. These concepts were chosen for the search because they are the key ideas in the posed research questions–"Key Performance Indicators" being used for measuring improvement. The following keywords were used to perform the database search: (1) Lean: *Lean manufacturing*, *Lean production*; (2) Mass customization: *mass customization*, *mass customization*; (3) Industry 4.0: *Industry 4.0*, *Industrie 4.0*, *smart factories*; (4) KPI: "*KPI*", *Key Performance Indicator*; (5) Assembly: *assembly*; (6) Operator: *operator*, *people*, *person*. The keywords were used for Title, Author Keyword and Keyword Plus (in WOS), except for KPI, which was also searched for in the Abstract field. From these six key concepts, 15 search groups were defined by intersecting each possible combination of two concepts, as shown in Table 1. Duplicates were removed at this point, resulting in 1026 publications identified.

Table 1. Search groups created by the intersection of each pair of key concepts and number of publications found.

Search Group	Publications WOS	Publications SCOPUS	Publications Identified after Duplicates Removed
Assembly and mass customization	58	52	97
Assembly and KPI	20	19	33
Assembly and Lean	81	106	168
Assembly and Industry 4.0	47	10	55
Assembly and operator	83	196	268
Industry 4.0 and Lean	48	8	55
Industry 4.0 and operator	33	16	45
Industry 4.0 and mass customization	17	2	19
Industry 4.0 and KPI	11	2	12
Lean and mass customization	14	19	32
Lean and KPI	31	58	74
Lean and operator	10	33	40
Operator and mass Mass Customisation	4	15	15
Operator and KPI	13	98	108
Mass customization and KPI	4	3	5

The publications resulting from this search were then screened—based on title, abstract, publication and year—to assess which of them met the inclusion and exclusion criteria shown in Table 2, resulting in 741 records being excluded and 285 articles being included.

Table 2. Eligibility and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Peer-reviewed publications	Book chapters
Recent: published in 2010 or later	Regarding construction, continuous production (e.g., petrochemical), energy efficiency
Language: publications in English	Regarding product design
	Regarding mathematical models or algorithms for scheduling, line sequencing, or line balancing

Finally, the 285 articles were reviewed within each one of the 15 search groups and assessed for eligibility, resulting in 51 articles being excluded because they were not relevant to the key concept being analyzed.

The resulting 234 articles were analyzed, and the outcome of such analysis can be found in Section 3—Results.

The number of articles included in the analysis shows an increasing trend over time, as shown in Figure 3. It should be noted that the database search was performed in June 2020. Therefore the results shown in this analysis only include articles published up until the first half of 2020. It can be seen that the number of articles related to some key concepts remain constant or grow slightly over time—assembly, mass customization and operator—while others grow significantly—Lean and KPI. The number of articles related to Industry 4.0 is rising since 2015, which is consistent with the fact that the term "Industry 4.0" was coined in 2011 [5]. Of the 234 articles included in this review, 54 are conference or proceedings articles (23%), and 180 are journal articles (77%). The articles were published in a total of 117 publications, with 18 journals including 50% of the total articles and 83 publications contributing with just one article to this review. This is consistent with the database search strategy, which looks at the intersections of 6 different concepts.

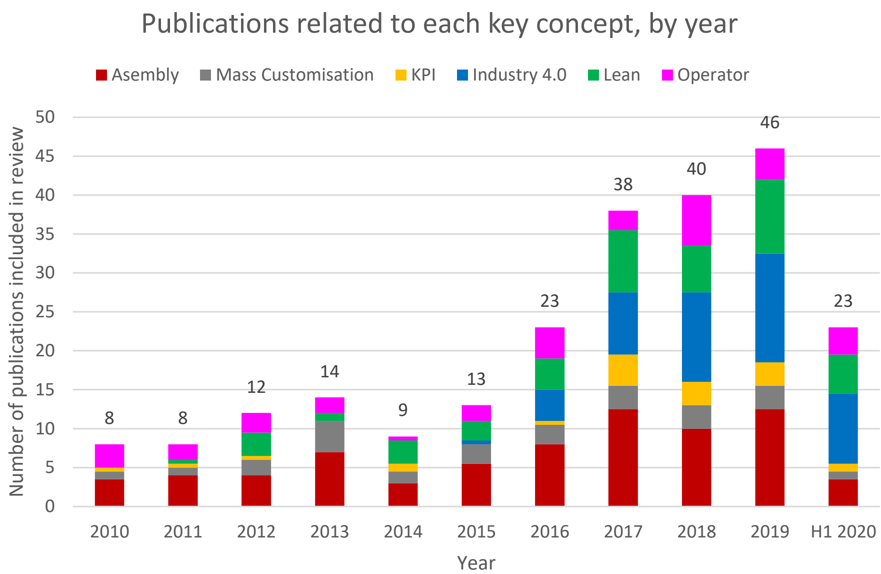

Figure 3. Publications related to each key concept, by year.

3. Results

This section shows the outcome of the systematic literature review carried out following the methodology described in the previous section, and that addresses the issue of improving assembly operations in terms of productivity, flexibility and quality by using novel digital technologies of Industry 4.0. To look into this question, four specific questions were presented in the first section of this article. In consequence, this section is composed of four parts made of the search key concepts most closely related to each one of the questions, as shown in Figure 4. Firstly, looking into "the characteristics and implications of mass customization for assembly operations", the key concepts used are "assembly" and "mass customization" (3.1). Secondly, to identify "the new Industry 4.0 technologies, how to make the most out of them and how to measure the improvement", the key concepts used are "Industry 4.0′ and "Key Performance Indicators" (3.2). Then, the key concept "Lean" is employed to determine whether Lean production is the best starting ground for implementing the aforementioned technologies (3.3). Finally, to explore "the effect of Industry 4.0 on people in assembly and to find out how to support them in transitioning to Assembly 4.0, the search key concept used is "operator" (3.4).

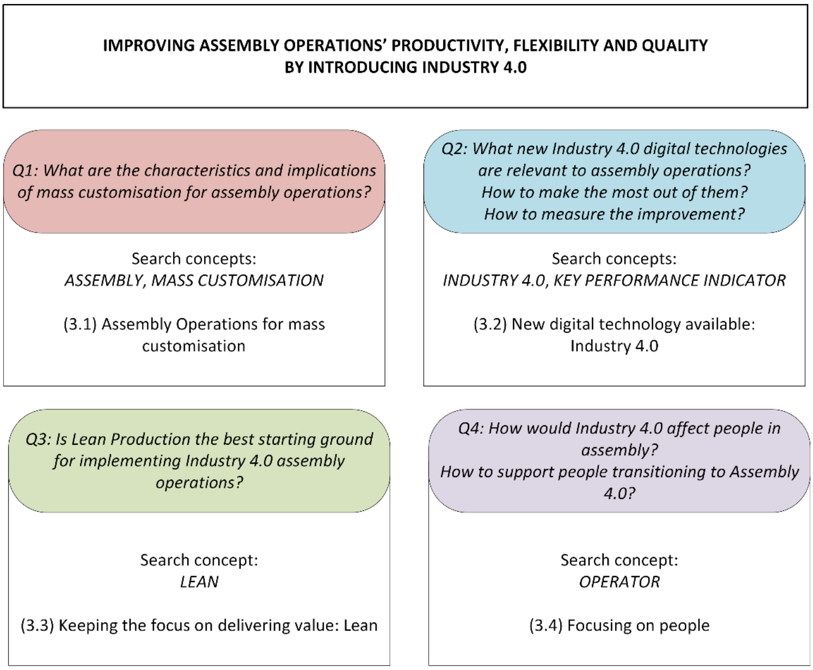

Figure 4. Research questions, search key concepts and their relationship to the literature review analysis topics.

3.1. Assembly Operations for Mass Customisation

In order to answer the first question, "What are the characteristics and implications of mass customization for assembly operations?" the systematic literature review publications related to the key concepts "assembly" and "mass customization" were analyzed. After a brief introduction, the five main topics to be considered will be presented, as shown in Figure 5: Modularity and product clustering; Mixed-model assembly optimization; Customer involvement and postponement strategies; The implications of complexity; and Mass customization impact on operators. Finally, the key conclusions will be summarized.

3.1.1. Introducing Assembly Operations for Mass Customisation

Mass customization demand is characterized by a combination of great variety, shorter product life cycles, and variable production volumes (medium or high for platform products, very low for personalized products); compared to Industry 2.0's stable market and Industry 3.0's volatile market—in terms of product volume, product variety and delivery time. In this new context, Toyota Production Systems (TPS) may prove limited, and its advantages and disadvantages with regards to *seru* were analyzed by Yin et al. [11]. The usage of new key digital technologies will bring forward the 4th Industrial Revolution (Industry 4.0), addressing many of the challenges of production systems for mass customization [11,12]. However, looking at isolated systems may not be enough since increased complexity requires a holistic approach to respond successfully and cost-effectively to shifting market demands [13]. Assembly is the final process to create a product, where component sub-assemblies come together into the final product. Demand-driven increasing product variety adds complexity, production cost and lead time to assembly operations, which goes against its goals. In the mass customization landscape, key assembly topics need to be reviewed, evaluated and adapted [2]: assembly representation and sequencing, especially non-sequential assembly; assembly system design—considering line balancing, delayed product differentiation and performance evaluation; assembly system operations—with a focus on exploring reconfigurable assembly planning, mixed-model assembly scheduling, and dealing with complexity resulting from different sources; and the changing role of human operators.

3.1 ASSEMBLY & MASS CUSTOMISATION

Q1: What are the characteristics and implications of mass customisation for assembly operations?

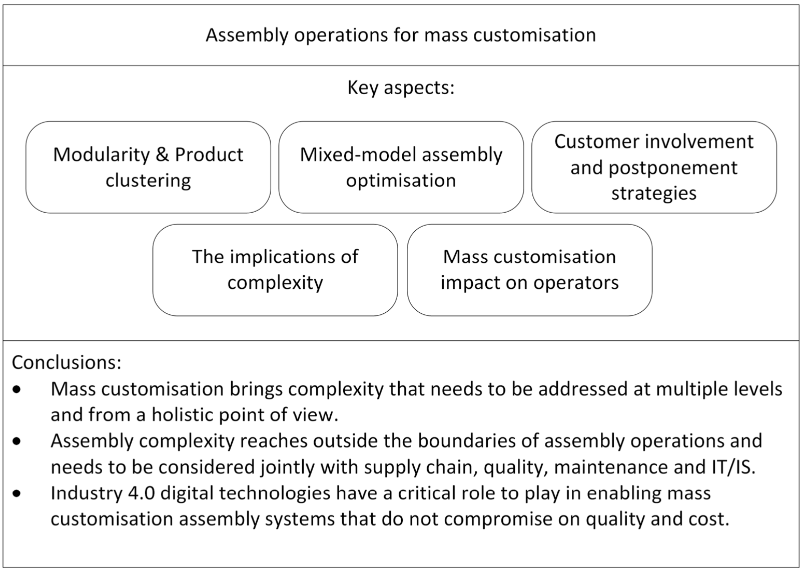

Figure 5. Key aspects of assembly operations for mass customization and main conclusions of the analysis.

In conclusion, mass customization brings increased complexity that needs to be addressed at multiple levels and taking a holistic point of view to ensure that optimizing a subsystem does not negatively affect another subsystem.

3.1.2. Modularity and Product Clustering

In order to flexibly assemble many different product variants using the same resources (such as people, equipment, management systems) to keep manufacturing costs down and productivity high. Efficient grouping of products into clusters or families is of paramount importance. The variables selected for clustering will depend on the assembly operation objectives, for instance: quality and cost to determine product family design [14]; product variety to determine assembly system layout [15]; assembly and disassembly for configuring product variants [16]; procedure, equipment and parts [17];

or involving worker's perspective for actual ease of assembly [18]. Modular production systems would also benefit from automated planning based on individual product CAD files [19].

In conclusion, product clustering, modularization, reconfigurable assembly systems and delayed product differentiation are valuable tools to maintain competitive assembly in a mass customization context.

3.1.3. Mixed-Model Assembly Optimisation

Another area greatly affecting the efficiency of assembly lines is its sequencing and balancing. Similar to clustering and modularization, different approaches are used depending on the focused goals of the optimization: cooperative sequencing or workstation analysis for assembly material consumption waviness, setup time and lead time [20,21]; multi-agent systems analysis for reducing the negative impact of material handling complexity [22]; monitoring manufacturing complexity for workload balancing [23]. New approaches have also been developed to optimize assembly line sequencing [24,25].

In conclusion, mixed-model assembly is needed to deal with mass customization while remaining competitive since it allows to address various operational goals depending on the business needs.

3.1.4. Customer Involvement and Postponement Strategies

Mass customization may be leading towards mass personalization, where individual products made to match the exact preferences of each customer are produced in large numbers [1]. Integrating the customer in the design phase could be done using web-based platforms [26], while Industry 4.0's Cyber Physical Systems (CPS) and a tailored assembly architecture would enable efficient mass personalization [27]. An alternative strategy is Postponement, which could help with dealing with high assembly complexity [28]. However, it requires designing the assembly line layout for delayed product differentiation [29,30] and would benefit from reconfigurable assembly stations [31].

In conclusion, assembly operations need to consider the increasing expectations of mass customization heading towards mass personalization. In order to adapt to it, Industry 4.0 Cyber Physical Systems could be used to develop reconfigurable assembly stations that can deal with high assembly complexity while maintaining high productivity.

3.1.5. The Implications of Complexity

Mass customization brings a great deal of complexity to assembly operations, which affect key elements of the system as well as other nearby areas, such as quality, supply chain or maintenance.Assembly complexity has can been evaluated from different perspectives: the number of product variants [32], induced task differences [33] or product configuration [34]. Complexity has a negative effect on quality, which could be minimized by using cognitive automation [35]. The increasing number of product features to be controlled makes the necessary new advanced quality management systems [36]. Supply chain implications of mass customization assembly range from assembly line feeding problems [37] and modularity-specific issues [38] to assembly supply chain configuration [39] and whole manufacturing networks [40]. Using Automated Guided Vehicles (AGVs) can be used efficiently to feed mixed-model assembly lines [41,42]. Maintenance resource allocation also needs to be prioritized to minimize the negative effects of increased complexity [43].

In conclusion, assembly complexity reaches outside the boundaries of assembly operations and needs to be considered jointly with supply chain, quality, maintenance and IT/IS.

3.1.6. Mass Customisation Impacts Operators

Fully automated assembly systems bring increased productivity for high-volume production but lack the flexibility and adaptability of human operators. People are better equipped for assembly tasks with small and frequent variations, but their potential for higher productivity is limited. In a context of market demand characterized by mass customization, which heads towards mass personalized production, reconfigurable assembly systems that incorporate both machines and people can lead to cost-effective systems that are flexible and scalable [2]. Automation needs to consider both the physical and cognitive abilities of the human operators it supports [44].

In order to improve the yield of assembly operations, providing support to human workers is necessary. Augmented Reality (AR) could be used, reducing the number of engineering/production management resources needed to provide assembly operators with cognitive support to perform their tasks [45,46]; as well as cognitive/handling skills transfer systems [47], self-adapting automatic quality control [48] or cognitive automation strategies [49]. Automation needs to ensure human safety, which led to research on Human–Robot Collaboration (HRC) plan recognition and trajectory prediction [50], and the concept of "safety bubble" [51]. When employing novel digital technologies for enhancing assembly systems performance, one cannot underestimate the strategic importance of IT/IS systems [52].

In conclusion, in a context of market demand characterized by mass customization, which heads towards mass personalized production, reconfigurable assembly systems that incorporate both machines and people can lead to cost-effective systems that are flexible and scalable. Industry 4.0 digital technologies have a critical role to play in making possible mass customization assembly systems that do not compromise on quality and cost and that do not achieve increased performance by affecting human operators negatively.

3.1.7. Assembly and Mass Customisation: Conclusions

In a context of market demand characterized by mass customization which heads towards mass personalized production, the increased complexity reaches the boundaries of assembly operations and needs to be considered jointly with other areas (e.g., supply chain, quality, maintenance, IT/IS) and taking a holistic point of view to ensure that optimizing a subsystem does not affect others negatively. To maintain assembly operations competitive despite the increased complexity, product clustering, modularization, delayed product differentiation, mixed-model assembly, and reconfigurable assembly systems are valuable tools. Reconfigurable assembly systems in which human operators work effectively alongside machines or robots, made possible with Cyber Physical Systems, can lead to cost-effective systems that are flexible and scalable. It seems clear that Industry 4.0 digital technologies have a critical role to play in making possible mass customization assembly systems.

3.2. New Digital Technology Available: Industry 4.0

In order to answer the previously presented questions "What new Industry 4.0 digital technologies are relevant to assembly operations?", "How to make the most out of them?" and "How to measure the improvement?"; the systematic literature review publications related to the key concepts "Industry 4.0' and "Key Performance Indicators" were analyzed. After a brief introduction on Industry 4.0 (I4.0), the eight main topics to be considered are presented, as shown in Figure 6: I4.0 technology for improving processes and decisions; I4.0 technology for mass customization; I4.0 technology for supporting human operators; I4.0 for mass customization; Key Performance Indicators for assembly; Key Performance Indicators for I4.0; and Small and Medium Enterprises (SMEs) in the I4.0 era. Finally, the key conclusions are summarized.

3.2.1. Introducing "Assembly 4.0"

According to Yin et al., industrial revolutions are related to distinct technologies, market demands and production systems. The 4th industrial revolution differs from industry 1.0–3.0 because it is expected to happen in the near future, as opposed to the previous three. The deep and intertwined changes in available technology and market demand paradigms create new possibilities; however, the industry 4.0 production systems are expected to be an evolution from the previously existing systems (characterized by *seru*, flow lines, Toyota Production System or TPS, job shops, cellular manufacturing and Flexible Manufacturing Systems or FMS) enhanced by the novel digital technologies [11].

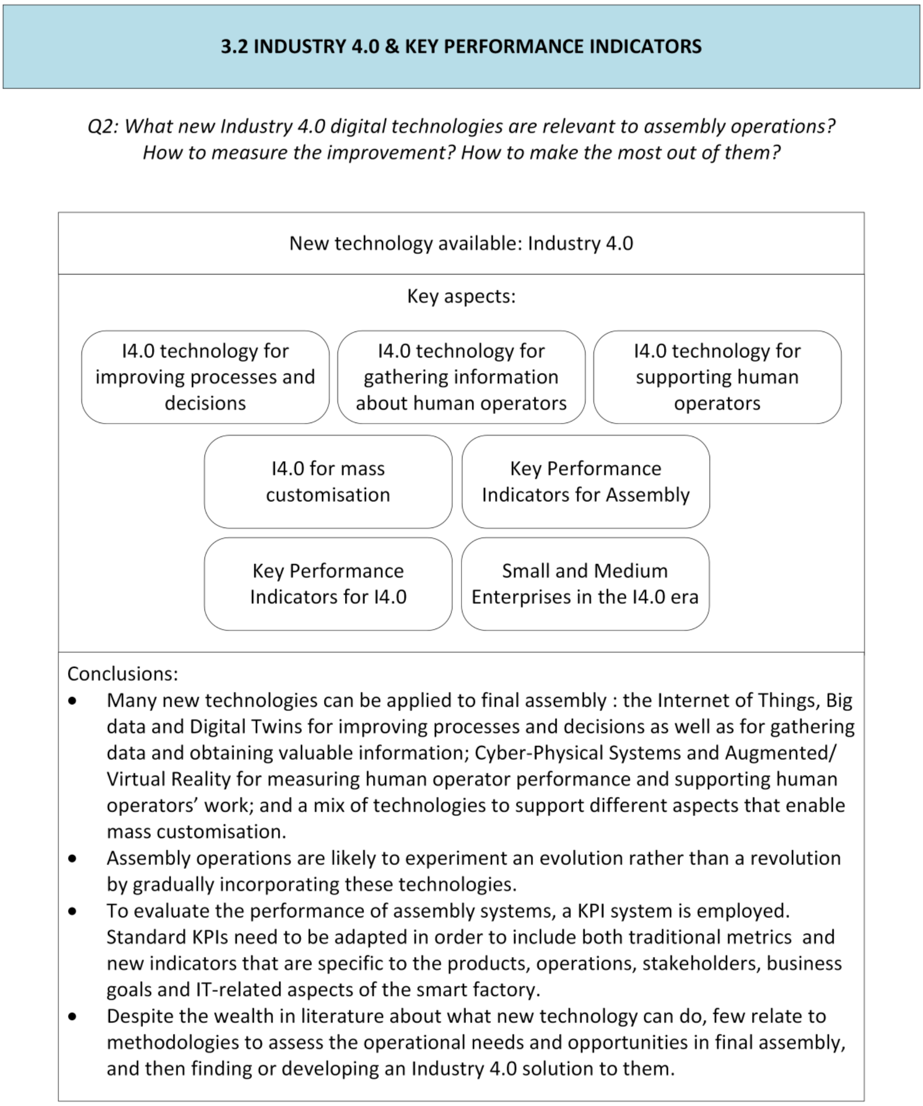

Figure 6. Key aspects of Industry 4.0 technologies for assembly operations and Key Performance Indicators (KPIs), and main conclusions of the analysis.

Bortolini et al. investigated in [53] the impact of the 4th industrial revolution on assembly systems design. The dimensions to consider are six: balancing, sequencing, material feeding, ergonomic risk, equipment selection and learning effect. The evolution of the industrial environment in European countries leads to an aging workforce, re-shoring of production facilities and more efficient and distributed communication networks. In this environment, nine are the enabling technologies of Industry 4.0 that have the most potential to affect assembly systems: big data, IoT, real-time optimization, cloud computing, Cyber Physical Systems, machine learning, Augmented Reality, cobots and additive manufacturing. The integration of these technologies in the design and management of assembly processes leads to what Bortolini et al. define as "*AS40*": Assembly Systems 4.0. The main characteristics of *AS40* are assembly control systems, aided assembly, intelligent storage management, late customization, product and process traceability and self-configured workstation layout [53].

Cohen et al. looked into how assembly system configuration would be affected by Industry 4.0 principles, understood as four incremental stages or steps to achieve the 4th revolution: connectivity, information, knowledge and *smart*, which involves "predictive and automated decision making processes, with possible self-adjustments and reconfiguration of the production system". The new paradigm would reduce the costs of assembly automation; reduce setup costs and learning curves; enable the assembly of small quantities of large products in flow lines; enable the assembly of very different products in the same system; better traceability of failures and defects; and smarter material handling. In the last stage of Industry 4.0 (*smart*), assembly systems would be Self-Adapting Smart Systems (SASS), and together with continuous support to operators (OSS), flexibility, agility and productivity would be greatly increased [54].

According to Cohen et al. in [7], the main goal of flexible assembly systems in the Industry 4.0 era is to address the mass customization demand paradigm. At this moment, operational, tactical and strategical issues remain unsolved for implementing "Assembly 4.0". A key aspect is the social effect of Assembly 4.0: the assembly workforce is expected to shrink—at least, in Western countries-, but additional technological job positions will appear, partially offsetting the operator reduction. The workforce would experiment a net decrease, thus increasing the productivity per employee. Therefore, the role of people in A4.0 will be increasingly important, which calls for future research that considers human operators back at the center of the production systems of the future [7].

When looking ahead in the evolution of assembly systems into the 4th Industrial revolution, Cohen et al. identify challenges when integrating new and existing technologies: uncertainty on the synergies of the I4.0 Key Enabling Technologies; the human–automation collaboration; incorporating Artificial Intelligence into assembly systems; and finding, developing and keeping the Assembly 4.0 human specialists. On top of the technical knowledge, Industry 4.0 operators will need a new set of non-technical skills, so education centers and companies will need to work together to meet this demand [55].

Developing an Assembly 4.0 system in a controlled environment, such as a Learning Factory, allows to better understand the complexity of such a system. The drone factory developed by Fast-Berglund et al. "focuses on the interaction and cooperation between humans and cobots to create collaborative applications in final assembly tasks". It was built with operator involvement from the start, and it incorporates a modular and event-driven IT architecture that creates a digital twin of both product and production system, allowing automated planning and preparation of operations [56].

Facing a mass customization demand, late customization is a strategy allowing customers to make changes to their orders even when the production has started. Industry 4.0 digital technologies bring additional tools for developing an assembly system able to cope with resequencing the production process [24]. Identifying information and data needs is a key step in the design of smart assembly factories to ensure that the increased complexity associated with addressing mass customization production can be managed by human operators [57]. Additionally, strategies for improving the use of IT/IS systems in assembly need to consider the whole digital strategy of the organization [52]. Optimizing the design of any Industry 4.0-enabled system at early stages is critical for SMEs in the manufacturing sector. Axiomatic design and *Acclaro* software have proven useful [58].

The analysis of literature allowed to organize Industry 4.0 technologies in four main categories depending on their goals in assembly operations: improving processes and decisions, gathering information on human operators, supporting people in assembly, and enabling mass customization. Table 3 summarizes the references to technologies employed for each goal.

3.2.2. Industry 4.0 Technologies for Improving Processes and Decisions

Novel Industry 4.0 technologies can be used to improve processes and gather meaningful data, which allows better-informed decisions. Big data can be used to maximize yield and machine uptime in precision assembly processes by detecting long term errors and enabling predictive maintenance [59]. Sensors from across the shop-floor can be used in conjunction with an IT/IS service to provide critical information about the processes in the white goods industry [61]. RFID can be used to track assembly execution and then to derive guidelines for smart assembly line development [62] and web-based systems (*saas*) to control smart internal logistics using mobile robots [68]. Motion Analysis System (MAS) to monitor and evaluate manual production processes [63,93]. The *Human Factor Analyzer* is a software/hardware architecture that can be used for manual work motion and time measurement employing depth cameras and automatic data processing aiming to evaluate work performance quantitatively [64]. Digital twins of assembly processes can be used to analyze the efficiency of the line [85], and it would also enable product-centric assembly [86]. Festo's *Cyber Physical Factory* can be used to implement an Industry 4.0 digital twin framework [87].

Table 3. Technologies of Industry 4.0 by usage.

Industry 4.0 Technologies [1]	Improving Processes and Decisions	Gathering Information on Human Operators	Supporting People in Assembly	Enabling Mass Customisation
Big data	[59]		[60]	
IoT	[61–64]	[65]	[66]	[67]
Real-time optimization	[68]	[69]		[24]
Cloud computing				[70]
Cyber Physical Systems			[71,72]	[67]
Augmented/Virtual Reality			[73–82]	[83]
Additive manufacturing				[83,84]
digital twin	[85–87]	[69]		
Other		[88,89]	[49,90–92]	

[1] Industry 4.0 Key Enabling Technologies based on [53].

3.2.3. Industry 4.0 Technologies for Gathering Information on Human Operators

Industry 4.0 technologies allow new ways of gathering information about human assembly operators that are less intrusive, more accurate or more capable than previously existing techniques: Mattson et al. propose a method of measuring the wellbeing and performance of operators at assembly stations [88]. Krugh et al. measure human–machine interaction using the Internet of Things (IoT) to understand the impact of people on Industry 4.0 assembly systems [65]. Eye-tracking can be used to analyze the user experience of engineering design and manufacturing [89]. A theoretical human-centered framework for operator 4.0 using digital twin based simulation and real-time human data capture can be used to provide insights on operator ergonomics and mental workload [69].

3.2.4. Industry 4.0 Technologies for Supporting People in Assembly

Cyber Physical Systems (CPS) for improving operator ergonomics [71]; vision systems for measuring and providing feedback on operator performance [90]; cognitive assistance for rework area [91]; strategies for cognitive automation that allow operators to deal with increased complexity [49]; Augmented Reality (AR) to assist manual assembly [73]; operator training using digital assistance [92]; training using Virtual Reality and process mining, allowing to replace traditional interpersonal demonstration and repetition [74] and real-time interface using data from many devices and an algorithm allowing manual assembly operators to deal with requests and report faults [66].

3.2.5. Industry 4.0 Technologies for Mass Customisation

Manufacturing flexibility is a strategic orientation for high-wage countries, and Industry 4.0 technologies bring solid benefits to operations management, especially in terms of technology management and Just-In-Time (JIT) production [94]. One technology in particular—additive manufacturing, can break the flexibility vs. cost trade-off, which most industrially developed countries face [84]. Compared to the volatile market of Industry 3.0, characterized by product variety, the smart market of industry 4.0 involves customer participation in individual customization of products [11]. Industry 4.0 KET enable mass personalization through short product development cycles [83] and individual customers' input [67,95]. Rossit et al. propose an approach based on tolerance planning strategies and resequencing capabilities to allow changes to the product to be made even after production has started [24]; while Chung et al. envisage a dynamic supply chain design for connected factories through cloud-based information systems as a way to achieve mass personalization [70].

In conclusion, Industry 4.0 not only offers new alternatives for cost-competitive mass customization but also opens the door to mass personalization, where the customer is involved in individual customization of the product.

3.2.6. Key Performance Indicators for Assembly

Key Performance Indicators (KPIs) are employed widely to assess the outcome of assembly systems. New concepts for novel assembly systems need to use KPIs to evaluate their potential performance. In most cases, traditional KPIs are used [96]: cost (investment, labor), quality (first pass yield, final yield) [97–99], throughput time, quantity and lot size; inventory costs [100], line productivity (e.g., OEE—overall equipment effectiveness) [101], energy consumption, cycle time and service level [102,103]. Integrating KPIs that link design, production, and quality goals through the product & process development has proven useful to limit late engineering changes, which delay the assembly system development [104]. A combination of economic and structural KPIs can be used to evaluate the adaptability of reconfigurable manufacturing systems [105]. Yang et al. propose that KPI selection for the smart automation of manufacturing systems needs to be company and location-specific and that the KPIs variation and sensitivity to the introduction of new Industry 4.0 technology needs to be a key driver for developing a strategy for smart assembly automation [106]. For evaluating the performance of Line-less Mobile Assembly Systems (LMAS), Hüttemann et al. developed a set of 11 specific KPIs, 6 of which are adapted from conventional KPIs to account for the wide variety of products being made in the assembly system, and 5 are specific to LMAS (e.g., overall traveled distance, number of station configuration reconfigurations) [107].

In conclusion, to evaluate assembly systems, standard KPIs need to be adapted in order to include both traditional metrics (e.g., cost, quality, throughput, inventory, lead time, productivity) and new indicators that are specific to the products, operations context and business goals.

3.2.7. Key Performance Indicators for Industry 4.0

Manufacturing flexibility is a strategic orientation for high-wage countries, and Industry 4.0 Key Enabling Performance measurement is a necessary management tool in any factory transformation. Traditional KPIs are valid to evaluate the impact of Industry 4.0 on production systems. However, new IT-related KPI classes will be required to assess data management (e.g., IT efficiency, availability of IT, the correctness of data, completeness of data), transparency & connectivity (e.g., degree of interconnectivity, digital coverage, the proportion of virtually controllable resources), and product management [108]. Industry 4.0 technologies bring the possibility of using IoT devices to gather real-time data from an immense number of devices in real time, enabling rapid responses to changing conditions [109]. KPIs for smart factories need to be reliable and targeting the right goals to support operational objectives. Therefore, correctly identifying the smart factory stakeholders and understanding their requirements is crucial [110]. Transforming a traditional factory—using legacy machines—into a smart factory is possible without buying expensive new machines, employing a continuous improvement approach, the IoT as enabling technology and establishing visible KPIs from the beginning so that the path to Industry 4.0 is clear to all stakeholders [111]. The increased network complexity and data traffic increase the probabilities of IoT failure. To address this, a data anomaly response model was proposed by Hwang et al. [112]. The changes brought by Industry 4.0 could affect people greatly. To make this impact on people more visible, human-centric KPIs have been proposed [113].

In conclusion, traditional and new IT-related KPIs classes (e.g., data management, transparency and connectivity, product management) would be used to assess and control the impact of Industry 4.0 on production systems. Identifying the smart factory stakeholders and their requirements is critical for obtaining meaningful KPIs. The Internet of things is the Key Enabling Technology that allows gathering data from multiple sources to produce real-time KPIs that allow rapid responses to fast changes in smart factories.

3.2.8. Small and Medium Enterprises in the Industry 4.0 Era

Although large corporations are more likely to benefit from adopting Industry 4.0 technologies, Small and Medium Enterprises (SMEs) could also obtain a competitive edge from Lean-digital manufacturing systems [114]; for example, improving the communication between shop-floor and the top-floor [115]. SMEs have different needs and requirements, which should be taken into account when designing smart manufacturing systems [116]. SMEs have started their digitalization journey, but further Industry 4.0 developments need to align with the particularities of SMEs, and their organizational structures need to fully embrace and support digitalization in order to benefit from its implementation [117]. Fast-Berglund et al. looked at 40 SME and 8 OEMs in order to establish collaborative robot (cobots) implementation strategies and to determine what KPIs to use for these cases [118]. The increasing penetration of intelligent machines to work alongside people and the benefits of *agile* production will turn SME operators into "Makers", skilled workers whose main activities are no longer assisting or monitoring machines, but creative tasks involving a wealth of information, alternatives, criteria and possible solutions [119].

In conclusion, Small and Medium Enterprises (SMEs) operators will be affected differently by I4.0 compared to corporate workers, but it is clear that I4.0 can bring competitive benefits for SMEs.

3.2.9. Assembly 4.0: Conclusions

The 4th Industrial revolution demand paradigm means mass customization of products, made possible by new digital technology. Conversely, production systems are most likely to experiment an evolution rather than a revolutionary change. Two key areas will be subject to change: the role of people in assembly operations—especially in terms of responsibility and skills; and the possibility of automated or hybrid assembly for low-volume production, including multi-mixed model assembly.

To evaluate the performance of assembly systems, standard KPIs need to be adapted in order to include both traditional metrics (e.g., cost, quality, throughput, inventory, lead time, productivity) and new indicators that are specific to the products, operations, stakeholders and business goals. The Internet of Things is the Key Enabling Technology that allows gathering data from multiple sources to produce real-time KPIs that allow rapid responses to fast changes in smart factories. The smart factory will need to consider also IT-related KPIs to ensure its smooth computer-dependent operations.

There are plenty of examples of new possibilities due to novel technologies applied to final assembly: improving processes, gathering data and obtaining valuable information, measuring human operator performance and supporting human operators" work. However, research articles mostly focus on what the new technology can do, but few relate to following a methodology to assess the operational needs or opportunities in final assembly and finding or developing an Industry 4.0 solution to them.

In order to ensure that the solutions enabled by Industry 4.0 technologies are aimed in the right direction, it is important to keep the focus on adding value.

3.3. Focusing on Delivering Value: Lean

In order to answer the third question, "Is Lean production the best starting ground for implementing Industry 4.0 assembly operations?" a systematic literature review of publications related to the key concept "Lean" was analyzed. After a brief introduction, the nine main topics to be considered are presented, as shown in Figure 7: Lean tools for assembly operations; Internal logistics; Ergonomics;

Assembly operations layout; Teaching Lean; Evaluating performance; Lean and Industry 4.0 interaction; Lean tools for Industry 4.0; and Lean management. Finally, the key conclusions are summarized.

3.3. LEAN

Q3: Is Lean Production the best starting ground for implementing Industry 4.0 assembly operations?

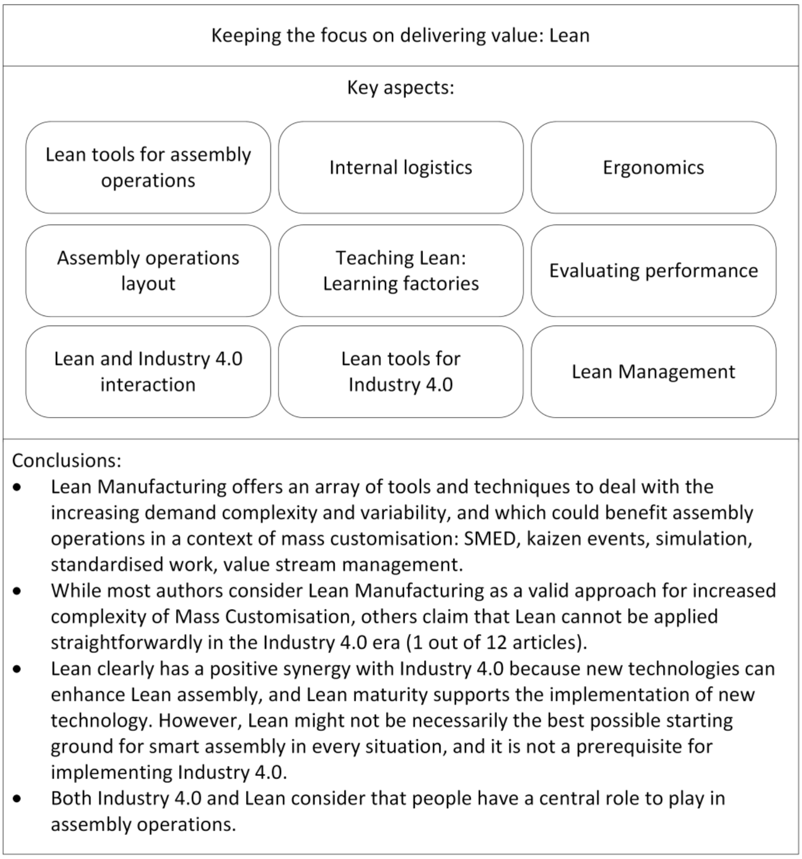

Figure 7. Key aspects of Lean assembly for Industry 4.0, and the main conclusions of the analysis.

3.3.1. Introducing Lean in the Era of Industry 4.0

According to Yin et al., one key characteristic of the Industry 3.0 market—product variety—changed is to change in the Industry 4.0 era to mass customization (customer participate in individual customization). However, the existing production systems will not change in a great way, as flow lines, Lean production, cells, and remain up to date when facing mass customization [11]. On the other hand, Stump et al. propose that despite the fact that Lean production can be applied easily to manufacturing situations with low levels of customization (i.e., product variety, Yin's Industry 3.0 market conditions), increasing levels of customization make it difficult to directly apply Lean principles of establishing flow and keeping low inventory levels [120].

Gunasekaran et al.'s review conclude that Agile manufacturing (which shares with Lean its focus on product value as defined by the customer) is key for sustainable competitive advantages; and identifies five enabling competencies that need to be deployed jointly to achieve its goals: transparent customization, agile supply chains, intelligent automation, total employee empowerment and technology integration [121]. To cope with mass customization with Lean objectives of continuous mixed-model flow, Chatzopoulos presented a production system design algorithm that employs production modules connected by Kanban [122].

3.3.2. Lean Production Tools for Assembly Operations

Lean manufacturing offers an array of tools and techniques to deal with increasing demand complexity and variability which could benefit assembly operations in the context of mass customization. Although Lean, a generalization of the Toyota Production System (TPS), originated in the automotive industry, it has expanded to many other manufacturing sectors—e.g., aeronautical, which demand characteristics are not similar to automotive [123]. One classic Lean tool is a single minute exchange of die (SMED), which is still a trending topic according to a recent review [124]. Looking at balancing manual assembly lines with a high number of product variants (mixed-model assembly), kaizen events and complexity reduction have proven useful since they fill the gap between mathematical balancing models developed by academia and actual techniques used in industry [125]. Mixed-model assembly lines throughput rate can be increased by using Lean in conjunction with simulation [126]. To increase productivity and reduce the necessary shop floor space, continuous flow can be achieved through the use of Standardized Work (SW), U-shape assembly lines and material handling systems [127]. Continuous improvement tools can be applied to increase throughput and reduce buffer capacity [128]. To address the increasing complexity of SW for mixed-model assembly, a reconfigurable approach to SW sheets and control and fabrication instructions has proven useful [129]. Value Stream Mapping (VSM), another classic Lean tool, has been evolved into value stream management at the University of Luxembourg Lean Manufacturing Laboratory [130]. A different approach to VSM is combining electronic-VSM with simulation, resulting in reduced lead times and non-value-added activities [131]. Three new methods were proposed to identify non-obvious constraints of mature production processes, where traditional Theory of Constraints methods fall short [132].

In conclusion, research on the application of Lean techniques and tools for assembly operations is still an open topic. The digitalization of some of the tools, such as Value Stream Mapping, has shown some success.

3.3.3. Internal Logistics

An adjacent key area to Lean assembly operations is Logistics, which makes the necessary components or materials available for assembly at the right time with minimum waste. Lean supply chain uses six classic KPIs: lead time, costs, inventory level, delivery service level and quality [100]. To increase the assembly line's value-add time and ergonomics, and to reduce waste and necessary space, using plastic containers instead of cardboard has been found an interesting option [133]. Looking into minimizing Work-In-Progress stock (WIP) and the required number of assembly operators, pre-kitting offers advantages as well as challenges [134,135]. Usta et al. propose a methodology for assessing the best design for part feeding system for Lean assembly, considering that the problems of pure kitting could be countered by hybrid systems (human & machine) [136]. Yamazaki et al. present a design method to reduce the cost of flexible automation of material handling systems [137]. In-house logistics for Lean assembly require evaluating and selecting from different transportation alternatives in order to feed part supermarkets [138].

In conclusion, internal logistics are tightly associated with assembly, and therefore both should be analyzed together since changes to one will affect the other as well.

3.3.4. Ergonomics

Lean production (LP) impact on ergonomics and psychosocial risks have been studied for decades, and the focus of the studies has varied over time, with a current view that considers that management style can make LP effects either negative or positive [139]. Da Silva et al. develop an index to assess the LP assembly cell work in terms of ergonomics and psychophysical demand [140]. The impact of line and assembly cells on breaks and worker's health has been assessed, finding that assembly cells tend to have higher Cycle Times, which increase the physicality of the work; while assembly lines posed no risks [141]. A different approach to evaluating the impact of LP on ergonomics is utilizing simulation: (1) for analyzing the effect of physical overload on assembly line performance, finding that Cycle Times too close to TAKT (i.e., low catch back time) leads to operator overload, which means absenteeism and low productivity in the long term [142]; (2) or for designing efficient hybrid assembly lines that are ergonomically safe [143].

In conclusion, Lean production can affect ergonomics negatively depending on management style.

3.3.5. Assembly Operations Layout

A key aspect of Lean assembly operations is the production layout. Classic Lean assembly is done in assembly lines or assembly cells. Assembly cells offer various advantages with regards to assembly lines, and a methodology for reconfiguring an assembly line into a cell is proposed by Carmo-Silva et al. [144]. The efficiency of Lean manufacturing production systems can be better analyzed when considering assembly as a macro-activity instead of a series of stations, and the identification of the waste is fine-tuned to assembly operations [145]. Lean assembly lines typically use Kanban to pull production and create material flow. In his paper, Savino et al. propose a method for using semi-automated parts feeding in O-shaped assembly lines [146].

Yin et al. analyzed in [147] the similarities and differences between Lean assembly (lines and cells), Agile manufacturing (Quick Response Manufacturing, QRM) and *seru* manufacturing. They found, based on two key industrial cases (Canon and Sony), that a production system that focuses primarily on responding to quick changes in demand and product instead of prioritizing waste reduction (i.e., Lean production) can be very competitive in high-cost environments. As a result, of this priority, *seru* focuses on "reconfigurability, resource completeness within cells, worker responsibility and buffering as needed to accommodate dimensions of demand variability". However, the applicability of *seru* assembly systems outside of high-cost, high variability, high innovation, short product development cycles remains to be seen [147].

In conclusion, Lean production systems typically employ assembly lines or cell layouts to establish pull and create material flow. For certain contexts involving high-cost, high-variability, short product development cycles, *seru* assembly systems are particularly competitive because they are focused on adaptability.

3.3.6. Teaching Lean for Assembly Operations: Learning Factories

Since operator engagement is at the core of Lean production, Lean-assembly-focused training has been explored over the past decades. Academia-driven teaching methods have not always been adequately adapted for non-students. Recreating industrially relevant environments for teaching Lean at Learning Factories aim to bridge this gap [148]. Lean techniques themselves have been used to design a Learning Factory, using a manual assembly line as a starting point, and employing theoretical knowledge as well as industrial experience for evolving the line into a Learning Factory [149].

Learning factories are incorporating Industry 4.0 technologies into their education and research facilities, focusing on dealing with complexity [150], intelligent logistics [151] or intelligent manufacturing in full-scale simulations [152]. Virtual Reality (VR) and Augmented Reality (AR) can be used to enhance the student's experience when learning Lean manufacturing. Using VR for training and AR for visualizing the assembly instructions improved the lessons [153].

In conclusion, Lean Learning Factories need to mimic real-life scenarios to become useful for non-academic learners with industrial backgrounds, such as assembly operators. Industry 4.0 technologies could be used to enhance the training environment of Learning Factories.

3.3.7. Evaluating Performance From a Lean Perspective

Lanza et al. propose a simulation-based method for assessing the performance improvement of production systems due to Lean techniques. As Key Performance Indicators (KPIs), either direct measures or monetary equivalents are used to compare initial vs. future scenarios. To relate cost-savings over time, cost–time profile charts can be employed [154]. Complex coefficient KPIs derived from delivery date and balanced production can be used to assess small-batch mixed-model scheduling models better than simple KPIs, although the potential use of such KPIs to manage real operations is reduced [25]. Multi-criteria KPIs can be used not only for management and control of operations but at earlier stages of flow planning projects [155]. For practical results, leading indicators are preferred over lagging KPIs [156], so Cyber Physical Systems (CPS), which lead to intra-logistics evaluation tools that use a wealth of data collected automatically, could be preferred over-relying on human input [157].

Evaluating the operational performance of Lean organizations can be done using tree-like KPI structures [158] or integrated performance assessment frameworks [159,160]. Cortes et al. proposed a "Lean & Six Sigma Framework" [161] to evaluate leanness in order to justify future investment—in a similar fashion to Lanza et al.'s [154]—and focus on a methodology for a solid KPI definition that allows and enables strategic-operational alignment. Kovacs et al. studied the relationship between Lean maturity, operational performance and investment; and concluded that implementing and sustaining Lean practices pays off because new technology cannot improve performance if the processes are not under control in the first place [162].

In conclusion, KPIs and performance assessment frameworks are used to measure the effects of changes in Lean production systems. Establishing a set of KPIs needs to take into account multiple stakeholders and to align the strategic and operational goals of the organization. Simulations and case studies show the beneficial effects of Lean methods and allow to estimate the economic return of investment of Lean management decisions.

3.3.8. The Interaction between Lean Production and Industry 4.0

Lean production is a key characteristic of the 3rd industrial revolution production systems. While other aspects have evolved (e.g., technology, from computers to smart digital devices) or radically changed (e.g., market focus from variety and lead time to customization and personalization), Lean is still up-to-date in the era of Industry 4.0 [11]. Moreover, the relationship between Lean and Industry 4.0 technologies is catching increasing attention from academia in the last decade [163].

The question posed by Mrugalska et al. [164] has been addressed by many authors, both theoretically and analyzing use cases across many countries: "Can Lean and Industry 4.0 coexist and support each other, and if so, how?" There are four main lines of thought when answering this question: (1) Lean techniques and Industry 4.0 technologies interact in a positive way, and there are many cases to illustrate this [8,9,165,166]; (2) Lean facilitates the change towards Industry 4.0 [167,168]; (3) Industry 4.0 supports Lean, i.e., makes the factory Lean [169–173]; (4) although Lean and Industry 4.0 aim for the same goals, their approach is essentially different regarding digital technology [174].

Five articles looked at answering Mrugalska et al.'s question [164] by surveying the industrial reality of different countries, all of them finding positive interactions between Lean and Industry 4.0 technologies. Dombrowski et al. analyzed 260 industrial companies in Germany and found Lean as an enabler of Industry 4.0 [168]. Tortorella et al. looked into 110 user cases in Brazil and found a positive Lean-Industry 4.0 correlation, as well as increased benefits of new digital technologies where Lean was also present [175]. Rossini et al. analyzed 108 cases of European manufacturers, concluding that Lean allows achieving higher levels of Industry 4.0 while lacking Lean production techniques makes it more difficult to change towards Industry 4.0 [176]. Chiarini et al. investigated 200 cases in Italy and found that most strategic, operational areas benefit from implementing Industry 4.0, such as design-to-cost, supply chain integration or machinery–electronics–database integration [177]. Lorenz et al. analyzed user cases in Switzerland and found that Lean maturity allows greater performance improvements from implementing Industry 4.0 [178].

In conclusion, there is a wealth of evidence showing that Lean manufacturing is a valid approach to improve assembly operation in the context of mass customization and that Lean and Industry 4.0 can benefit from synergies because each one enhances the other. However, according to some authors [174], Industry 4.0 and Lean have essentially different approaches regarding the role digital technologies should have.

While some authors deem that TPS considers robots, machines and computers in the opposing side of *jidoka* ("automation with a human touch"), it should be noted that the lack of enthusiasm of TPS towards digital technologies could have been influenced by the current digital technologies of that era (the 1950s–1980s). Since the rate of change in digital technology has been particularly remarkable in the past four decades, it seems bold to assume that TPS's views on computers in the second half of the 20th century still apply.

3.3.9. Lean Tools for the Industry 4.0 Era

The arrival of the 4th industrial revolution could mean changes in the role or the value of existing Lean production tools. For example, Value Stream Mapping (VSM) could no longer be a sustainable tool since it might lack flexibility when dealing with digital processes, although evolutionary improvements to this tool could correct this shortcoming [179]. On the other hand, Lean automation aims at achieving the best possible combination of Lean and Industry 4.0 automation [180]. Industry 4.0 will create new forms of waste, digital waste, and Romero et al. conclude that future research would need to focus on new techniques developed to eliminate it [181,182]. Using simulations of Lean production environment can be used to find clustering alternatives that reduce the waiting time without compromising the business productivity [183]. Malik and Bilberg proposed a method for assigning tasks to robots or people in Human–Robot Collaborative (HRC) assembly, based on the physical properties of the components, HRC safety, and the dynamics of the HRC environment such as part presentation and feeding [184]. The IoT and simulation could be used to support expert-less decision making, in a similar way to the classic Andon tool does [185]. In any case, systems integration will be needed to ensure that Lean manufacturing systems meet the Industry 4.0 requirements [186].

In conclusion, classic Lean tools—e.g., value stream map—might need to change in order to remain useful for analyzing digital processes. The appearance of "digital waste" should be taken into account, but in general terms, Industry 4.0 technologies are expected to support the ability of people to make Lean-oriented decisions.

3.3.10. Lean Management Affected by the 4th Industrial Revolution

The evolution of Lean management in the context of Industry 4.0 leads to risks and opportunities. According to Rother et al. [187], the success factors of the coming transformation are three: management engagement, involvement and interaction. Therefore, the proposed approach is to use the technological advances to free up manager time and use it to focus on the human relationships: sharing knowledge, developing the workforce's skills and managing progress [188]. Total Quality Management will need to evolve as quality planning, quality control, quality assurance and quality improvement are different in a digital manufacturing framework compared to the previous human-capabilities-based era [189].

In conclusion, management has a key role to play in the successful transition to Industry 4.0. From the Lean perspective, changes brought by Industry 4.0 could be used to free up manager time to be invested focusing on human relationships.

3.3.11. Lean and Industry 4.0: Conclusions

Research on Lean tools for assembly operations is still an open topic. Firstly, it should be noted that since internal logistics are tightly associated with assembly, both should be analyzed together because changes to one will affect the other as well. Lean production systems typically employ assembly line or cell layouts to establish pull and create material flow. For certain contexts involving high-cost, high-variability, short product development cycles, *seru* assembly systems are particularly competitive because they are focused on adaptability. KPIs and performance assessment frameworks are used to measure the effects of changes in Lean production systems. Establishing a set of KPIs needs to take into account multiple stakeholders and to align the strategic and operational goals of the organization. Simulations and case studies show the beneficial effects of Lean methods and allow to estimate the economic return of investment of Lean management decisions.

The Toyota Production System (TPS) considers robots, machines and computers in the opposing side of *jidoka* ("automation with a human touch"), but it should be noted that their lack of enthusiasm towards digital technologies could have been influenced by the current digital technologies of that era (1950–80's). Since the rate of changes in digital technology has been particularly remarkable in the past four decades, it seems bold to assume that TPS's views on computers in the second half of the 20th century still apply. Currently, there is a wealth of evidence showing that Lean manufacturing is a valid approach to improve assembly operation in the context of mass customization and that Lean and Industry 4.0 can benefit from synergies because each one enhances the other. Some classic Lean tools—e.g., Value Stream Map—may need to change in order to remain useful for analyzing digital processes. In general terms, Industry 4.0 technologies are expected to support the ability of people to make Lean-oriented decisions. Management has a key role to play in the successful transition to Industry 4.0. From the Lean perspective, changes brought by Industry 4.0 could be used to free up manager time to be invested focusing on human relationships. Learning Factories could be a great tool to share the vision of Lean 4.0 assembly, but they need to mimic real-life scenarios to become useful for non-academic learners with industrial backgrounds, such as assembly operators. Industry 4.0 technologies could also be used to enhance the training environment of Learning Factories. Since both Lean and Industry 4.0 stress the importance of people, it seems only natural that supporting human capabilities becomes a priority in Lean 4.0 assembly

3.4. Focusing on People

In order to answer the fourth and last set of questions, "How would Industry 4.0 affect people in assembly?" and "How to support people transitioning to Assembly 4.0?", the systematic literature review publications related to the key concept "Operator" were analyzed. After a brief introduction, the six main topics to be considered will be presented, as shown in Figure 8: Line balancing, sequencing and job rotation; Lean: Operators at the center; Frameworks for operators in Industry 4.0; Automation and Human–Robot Collaboration; Supporting operators with Industry 4.0 technology; and Implications of smart factories for operators. Finally, the key conclusions will be summarized.

3.4.1. Introducing People in Assembly Operations

Human operators are critical for competitive assembly systems when considering information flows, competence needs and the requirements for effectively making use of automation. In such an environment, human teams—rather than individuals, are key [190]. The role of operators depends strongly on the type of production system (e.g., high-volume production vs. low-volume high-variety). Traditional automation allows increased productivity, but it lacks the adaptability of human operators. The design of reconfigurable assembly systems by incorporating both machines and people can lead to cost-effective system flexibility and scalability. However, the collaboration between people and robots can create safety issues. These can be addressed in two clearly separated ways, according to Hu et al.: (1) employing vision systems to stop robots; (2) robots so light and low force that they can be stopped safely by people. Safely increasing flexibility and efficiency in mixed-model assembly lines is one of the problems that Industry 4.0 technologies seek to address [54].

In conclusion, the role of operators depends on the type of production system, and there is usually a trade-off between the increased productivity of automation and the adaptability of human operators. Reconfigurable, hybrid assembly systems that incorporate machines and people could lead to cost-effective flexibility and scalability. However, the collaboration between people and robots can also create safety issues.

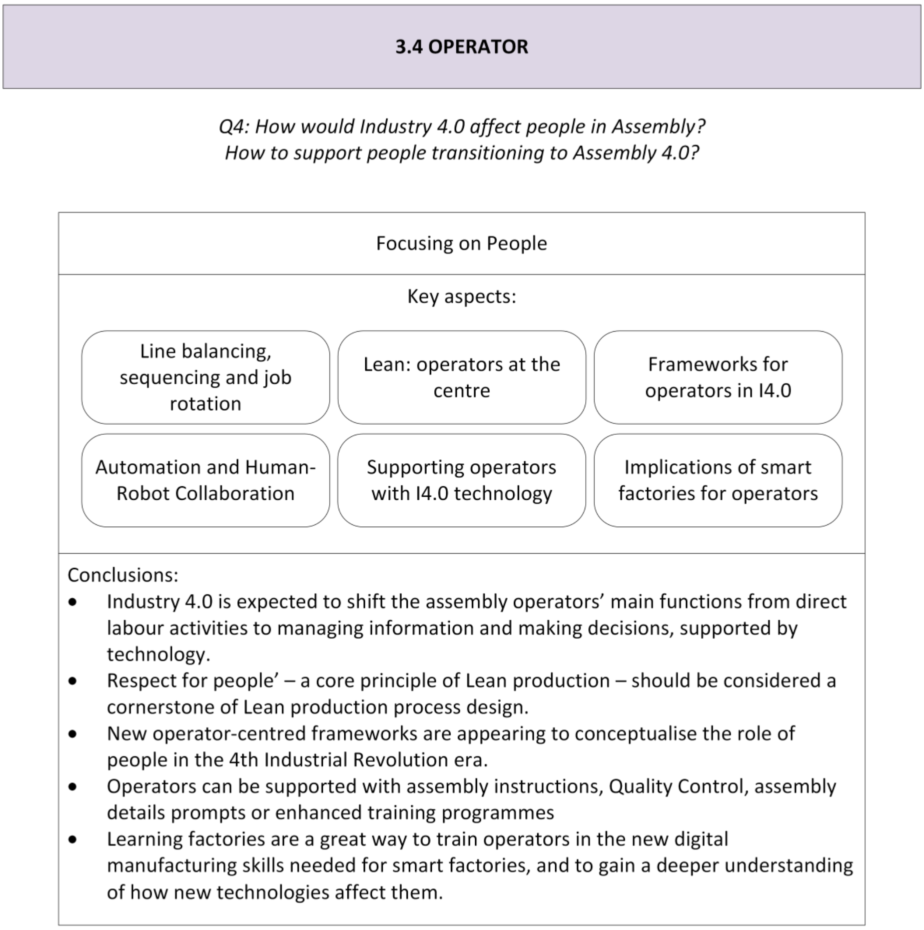

Figure 8. Key aspects of operators in Industry 4.0, and main conclusions of the analysis.

3.4.2. Line Balancing, Sequencing and Job Rotation

Having a flexible and cross-trained workforce is a recurrent approach to deal with the complexity and changing demand conditions of mass customization [191–193]. Operator job allocation can also be adjusted to address an array of situations: one-of-a-kind production [194], minimizing costs in *seru* production systems [195], high turnover and slow learning processes [196], a heterogeneous workforce with varying degrees of absenteeism [197], remarkable ergonomics and walking costs [198], or operator-intensive assembly optimization—along with sequencing [199]. Alternatively, sequencing algorithms can be used for minimizing operator headcount in reconfigurable assembly systems [200].

Although line reconfiguration is a common approach in mixed-model assembly, output can be increased in peak demand without it [201].

Analyzing the human operator characteristics and the process complexity can be used to maintain the process KPIs [202], to predict operator overload [203], or to assess human-originated quality problems [204]. Operator walking distances are a key input for kitting vs. line stocking decisions [205], and JIT kitting can be optimized by incorporating hybrid HRC systems [206].

In conclusion, a flexible and cross-trained workforce is key for dealing with changing demand conditions, allowing dynamic job assignation and efficient line balancing and sequencing.

3.4.3. Automation and Human-Robot Collaboration

Human-Robot Collaboration (HRC) expects to obtain the best of both human and automation worlds. Costa Mateus et al. developed a methodology for transitioning from manual to HRC assembly: (1) operation decomposition, (2) resource evaluation, (3) resource allocation, (4) collaborative assembly operation. [207]. However, HRC brings quality and reliability problems associated with robots and human operators separately, on top of their interactions, which needs to be addressed when establishing Quality Control [208]. Additionally, collaborative work with a robot has been found to cause stress in operators [209]. Moreover, operator safety remains a key concern for HRC systems. A safety strategy for HRC should consider the following key design areas: Human–Robot Collaboration spaces, robot safety systems, computer vision monitoring of safety conditions, and an operation control system that coordinates human–robot interaction [210]. Regarding the vision monitoring of safety conditions, Anton et al. used depth sensors so that robots avoid collisions with operators [211]. Another way of ensuring human operator safety in HRC would be the "safety bubble" concept, which is based on live data sharing between reconfigurable assembly systems [38].

In conclusion, Human–Robot Collaboration aims to obtain systems that are both flexible and highly productive. However, quality and safety concerns are yet to be solved.

3.4.4. Lean: Operators at the Centre

One key aspect of Lean production Systems (LPS) implementation is *respect for people*, which has been typically overseen [212]. Worker development defines the Toyota Production System (TPS) culture of respect and teamwork, and although it does not directly relate to bottom-line results, it is an integral component of the TPS implementation of *kaizen* (continuous improvement) [213]. There are simple ways to involve operators and supervisors in the continuous improvement journey, and they are built on showing the importance and effect of everyone's actions towards addressing the problems together [214]. One-point lessons have been found effective in sustaining the standardization and optimization in LPS [215].

There must be a balance between worker autonomy and creativity versus process and cost control, and De Haan et al. found that "challenging and enabling workers to creatively use their talent and skills in daily work will most likely lead to positive results" [216]. Another tension exists related to judgment-based operator adjustments to processes, which could be considered as tampering from the Statistical Process Control (SPC) point of view. Operator adjustment is not always bad, but a necessity in real production plants, and there are methods to determine whether the operator judgment was appropriate or not [217].

Romero et al. looked towards *Jidoka* (or "automation with a human touch") when analyzing the future relationship of people and machines in the emerging 4th Industrial Revolution. They stress that *Jidoka* needs to be understood not only as an approach to automation but also as a "learning system" in which machine and human benefit from each other [4]. "Employee development system", a tool of Lean production management, can be used to enhance the problem-solving capabilities of the workforce, which leads to improved results measured by KPIs [218].

New frameworks consider people as the cornerstone of LPS: either depicting them as one of the fundamental pillars—alongside processes and tools [219]; or directly as the center of a layered model for Lean factory design [220].

In conclusion, "respect for people"—a core principle of Lean production—should be considered a cornerstone of Lean production process design. There must be a balance between worker's autonomy and process control, keeping in mind that operators' involvement in the continuous improvement journey is necessary for success in the long term.

3.4.5. Frameworks for Operators in Industry 4.0

The concept of Industry 4.0 appeared to provide cohesion to different visions regarding the future of manufacturing, connected by Key Enabling Technologies (KET). Alongside the development of such technologies, recent research has focused on theoretical frameworks to conceptualize the use of the KET and its impact on human operators. Lindblom et al. [221] studied how to evaluate the Human–Robot Collaboration in terms of safety, trust and operator experience; Golan et al. [222] looked into the future Industry 4.0 interaction between operator and workstation, composed of three subsystems: observation, analysis and reaction.

The key role of operators in the era of the 4th Industrial Revolution has been identified by numerous authors, coining the term *Operator 4.0* [223]. Industry 4.0 technologies should support operators in their tasks, either by directly helping them or by providing meaningful information to assembly system design engineers. Peruzzini et al. developed a theoretical human-centered framework for Operator 4.0 using digital twin-based simulation, and real-time human data capture can be used to provide insights on operator ergonomics and mental workload [69]. In a similar way, Mattson et al. propose a method of measuring the wellbeing and performance of operators at assembly stations using electro-dermal activity [88]. Industrial IoT is another technology that can be used for capturing human and machinery data for understanding human impact on Industry 4.0 assembly systems [65]. Understanding the operator's information needs is vital for the design of smart assembly factories [57].

In conclusion, new operator-centered frameworks are appearing to conceptualize the role of people in the 4th Industrial Revolution era. The key role of operators has been identified by numerous authors, coining the term operator 4.0 [223]. Industry 4.0 technologies should support operators in their tasks, either by directly helping them or by providing meaningful information to assembly system design engineers.

3.4.6. Supporting Operators with Industry 4.0 Technologies

Industry 4.0 technologies offer new ways to support human operators in their duties—see Table 3: training can be made easier with Virtual Reality (VR), Augmented Reality (AR) and motion tracking [74–76]; instructions can be generated in real time and displayed using AR [77–79]; or projection AR can be used to provide process information [80], assembly assistance [81], safety in HRC "chaotic" smart warehouses [224], shipyard worker assistance [225] or to enhance the operator's capabilities and competencies [82]. In general, human operators are positive about the use of AR for assembly support [226]. The technology-enhanced operator is a growing field of research, with many other Industry 4.0 KET involved in achieving varied goals: IoT-based human–Cyber Physical Systems for providing feedback to operators working in an intelligent space [72]; reducing big data to smart data to assist people [60]; software robots (softbots) to interface between machines and computer information systems [227]; mobile devices in order to allow dynamic job rotation in multi-variant assembly lines [228]; verbal and visual prompts for assisting workers with intellectual disabilities [229]; wearables for audio commands [230] or detecting potentially hazardous or risky situations [231]; or a combination of many technology-enabled tools [232–234].

In conclusion, varied Industry 4.0's Key Enabling Technologies can be used to support production operators to obtain different benefits. In particular, Virtual and augmented reality and wearable devices have attracted great attention. Operators can be supported with assembly instructions, quality control, assembly details prompts or enhanced training programs, which can be provided in a way that is satisfactory for the users.

3.4.7. Implications of Smart Factories for Human Operators

Digital technologies' progressive presence in factories will change the role of human operators, which will shift from work-focused activities towards dispositive tasks, supervision and decision activities [235]. Operators will, therefore, need more information than ever before, and these requirements need to be carefully assessed [57]. Considering the operator at the center, human activities with Cyber Physical Systems (CPS) have been modeled, and new KPIs proposed to make visible how business and operational decisions affect operators [113]. Empowering operators seems one possible way of making Smart factories happen, and such empowerment will make visual computing technologies necessary, according to Segura et al. [236].

Digital technologies can also be used to obtain insights into human–machine interactions [65] or worker's wellbeing [88], which then lead to forming strategies for cognitive automation [49]. Despite recent advances, digital maturity in manufacturing companies has a long way to go, and most operator-machine interaction is done by mouse and keyboard hardware instead of by using CPS [237].

In conclusion, human operators will need to receive and manage more information than ever before, make decisions and supervise instead of focusing on mechanical work-related activities. Therefore, empowering operators to act more autonomously and supporting them accordingly seems necessary. To understand the situation of Industry 4.0 operators can be done using new digital technologies, obtaining meaningful data in ways that were not possible before.

3.4.8. Focusing on People: Conclusions

The role of operators depends on the type of production system, and there is usually a trade-off between the increased productivity of automation and the adaptability of human operators. Reconfigurable, hybrid assembly systems that incorporate machines and people could lead to cost-effective flexibility and scalability. However, the collaboration between people and robots can also create safety issues. There must be a balance between worker's autonomy and process control, keeping in mind that operators' involvement in the continuous improvement journey is necessary for success in the long term. "Respect for people"—a core principle of Lean production—should be considered a cornerstone of Lean production process design. A flexible and cross-trained workforce is key for dealing with changing demand conditions, allowing dynamic job assignation and efficient line balancing and sequencing. New operator-centered frameworks are appearing to conceptualize the role of people in the 4th Industrial Revolution era. The key role of operators has been identified by numerous authors, coining the term operator 4.0. Industry 4.0's Key Enabling Technologies can be used to support production operators to obtain different benefits. In particular, Virtual and Augmented Reality and wearable devices have attracted great attention. Operators can be supported with assembly instructions, quality control, assembly details prompts or enhanced training programs, which can be provided in a way that is satisfactory for the users. Human operators will need to receive and manage more information than ever before, make decisions and supervise instead of focusing on mechanical work-related activities. Therefore, empowering operators to act more autonomously and supporting them accordingly seems necessary.

4. Discussion

This section outlines the key ideas of the four areas considered in the previous section, organized as answers to the four sets of questions posed in the introduction.

4.1. Assembly & Mass Customisation

The question related to Assembly and Mass customization is: "What are the characteristics and implications of mass customization for assembly operations? "

Mass customization brings increased complexity that needs to be addressed at multiple levels and taking a holistic point of view to ensure that optimizing a subsystem does not negatively affect another subsystem. Assembly complexity reaches outside the boundaries of assembly operations and needs to be considered jointly with supply chain, quality, maintenance and IT/IS. Industry 4.0 digital technologies have a critical role to play in making possible mass customization assembly systems that do not compromise on quality and cost.

4.2. Industry 4.0 & Key Performance Indicators

The set of questions related to Industry 4.0 and KPIs are: "What new Industry 4.0 digital technologies are relevant to assembly operations?", "How to measure the improvement?" and "How to make the most out of them?"

There are many examples of new technologies applied to final assembly—see Table 3: the Internet of Things, big data and digital twins for improving processes and decisions as well as for gathering data and obtaining valuable information; Cyber Physical Systems and Augmented/Virtual Reality for measuring human operator performance and supporting human operators' work; and a mix of technologies to support different aspects that enable mass customization. However, assembly operations are likely to experiment an evolution rather than a revolution by gradually incorporating these technologies. Two key areas will be of particular interest: enhancing the role of people in assembly operations—especially in terms of responsibility and skills; and making possible human–machine hybrid systems capable of efficient low-volume high-variability production.

To evaluate the performance of assembly systems, a KPI system is employed. Standard KPIs need to be adapted in order to include both traditional metrics (e.g., cost, quality, throughput, inventory, lead time, productivity) and new indicators that are specific to the products, operations, stakeholders, business goals and IT-related aspects of the smart factory.

Despite the wealth in the literature about what new technology can do, few relate to methodologies to assess the operational needs and opportunities in final assembly and then finding or developing an Industry 4.0 solution to them.

4.3. Lean Assembly for Industry 4.0

The question related to Lean production is: "Is Lean production the best starting ground for implementing Industry 4.0 assembly operations?"

Lean manufacturing offers an array of tools and techniques to deal with the increasing demand complexity and variability, and which could benefit assembly operations in the context of mass customization. While most authors consider Lean manufacturing as a valid approach for increased complexity of mass customization, others claim that Lean cannot be applied straightforwardly in the Industry 4.0 era. Lean might not be necessarily the best possible starting ground for smart assembly in every situation. However, it clearly has positive synergy with Industry 4.0 because new technologies can enhance Lean assembly, and Lean maturity supports the implementation of new technology. Moreover, both Industry 4.0 and Lean consider that people have a central role to play in assembly operations.

4.4. Assembly Operators in Industry 4.0

The questions related to human operators are: "How would Industry 4.0 affect people in assembly?" and "How to support people transitioning to Assembly 4.0?"

Industry 4.0 is expected to shift the assembly operators' main functions from direct labor activities to managing information and making decisions, supported by technology. A flexible and cross-trained workforce would be key for dealing with changing demand conditions, allowing dynamic job assignation, line balancing and sequencing. Learning factories are a great way to train operators in the new digital manufacturing skills needed for smart factories and to gain a deeper understanding of how new technologies affect them.

5. Conclusions

This article looked at the issue of how Industry 4.0 technologies could improve the flexibility, productivity and quality of assembly operations. To do so, a systematic literature review was carried out, and 239 articles were analyzed. The resulting analysis was structured into four main topics, each one addressing one of the questions posed in the introduction.

It was found that mass customization brings complexity into assembly operations, which need to be looked at from a holistic point of view—joining assembly, supply chain, quality, maintenance and IT. New technologies—such as big data, the Internet of Things, real-time optimization, cloud computing, CPS, Virtual/Augmented Reality, additive manufacturing and digital twins–allow obtaining meaningful information in real time about the assembly operations, making better decisions and supporting human operators in their activities. A combination of conventional and new KPIs to evaluate IT-related aspects of the smart factory will be needed to measure the impact of these technologies. Although it might not necessarily be the best starting point in each and every situation, Lean is definitely a great starting ground for smart factories. Since both Industry 4.0 and Lean consider that people have a critical role to play in assembly operations, frameworks that place human operators at the center of Lean 4.0 have started to appear. This focus will need to be translated into supporting people to acquire the digital manufacturing skills they will need. Learning Factories are great to this end.

The literature analysis also uncovered the relative lack of methodologies for implementing Industry 4.0 technologies in assembly operations to address concrete business goals, which remains an open question. There is also room for developing operator-centered frameworks for Industry 4.0 that are specific to assembly operations in the demand context of mass customization.

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Operator-centred Lean 4.0 framework for flexible assembly lines

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Abstract

This article provides a starting point for developing a methodology to successfully implement Industry 4.0 technology for assembly operations. It presents a novel multi-layer human-centred conceptual model in line with Lean philosophy which identifies the assembly operator functions and relates them to other production departments, identifying how they would be affected by incorporating new digital technologies. The model shows that assembly operators would only be directly supported by hardware digital technologies, while the production support departments would mainly employ Industry 4.0 software technologies. The work presented here paves the way for developing a methodology for implementing Lean Assembly 4.0.

Keywords: Assembly; Lean; Industry 4.0; Human-centred, Operator.

1. Introduction

The term Industry 4.0, initially adopted by a German strategic program [1], is used nowadays to express the relationship between different elements of the current manufacturing sector and the new digital technologies. Recent research on Industry 4.0 tends to focus on the possibilities brought by a certain new digital technology or develops a framework to understand what the effect of would be incorporating such new technologies.

Scarcely explored is the development of implementation methodologies that bridge Industry 4.0 conceptual frameworks with the current state of industrial environments, and the process to successfully deploy new digital technologies that bring the expected returns of investment [2]. Additionally, if the Lean production approach and its techniques are also related to this implementation, the concept of Lean 4.0 could be used as shown in the literature [3].

This article aims to provide a starting point for developing a methodology for successfully implementing Industry 4.0 technology for assembly operations, in line with Lean production principles. To do so, the model presented here links assembly elements and ancillary departments to Industry 4.0 Key Enabling Technologies for assembly operations, considering the operator as the centre of the model, which is coherent with Industry 4.0 principles [4,5], Lean manufacturing [6] and the EU prospects for Industry 5.0 [7].

In section 1.1 changes in demand trends are presented, introducing a particular issue resulting from mass-customisation: high-mix low-volume. Section 1.2 describes the focus shift towards people in both Lean production and Industry 4.0. Section 1.3 introduces the role of new technology to support humans in assembly: Operator 4.0. Section 2 introduces an operator-centred Assembly 4.0 model which identifies which digital technologies have a place in supporting operator functions and interactions in the Industry 4.0 factory. Finally, Section 3 presents the conclusions of the article.

1.1. Demand trends: mass customisation requires flexibility

Although a clear segmentation traditionally existed between mass-produced goods and made-to-order products, the market

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trends have been shifting towards the customisation of mass-produced items [8]. Despite this not being economically sustainable in the past; technological advances have made it possible. Managing the complexity associated with mass customisation remains one of the main challenges for global production networks [9]. In the near future, mass customisation could not only become desirable, but expected of any company wanting to remain competitive. In this context, adaptable, changeable, and decentralised manufacturing networks will possess key competitive advantages [9,10].

Mass customisation leads to a particular production demand problem, high-mix low-volume: a large number of items being demanded, in small amounts each one, and with a variation not depending on seasonal trends, making its forecast difficult and inefficient. To stay competitive in such a context, manufacturing companies will need to become more flexible without compromising their productivity.

Fortunately, several Industry 4.0 digital technologies are expected to prove useful in achieving this as already shown in the literature [11–13].

1.2. Production evolution: Lean 4.0 and focusing on people

New digital technologies have set the landscape for a fourth industrial revolution, conceptualised as Industry 4.0, which describes a vision of increased flexibility and automation; data and information flow across processes, functions, and companies; enhanced quality achieving zero-defect production; leveraging big data, neural networks, machine learning and Artificial Intelligence, among other digital technologies, to maximise efficiency [4].

Lean manufacturing, a generalization of world-leading Toyota Production System, has proven its efficiency in high demand variability, shorter new product development cycles and customer-focused, highly competitive environments [14, 15]. It is therefore a solid starting ground for any manufacturing system evolution seeking to improve productivity and flexibility at the same time. One of the key characteristics that set apart Lean production systems is its respect for people and people's key role in their company's continuous improvement journey [16, 17].

Hence, Lean production needs to be the cornerstone on which Industry 4.0 technologies rely to enhance production. Lean automation is then the synergy between the Lean approach and the new digital technologies – Lean 4.0 [12]. According to Kolberg and Zühlke [18], Computer Integrated Manufacturing (CIM) failed due to the complexity required for the automation technology, while the Lean approach was successful because of its high effectiveness, achieved by reducing complexity and avoiding non-value-added processes.

Although Industry 4.0 solutions to specific Lean production issues may prove useful, either replacing or enhancing existing Lean tools, it is looking at the production system from a holistic perspective where the maximum benefits of disruptive digital technologies could be achieved [3,12].

1.3. Assembly and Operator 4.0

The goal of flexible assembly systems in the Industry 4.0 era, named 'Assembly 4.0' by Cohen and Faccio in [19] –a term that will be used in the present article– is to address the mass customisation demand paradigm. The most relevant key enabling technologies for assembly are –according to [20]– the Internet of Things, Big Data, Real-time optimisation, Cloud computing, Cyber-Physical Systems, Machine Learning, Augmented Reality, Cobots and Additive Manufacturing.

Considering the critical role of assembly line level operators on Lean production systems performance, it is only natural to consider how new digital technologies would enhance the human operator best traits, and help to cover their weaknesses, aiming for a 'human-automation symbiosis' [5]. To analyse this human-technology interaction, it would be useful to start from the operator's perspective to ensure that the implementation of changes does not negatively affect people but supports them [21].

As proposed in this novel work, keeping the operator at the centre is the focus of the methodology approach proposed and described in the following section, where all the interactions between an assembly operator and production activities and its environment have been established and analysed.

2. Operator-centred assembly 4.0 model

Due to the success of Lean production systems and because respecting people is one of its key features, human operators need to be at the centre of any methodology seeking to integrate Industry 4.0 digital technologies for assembly operations.

This model aims to explain, from the point of view of the assembly operator, which of its productive functions would be affected by Industry 4.0 technologies, and how. It also explains how new digital technologies would affect the material and information flow between the operator and the main Departments which support assembly operations, such as Logistics & Planning, Maintenance and Quality Control.

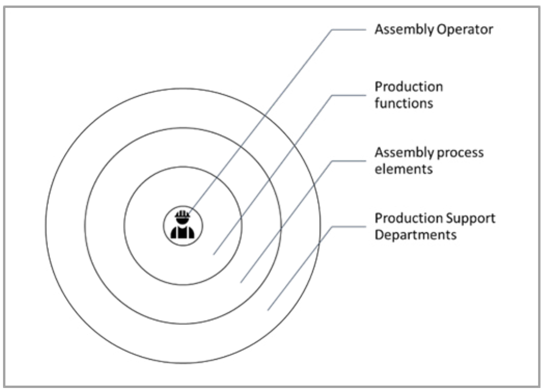

Fig. 1. First stage of the human-centred model of assembly systems

The model proposed consists of two stages. The first stage (see Figure 1) develops three concentric layers: the productive functions carried out by the operator, the elements used to do so, and the Production Support Departments involved with the operator; along with how they interact with the operator (Sections 3.1 – 3.4, respectively). The second stage relates Industry 4.0 digital technologies with its specific point of application from the first stage (Figure 4, Section 2.5).

2.1. Production functions

The first layer considered in the model presented in Figure 1 –the most closely related to the operator– consists of the production functions. Manual assembly operators carry out four main productive functions:

- Assembly (AS): attachment of parts together or to the previously processed unit, including manipulation of the units into and out of the workstation
- Quality Control (QC): building quality in each process step, along with the required tests performed by the operator
- Changeover (CO): adjustments to the workstation, tools, parts, and fixtures to assemble a different product model
- Communication (CM): recording, sending, and receiving data or information.

2.2. Assembly process elements

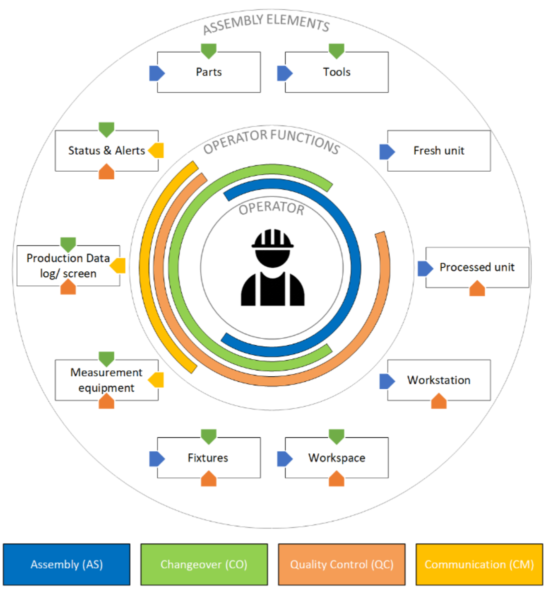

Fig. 2. Assembly operator functions and process elements utilised to perform them

To develop these production functions in 2.1, several assembly process elements are used, which constitute the second layer, as shown in Figure 2:

- Workspace: the actual space in which the assembly task is carried out. Involved in AS, QC and CO.
- Workstation: the physical space where the in-process unit is held while parts are assembled. Involved in AS and QC
- Fresh unit: the next upcoming unit to be processed. Involved in AS
- Processed unit: the previously assembled unit. Involved in AS and QC
- Tools: devices employed to attach parts to the unit. Involved in AS and CO
- Parts: components to be assembled to the in-process unit. Involved in AS and CO
- Status & alert display: devices which function is to inform of the production status and visually or audibly alert of any anomalous situation. Involved in AS, CO and CM
- Production data log/ screen: physical or digital means of tracking the production schedule, recording data, and displaying supporting information. Involved in AS, CO and CM
- Measurement equipment: devices utilised to gauge or test relevant characteristics of the in-process unit. Involved in QC, CO, and CM
- Fixtures: devices employed to hold the unit while performing assembly or QC operations. Involved in AS, QC and CO

2.3. Production Support Departments

Assembly operators are supported by five key departments of the organisation: (i) Assembly: other operators, situated upstream, in parallel or downstream in the process stream; (ii) Production Management: including team leaders and assembly managers, they typically deal with non-conforming situations; (iii) Maintenance: they ensure the tools, fixtures and machines; (iv) Quality: they establish Quality Control policies, calibrate and validate testing equipment; (v) Logistics & Planning: they provide the correct materials and parts at the right time, retrieve empty packaging and schedule production.

2.4. Operator – Supporting Departments interaction

As Figure 3 depicts, operators interact with the supporting departments using a combination of process elements. White arrows indicate material flow, while black arrows indicate data flow.

As shown in Figure 3.a, operators receive fresh units from upstream process steps; and send processed units towards downstream process steps. Information relating non-conformities or upcoming changeovers in shared typically verbally in an informal manner. Formal information about the production status is shared using Status & Alerts process elements, such as Andon lights or display screens. Operators also exchange information formally with Production Management using Production Data logs and screens. Measurement equipment often sends test data to an IT system that stores it and provides Data Analytics.

Operators and Maintenance exchange information via Status & Alerts and Measurement Equipment (see Figure 3.b). Also, Maintenance provides and maintains Tools and Fixtures, in response to the operator’s information regarding its state.

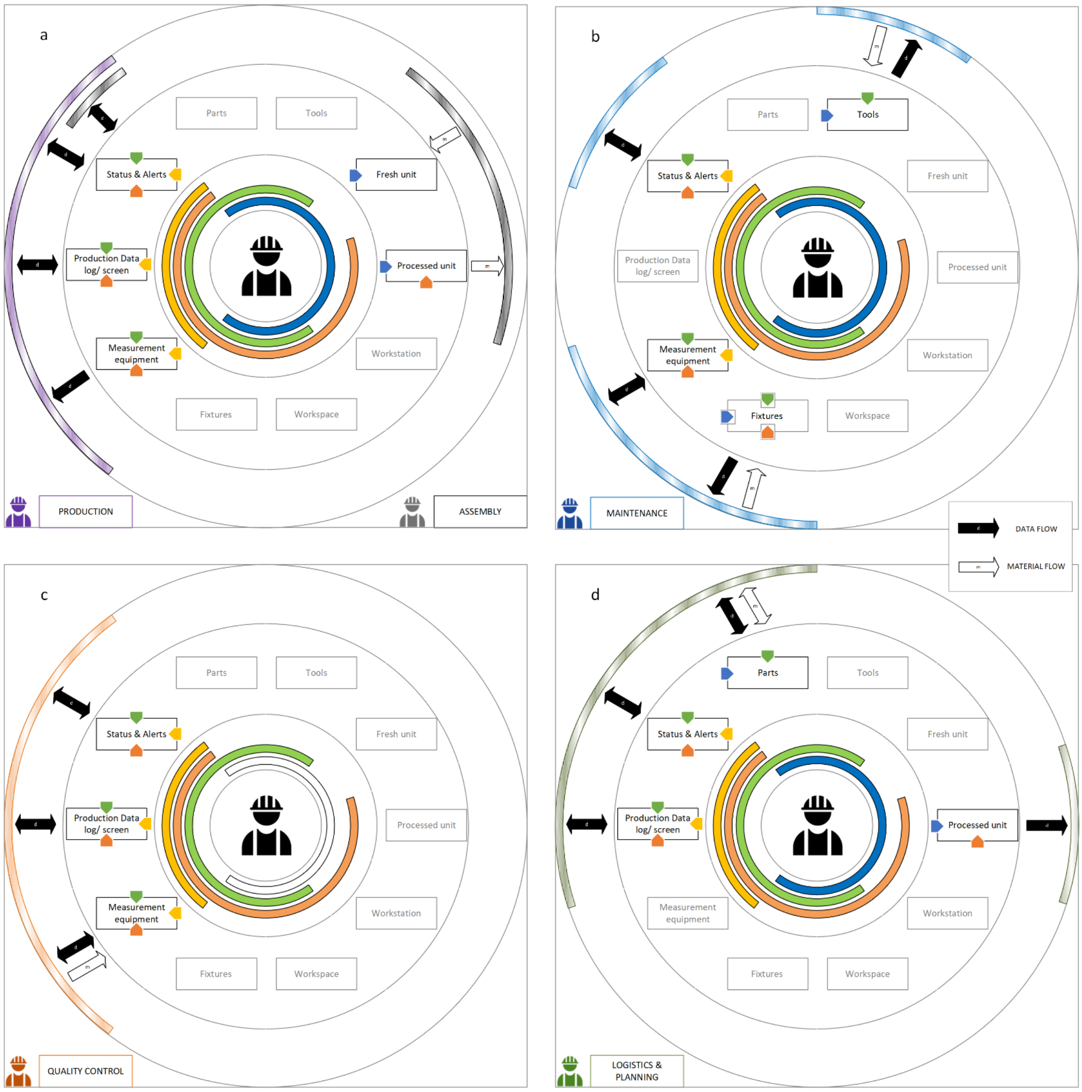

Fig. 3. Operator – Supporting Departments interaction: (a) Production Management & Assembly; (b) Maintenance; (c) Quality Control; (d) Logistics & Planning.

Operators and Quality exchange information via Status & Alerts, Production Data log/screens and Measurement Equipment. Additionally, Quality provides and maintains the Measurement Equipment (see Figure 3.c) that Operators use to perform QC.

Figure 3.d shows that Logistics & Planning provide the operator with parts to be assembled onto the unit, and they retrieve empty packing (material flow) Along with parts or empty boxes, information is transmitted, e.g., when using a Kanban or a twin-bin system. Operators also provide implicit information through successfully processed units, which are a measure of production output. They also exchange information via Status & Alerts, Production Data log/screens. A key piece of information provided by Logistics & Planning is the production schedule, specifying batch sizes and changeovers, which can impact the operator's productivity.

2.5. Industry 4.0 enabling technologies for Assembly

To connect the proposed model with Industry 4.0, nine enabling technologies have been considered as particularly relevant for Assembly Systems [20]. Six of them are software technologies (Internet of Things, Big Data, Real-time optimisation, Cloud computing, Cyber-Physical Systems, Machine Learning), and three are hardware technologies (Augmented Reality, Cobots, Additive Manufacturing).

While the assembly operator's main functions are not expected to change due to the availability of new digital technologies, the way these functions are developed will need to evolve to enjoy its benefits. The relationship with Supporting Departments also shows potential for improvement. Lastly, Supporting Departments are expected to integrate new digital technologies to obtain increased benefits. Although the latter technologies will not be employed directly by the assembly operator, they will affect his work. Therefore, the implementation of new digital technologies at all levels needs to consider the impact on assembly workers to be successful. Figure 4 depicts which Industry 4.0 digital technologies would be beneficial at each layer of the model.

Three key technologies could be used by operators to carry out its functions, as shown in Figure 4: Augmented Reality or Mixed Reality (AR/ MR) [22], collaborative robots (cobots) [23] and Cyber-Physical Systems (CPS) [24].

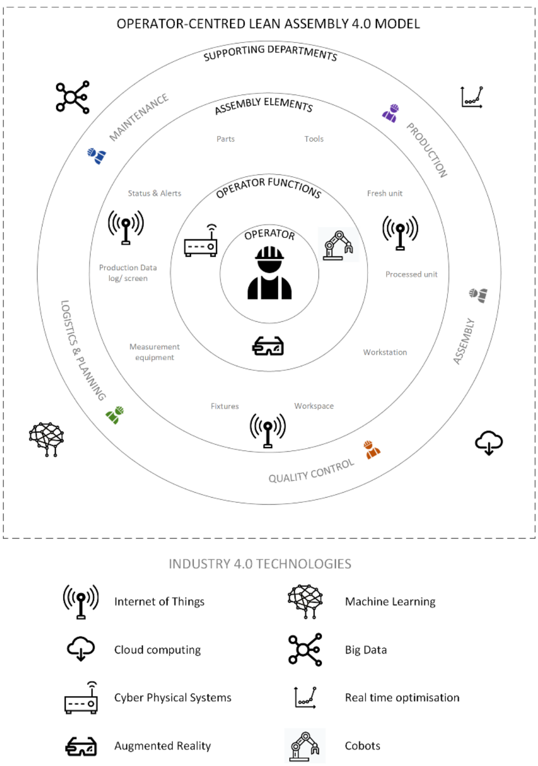

Fig. 4. Industry 4.0 technologies to be employed at each layer of the Human-Centred Assembly 4.0 model.

Aiming to support the assembly operator main functions (see section 2.1), Augmented Reality/Mixed Reality could be widely used: enhancing the operator cognitive ability while performing a changeover –which would need to be streamlined and mastered to achieve mass customisation, and supporting a zero-defect assembly and Quality Control, as introduced in [25]. Cobots are to be used not only for assembly tasks, but also to flexibly present the unit-in-process in the best orientation and position for an ergonomic human operation or inspection; even contributing to quick changeovers. Finally, CPS would gather and receive data, reducing the cognitive load of the operator while ensuring the quality and reliability of the data captured and sent in the workstation.

Regarding the Operator's interaction with the Supporting Departments, the Internet of Things could be employed to communicate the vast amount of data required to and from them. Industrial IoT can be combined with Augmented Reality technology to provide real-time maintenance assistance remotely to assembly operators, reducing the equipment downtime in the event of a breakdown, in a similar fashion to systems used to facilitate engineering knowledge to maintenance technicians [26]. Augmented Reality can also provide enhanced tools for communication between Operators and the Supporting Departments, enabling collaborative assembly process design, analogously to the product process design presented in [27].

Finally, Supporting Departments could benefit from using Cloud computing, Big Data, Machine Learning and Real-Time optimisation, which would affect assembly operations positively in the long term. These software technologies would influence greatly the bottom-line results, but these will not be directly perceived by assembly operators since they will not be in close contact with such technologies. For example, Big Data and Digital Twins for Logistics & Planning would help optimise in-factory stock levels while ensuring reliable feeding of components to assembly cells, but this optimisation is hardly seen from the operator point of view.

2.6. Discussion

The multi-layer model presented previously explains an Assembly operator functions, the tools utilised for such end, and its interactions with the Production Support Departments, from a human-centric perspective. It then establishes which of the previous layers could be affected by Industry 4.0 digital technologies, and which technologies would enhance each particular function or relationship.

As Figure 4 shows, there is a clear differentiation between the technologies used by the operator to perform its functions (hardware technologies), and the technologies used by the Production Support Departments – not directly by the operators (software technologies).

Although this model does not reveal how to successfully implement Industry 4.0, its necessary prerequisites, or the expected order of magnitude of the benefits it would bring; it does identify which technologies could be used to support each one of the operator's duties, making it a solid starting point for future research.

This model is builds on top of the foundations laid by solid previous research: the central role of people for Industry 4.0 [4, 5] and for Lean assembly systems [6], as well as the EU prospects for Industry 5.0 [7]. However, it has not been validated experimentally to date.

To determine the prerequisites and the potential benefits of implementing Industry 4.0 technologies according to the framework presented here, validation in an industrial real study case is deemed necessary.

3. Conclusion

Aiming to achieve mass customisation, production systems in the Industry 4.0 era will need to support the Assembly operators when and as needed. The importance of people in Manufacturing systems was already a key point in successful Lean production systems, and Industry 4.0 technologies need to embrace this perception.

A human-centred model was presented, explaining, from the point of view of the assembly operator, which of its productive functions would be affected by Industry 4.0 technologies, and how so. One clear differentiation appears between the technologies used by the operator to perform its functions (hardware technologies), and the technologies used by the Production Support Departments – not directly by the operators (software technologies).

This model does not aim to be exhaustive for all kinds of manual assembly process, but it does include everything related to most manual high-mix low-volume processes, and it is open enough to allow additions from specific processes to adapt it where necessary.

Future lines of work would employ this model to develop an explicit methodology for implementing Industry 4.0 digital technologies aiming to support the human Assembly operator and evaluating the potential gains in industrial contexts, thus providing empirical validation in real industrial study cases. This would correlate Assembly 4.0 implementation to key operational KPIs (e.g., productivity, on-time delivery, first time yield) when analysing a particular case study, whose boundary conditions and approach could be properly established by the model.

Acknowledgements

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B.3 Conference Article: IOP Conf. Series (2021)

Labour productivity in mixed-model manual assembly 4.0

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Abstract: Manual assembly lines productivity is threatened by the increased complexity brought by mass customisation demand trends. Industry 4.0 offers potential solutions to address this situation, but the methodology to implement it is still a subject of study. As a preliminary step, this article aims to identify the dominant factors affecting the Key Performance Indicators of mixed-model assembly lines. To do so, parametric and discrete-events simulation models were developed, and Design of Experiments techniques were used. The results show that the key drivers for assembly line performance are number of work stations and batch size, and that increasing the work content ratio of the products assembled does not interact negatively with other factors. The results presented here pave the way for developing Industry 4.0 projects that address specifically the most relevant factors that affect assembly lines performance.

Keywords: Assembly operations, Productivity, Mixed-model assembly, Industry 4.0.

1. Introduction

The demand trends in the recent decades are the mass customisation of products or even the mass personalisation of goods [1]. The growing number of available options for both final consumers and industrial customers requires focusing on increasing the flexibility of assembly systems while maintaining high productivity levels [2,3]. The advances in new digital technologies that could bring forward a 4th industrial revolution were conceptualised under the tag 'Industry 4.0' by a German strategic programme, and are namely: Big Data and Analytics, Autonomous robots, Simulation, Horizontal and vertical system integration, the industrial Internet of Things, Cybersecurity, The Cloud, Additive Manufacturing and Augmented Reality [4]. Some of these technologies arrive with the promise of new opportunities for assembly systems design and operations, allowing them to fulfil the latest market requirements [5]. In particular, manual assembly lines and cells show potential for improvement when facing the complexity associated with producing a large number of products – or variants of similar products [6].

Despite new technologies have been developed and their potential benefits have been outlined, implementation methodologies are still a hot topic [7]. The focus in this article is therefore to identify the dominant factors affecting the mixed-model manual assembly lines Key Performance Indicators (KPIs) – such as labour productivity, line capacity and lead time – as a preliminary step in order to ensure that Industry 4.0 implementation projects address the right areas, ensuring that the operational business goals are achieved.

From the initial analysis of the situation, a list of relevant factors was put together along with the operational KPIs that measure the system performance: productivity, lead time and line capacity. Design of Experiments (DoE) is used to find out which factors and their interactions have the greatest effects on the KPIs, and therefore are more important for the system performance. DoE allowed to prepare two phases of analysis: Screening (I) and Interactions (II).

Aiming at exploring how to use a commercial software for mixed-model assembly line simulation, an initial parametric model was used as reference, followed by a second model which uses a commercial simulation package (Methodology, Section 2). In both cases, parametric – MATLAB® – and simulation–FlexSim®– software tools are employed to calculate the Output KPIs from different values of Input factors (Results, Section 3). The results of the two models are compared and conclusions are extracted, along with a final discussion of the limitations and future outlines of this study (Discussion and Conclusions, Section 4).

Data from a real case of study is used to validate the results of the analysis. The input data for the simulation is based on the situation of a manufacturer of white-goods located in northern Spain. The company is evaluating merging two mixed-model manual assembly lines into one, which would increase the complexity of managing the line, but could bring operational performance benefits if done correctly – especially in terms of labour productivity, without compromising operators working conditions or product quality. Industry 4.0 would be the enabler of such complexity-dealing transformation, but it is deemed necessary to ensure that the investment only targets the critical elements that would allow improving the desired KPIs.

2. Methodology

This section presents declares the input variables and output KPIs used, describes the two analysis models developed and their verification, and the Design of Experiments to be used in the next section. Figure 1 summarises all of this information and schematizes the followed methodology considered in this study.

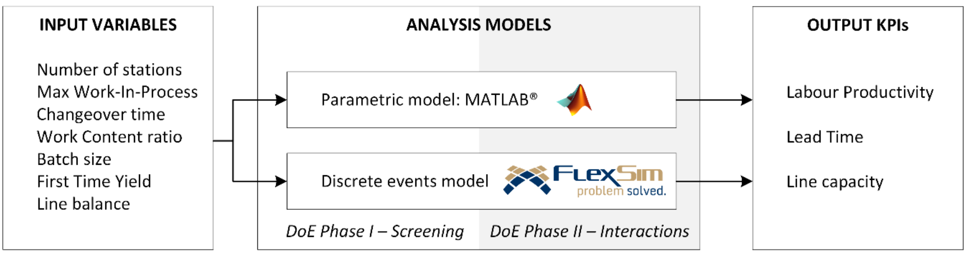

Figure 1. Diagram of Input factors and Output KPIs used for the analysis of mixed-model manual assembly lines.

2.1.1. Variables considered

Aiming to explore the effect of various relevant factors on mixed-model manual assembly lines, the following seven were selected for this analysis: Number of workstations, maximum Work-in-Process units in-between stations (WIP), Changeover Time, Work Content Ratio between different models, Batch size, First Time Yield (FTY) and Line Balance. Factors related to internal logistics, lack of Quality and Overall Equipment Effectiveness (OEE) of assembly equipment were not considered in this study in order to keep the models simple, and they will be included in future research. The KPIs of interest are three:

- Labour productivity (*Prod*, %): ratio of operator value added time over the total time employed.
- Lead Time (hours): time to assemble a complete batch of product.
- Line Capacity (*Capacity*, units/hour): average output of the assembly line per unit of time.

Table 1 includes the input and output variables with the abbreviations used in this article, as well as the base values from the industrial case study. The work content ratio used is the result of dividing the maximum work content by the minimum work content used in a given scenario.

Table 1. Input variables and output KPIs used in models.

Type	Description	Notation	Case study base values
Input	Number of Stations	$N_{stations}$	4 stations
	Max Work-in-Process	*WIP*	1 unit
	Station changeover time	t_{co}	480 s
	Line balance	*Bal*	99%
	First Time Yield	*FTY*	95%
	Batch size	$N_{batch\ size}$	48 units
	Number of models built in the line	*M*	4 models
	Work Content	*WC*	600 … 1400 s
	Work Content ratio	WC_{ratio}	1 - 2
	Cycle time	*CT*	~ 150 … 350 s
Output	Productivity	*Prod*	~ 90%
	Lead time	*Lead Time*	~ 5 h
	Line capacity	*Capacity*	~ 10 units/h

2.1.2. Models for Analysis

In this work, two models have been used. A simple initial model was developed in order to establish a baseline to which compare later and more complex models. Such model needed to be versatile and scalable, so the parametric tool MATLAB® was used. Aiming at exploring the potential gains of using commercial software for mixed-model assembly line simulation, the free version of the software FlexSim® was chosen.

2.1.3. Parametric model: MATLAB®. A parametric model was employed to calculate the KPI values as a function of the input factors. The software package MATLAB® (R2019b, The MathWorks Inc., Natick, MA, United States) was chosen to implement an algorithm relating the variables presented before.

Firstly, for each model M, the cycle time is calculated based on the work content, number of stations and line balance - equation (1).

$$CT = \frac{WC}{N_{stations} \cdot Bal} \tag{1}$$

For each model M, the time employed to build correct and defective units are calculated using equation (2) and equation (3), which use the batch size, number of stations, cycle time and first time yield.

$$t_{correct} = N_{batch\ size} \cdot N_{stations} \cdot CT \tag{2}$$

$$t_{defects} = N_{batch\ size} \cdot N_{stations} \cdot CT \cdot (1 - FTY) \tag{3}$$

For each model M, the time used to build the batch is given by the time to build correct and defective units, as shown in equation (4). The time to complete the batch is calculated by adding the time spent on changeover and the time to build the batch, as shown in equation (5).

$$t_{build} = t_{correct} + t_{defects} \tag{4}$$

$$t_{complete\ batch} = t_{build} + t_{co\ total} \tag{5}$$

For each model M, the time recovered (spent assembling correct products) is found using the work content and the batch size, as shown in equation (6).

$$t_{recovered} = WC \cdot N_{batch\ size} \tag{6}$$

The KPIs can be calculated using equations (7-9). Productivity is determined by the sum of time recovered and the sum of time to complete all batches of products. Lead time is calculated as the maximum time to complete a batch, and Line capacity is worked out from batch size, number of models, number of stations and the sum of time to complete all batches of products.

$$Productivity = \frac{\sum_{i=0}^{M} t_{recovered,i}}{\sum_{i=0}^{M} t_{complete\ batch,i}} \tag{7}$$

$$Lead\ time = max\{t_{complete\ batch}\}_M \tag{8}$$

$$Capacity = \frac{N_{batch\_size} \cdot M \cdot N_{stations} \cdot 3600}{\sum_{i=0}^{M} t_{complete\ batch,i}} \tag{9}$$

2.1.4. Discrete events model: FlexSim®. FlexSim® is a 3D discrete events simulation software for modelling and analysis of manufacturing, operations and logistics systems.

The simulation results were contrasted against the output from the parametric model described previously in subsection 2.2.1. The free licensing version of the simulation software led to several limitations: (1) a maximum of 30 simulation elements, e.g. stations or buffers; (2) the maximum process flow activities is 35; (3) changeover activities do not start until the new batch of units arrives to a workstation, causing unrealistic additional idle time; (4) the number of different random seeds are limited to just one, preventing any variability analysis.

Due to the aforementioned limitations, two different simulation configurations were used: Configuration A and B. Configuration A maintains the FTY at 100% - disregarding the effects of poor Quality – but in return, allows to overcome the unrealistic changeover limitation mentioned previously. This configuration does not consider WIP as a factor neither, since the only source of variability (poor Quality) is neglected. Configuration B considers FTY: two Quality Control checkpoints are implemented in this configuration to evaluate whether a unit has defects, and if this is the case, the unit is sent back to the previous assembly station for in-line reworks, as shown in figure 2.

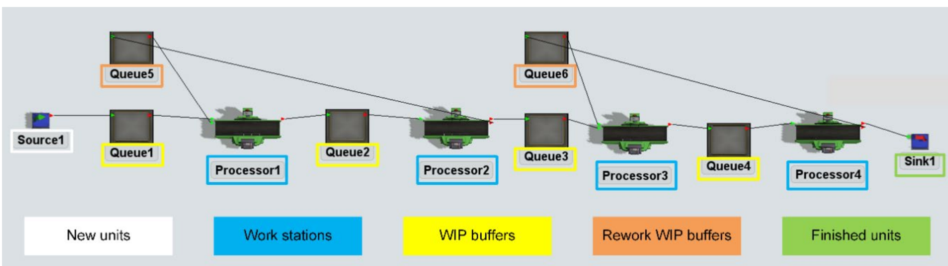

Figure 2. FlexSim® simulation model used for Configuration B.

2.1.5. Verification of the models

In order to compare the two models described in subsections 2.2.1 (parametric) and 2.2.2 (discrete events simulation), a base scenario made of the 7 input factors was used for each configuration (A and B). From this base scenarios, 24 additional scenarios were generated by changing just one factor at a time (-1 and +1 levels), 10 scenarios for Configuration A and 14 for Configuration B. The results of two KPIs (Productivity and Lead Time) were registered to compare the performance of the two models. Both models obtain comparable results for productivity and lead time: the average difference is 2.39%, the standard deviation is 4.58% and the maximum difference is 19.45%, corresponding to the particular case of a large number of workstations, which causes abnormally high idle times during changeovers in the FlexSim® model Configuration B.

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2.1.6. Design of Experiments

Considering the relatively high number of factors (k = 7 factors, as show in figure 1), the analysis of their interactions and effects on the selected KPIs would require a great number of experiment runs (n^k): $2^7 = 128$ experiments for two levels ($n = 2$) per factor, or $3^7 = 2{,}187$ experiments for three levels ($n = 3$) per factor. Instead, the analysis was structured in two phases [8]: screening (I) to identify most relevant factors; and analysis of interactions (II) – summarised in table 2.

The values used for each level (-1), (0) and (+1) were chosen by modifying the industry case study values and stretching them slightly beyond what the company considers achievable in the short term, in order to include minimum and maximum range values for each factor.

Table 2. Design of Experiments employing two phases due to the large number of factors involved.

Phase	Goal	Experiment Design	No. of factors (k)	No. of levels (n)	No. of runs
I – Screening	Identify most relevant factors	Fractional Factorial	7	2	16
II – Interactions	Analyse influence and interactions	Full Factorial	3	3	27

2.1.7. Phase I – Screening. The Screening phase employs a Fractional Factorial design for 7 factors with 2 levels per factor. Table 3 shows the values used for each factor.

Table 3. Values used for each factor in the DoE phase I – Screening: Fractional Factorial.

Factor	Code	Values	
		-1	+1
Batch Size	A	12 units	48 units
Number of Stations	B	3	8
Max Work-In-Process	C	0	1
Line Balance	D	95%	99%
Station changeover time	E	300 s	600 s
First Time Yield	F	95%	97%
Work Content ratio	G	2	3

2.1.8. Phase II – Analysis of Interactions. The Analysis phase consist of a Full Factorial design of 3 factors with 3 levels per factor. The three factors chosen for this phase resulted from analysing the results from the Screening phase. Table 4 shows the values used for each factor in phase II - Analysis. The other 4 factors that were not studied in this phase remained fixed at their 0 values.

Table 4. Values used for each factor in the DoE phase II – Interactions: Full Factorial.

Factor	Code	Values		
		-1	0	+1
Batch Size	A	12 units	24 units	48 units
Number of Stations	B	2	4	8
Work Content ratio	G	1	2	4
Max Work-In-Process	*Fixed*	-	1	-
Line Balance	*Fixed*	-	95%	-
Station Changeover time	*Fixed*	-	480 s	-
First Time Yield	*Fixed*	-	95%	-

3. Results

The methodology described in the previous section allowed to obtain the following results for each

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phase of the study.

3.1.1. Phase I – Screening. The experiment results of the design described in table 3 calculated using the MATLAB model described in Section 2.2 are shown in figure 3.

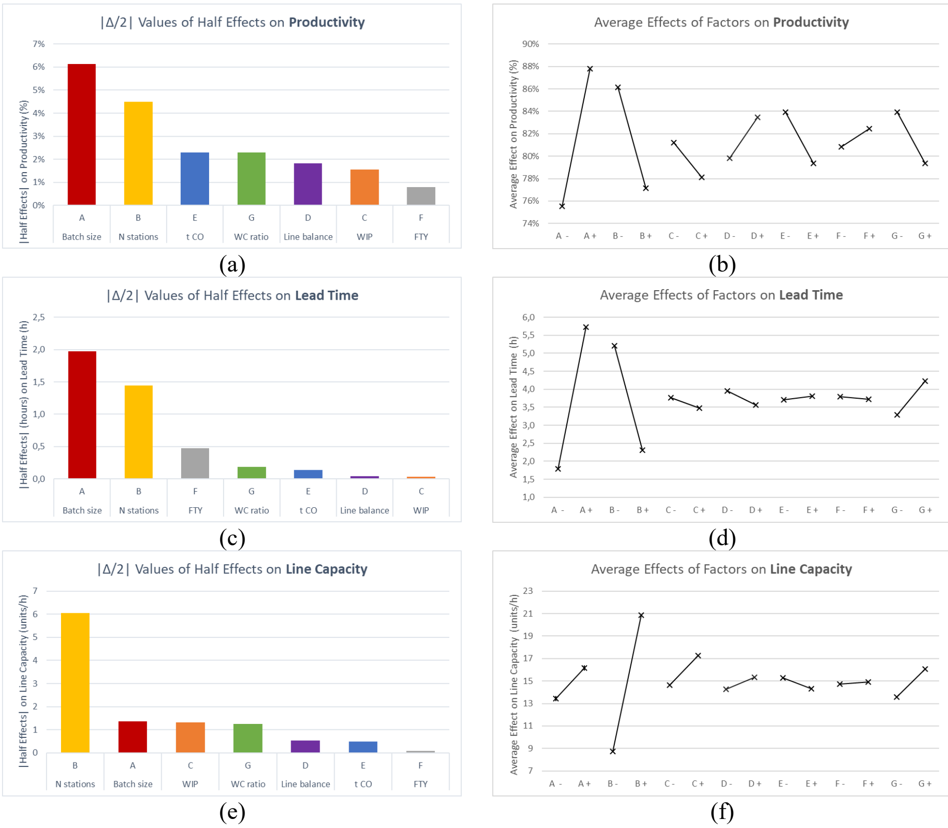

Figure 3. Left: bar charts for values of half-effects of Input factors on **(a)** Productivity, **(c)** Lead Time and **(e)** Line Capacity in a Fractional Factorial experimental design. Right: average effects of input factors on **(b)** Productivity, **(d)** Lead Time and **(f)** Line Capacity in a Fractional Factorial experimental design.

From the results shown in figure 3, it can be inferred that the two most relevant factors are the Number of Stations (which affects all three KPIs) and the Batch size, which affects Productivity and Lead time.

3.1.2. Phase II – Analysis of interactions. In this phase the focus is the interaction between the most influential factors, namely Number of Stations and Batch size. Since one of the initial goals of the study was to assess the viability of merging two manual assembly lines into one, which would increase the number of models being made and therefore increasing the Work Content ratio of the newly formed assembly line, a third factor – WC_{ratio} – was introduced at this stage of the analysis.

The results of the DoE described in table 4 calculated using the MATLAB model described in Section 2.2 — are shown in figure 4. The parametric model was employed because it had been developed

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specifically to analyse these interactions.

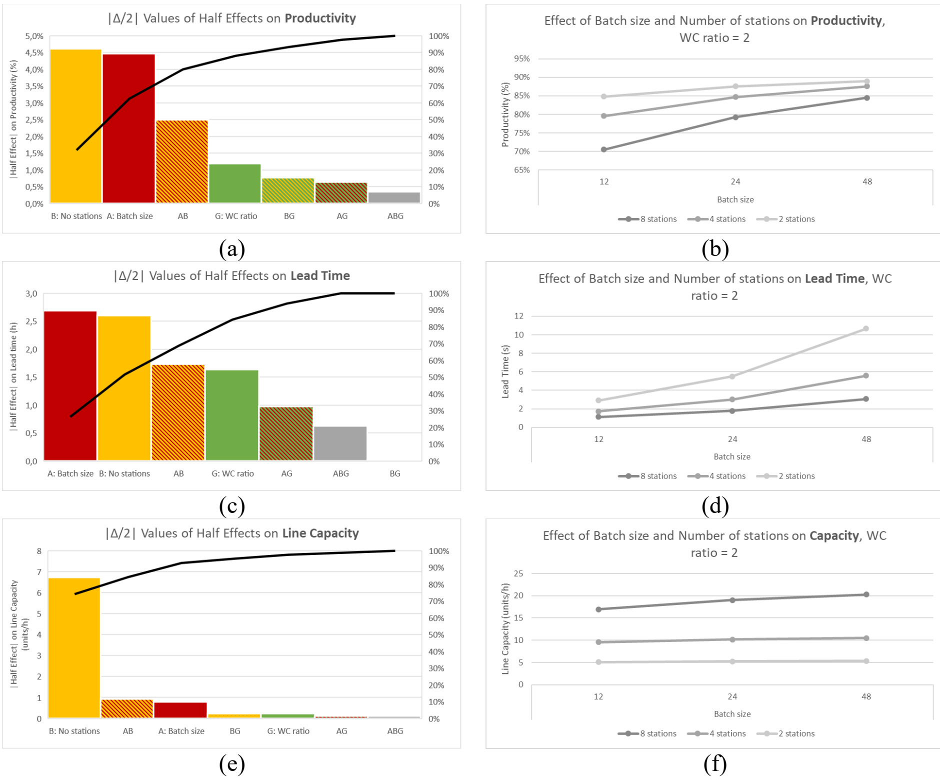

Figure 4. Pareto charts for values of half-effects of Number of Stations, Batch size and Work Content ratio on **(a)** Productivity, **(c)** Lead Time and **(e)** Line Capacity in a Full Factorial experimental design. Average effects of Number of Stations, Batch size and Work Content ratio on **(b)** Productivity, **(d)** Lead Time and **(f)** Line Capacity in a Full Factorial experimental design.

The results presented in figure 4(a-c) show that although the interaction of factors A (Number of stations) and B (Batch size) is relevant for assembly line Productivity and Lead time, it is secondary to the separate effects of any of the two factors.

4. Discussion and conclusions

The results presented in Section 3, obtained following the methodology described in Section 2 allow to reveal the most impactful factors affecting the performance of manual assembly lines in terms of Productivity, Lead time and Line Capacity. Two models were developed, which results are comparable: the average difference is 2.39%, the standard deviation is 4.58% and the maximum difference is 19.45%.

It was found that the two most critical factors are the Number of stations and the Batch size. It is important to note that both factors have opposing effects on two of the KPIs – i.e. the increase of Productivity and reduction of Lead time cannot be optimised simultaneously by changing these two factors alone.

The great importance of the Number of stations is partially explained by the assumption that any additional station needs a changeover time of a similar order of magnitude to that of the existing stations, which may not always be the case. In consequence, the only way of maintaining a high labour productivity when increasing the number of stations (to merge two assembly lines into one or in order to reduce the Lead time) relies on decreasing the changeover time per station to ensure that the total changeover time incurred remains constant or decreases.

The results presented in this article show that an increase in product variety – represented by the variable Work Content ratio – does not interact negatively with any of the two key factors, which suggests that merging two manual assembly lines into one would not suffer from additional Productivity losses. The potential impact of this finding for mixed-model assembly lines lies on the assumption that the stations changeover times would not significantly increase as a result of introducing additional models.

In order to maximise the return of investment of any Industry 4.0 solution, they should be aimed at the most influential factors identified before: (1) to address the productivity loss due to the increase in Number of stations required to increase line Capacity and reduce Lead time, collaborative robots could be integrated in the line. Alternatively, (2) to ensure that the total changeover time remains constant despite an increase in the number of stations, cognitive support to complex or infrequent changeover operations could be provided by Augmented or Mixed Reality.

Future research in this field could focus on enhancing the analysis models by using discrete events software actually incorporating variability, and expanding the model to incorporate the internal logistics constraints due to an increased number of different models in smaller batch sizes. Another potential research route would be scanning the current state of the art Industry 4.0 technologies to find compatible matches for the identified areas as preliminary step before implementing Industry 4.0 technologies in the assembly lines.

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Models to evaluate the performance of high-mix low-volume manual or semi-automatic assembly lines

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Abstract

To address mass customisation demand trends, assembly line flexibility and productivity are critical. Industry 4.0 technologies could support assembly operations to this end. However, clear implementation methodologies are still lacking. This article presents two models for evaluating the most relevant Key Performance Indicators (KPIs) of manual or semi-automatic assembly lines, allowing to maximise the return of investment of any digital technology addition. MATLAB® was used to implement a parametric model, and FlexSim® was employed to build a discrete event simulation model. The models were validated using data from two industrial study cases from a global white goods manufacturer.

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Keywords: assembly lines; productivity; mathematical modeling; simulation; key performance indicators

1. Introduction

The current demand trends have been shifting from mass production to mass customisation since the end of the 20th Century, and even further towards mass personalisation [1]. As a result, an increasing number of industries are facing an atomised demand, which could be denoted as 'high-mix low-volume' [2]: a great number of products -and product variants- are in demand in small quantities each. Moreover, the expected shortening of production lead times and reduction of inventory levels put additional pressure on businesses to streamline their processes to compete in the global marketplace [3]. In this context, assembly operations need to be flexible while achieving high productivity, which confronts the traditional dichotomy between manual (highly flexible, not quite productive) and automated assembly (highly productive, not quite flexible).

Since the term Industry 4.0 was introduced by the German government in 2011 [4], it is used to refer to an array of disruptive digital technologies which are expected to bring forward the fourth industrial revolution [5]. Some of these Key Enabling Technologies have been shortlisted to be most impactful on the performance of assembly operations [6] -namely the Internet of Things, big data, real-time optimisation, cloud computing, cyber physical systems, machine learning, augmented reality, collaborative robots and additive manufacturing - by enabling the main characteristics of Assembly 4.0 [7]: late customisation, assembly control systems, aided assembly, intelligent storage management, self-configured workstation layout and product and process traceability.

Nonetheless, questions arise following these analysis, such as the following: Which of the features brought by Industry 4.0 technologies would have the most positive impact on the operational and business goals of assembly operations? What would be the best method of implementing these changes to achieve the maximum return on investment? Previous work [8] established that it is clear that Lean Manufacturing has a critical role to play in this transformation due to the similarities and synergies with Industry 4.0, and that there is a lack of methodologies for implementing the new digital technologies of Industry 4.0 to address concrete business goals.

The main approaches to evaluate alternative scenarios and the impact of design variables on the assembly operations Key Performance Measures (KPIs) include mathematical modelling, simulation, and other techniques such as Petri nets or artificial intelligence, among others [9]. Mathematical models that consider setup times usually do so in a simplified way, as either sequence-independent or sequence-dependent times, al-

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though some authors have considered the importance of product change dependent inter-task times [10–12]. On the other hand, Discrete Event Simulation inherently considers the assembly stations waiting and blocking times induced by finite buffers and cycle time differences between distinct products. However, simulation models are more complex and require larger time investments to be built. A simplified mathematical formulation with a focus on changeover losses would allow a quick initial assessment of operational KPIs in a high-mix low-volume demand environment where small batch sizes and frequent changeovers are major drivers of the assembly system's performance.

The goal of this article is to introduce two simple yet comprehensive models that can be used to evaluate the performance of high-mix low-volume manual or semi-automatic assembly lines, allowing to gain a deep understanding of the implications of different parameters on the line KPIs.

The present article is structured as follows: Section 2 - Methodology - presents the two models developed and the real case from an industrial partner used to validate them. Section 3 includes the Results and analysis of the aforementioned validation cases, and Section 4 present the Discussion and Conclusion of the article.

2. Methodology

Two assembly line performance evaluation models were developed, using MATLAB® and FlexSim® respectively. They consider a series of input parameters that are processed to produce the line KPIs as output.

This section is comprised of five Subsections. The general framework employed is presented in Subsection 2.1; Subsection 2.2 introduces a parametric model implemented using MATLAB®; Subsection 2.3 describes a discrete events simulation model implemented using FlexSim®; Subsection 2.4 compares the advantages and disadvantages of both models, and Subsection 2.5 describes the industrial case used to validate both models against real data from the manufacturing plant of a research business partner.

2.1. Framework

The models used for evaluating the performance of multi-product assembly lines consider a single linear series of workstations, with one or two quality control (QC) stations integrated with them, as depicted by Fig 1.

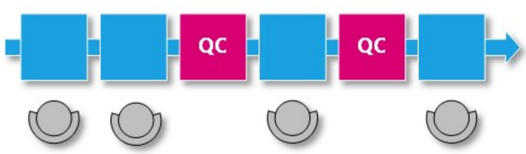

Fig. 1: Multi-product assembly line with quality control stations.

The model is defined by a set of input variables -divided into design, fixed and disturbance parameters- which produce a set of KPIs as a result, as shown in Table 1.

Table 1: Input variables and KPIs considered in the models.

Type	Variable	Notation
Design parameters	No. workstations	$N_{stations}$
	No. of products	$N_{products}$
	Batch size	$N_{batchsize}$
	Max. WIP between stations	WIP
Fixed parameters	Cycle time	T_{cycle}
	Work Content	WC
	Line balance	Bal
	Setup time	T_{setup}
	First Time Yield	FTY
	Work Content Ratio	WC_{ratio}
Disturbances	Variability of process time	$Var_{process}$
	Variability of setup time	Var_{setup}
KPIs	Output	$Output$
	Throughput	$Throughput$
	Lead time	$LeadTime$
	Labour productivity	$Prod_{labour}$
	Line productivity	$Prod_{line}$

The models consider a manual assembly line capable of producing multiple products. After finishing a batch of units of a certain product, the workstations need to change over to the next product, by carrying out a setup. The setup time depends both on the outgoing and the incoming products.

2.2. Parametric Model

Firstly, a parametric model was developed to obtain the desired KPIs. It calculates the productive time from the available time minus the changeover time. It then works out the actual productive time of each batch of products by subtracting the time lost due to line imbalance, minor stops and defects, as illustrated conceptually in Fig. 2.

The software MATLAB® (2019b, The MarhWorks Inc., Natick MA, United States) was used to implement the algorithm described below. MATLAB® was chosen because of its user friendliness since the algorithm presented here does not require the use of an optimised programming language (e.g. C/C++) to complete the calculations in a very short time.

In the first place, the cycle time of each batch of products in the sequence is calculated using Equation 1.

$$T_{cycle} = \frac{WC}{N_{stations} \cdot Bal} \tag{1}$$

For each batch, the time lost on changeover depends on the previous product (p_{out}) and the product of the current batch (p_{in}). Equations 2-7 describe its calculation. For each workstation i, the start and finish times of the previous batch are calculated using Equations 2-4.

$$t_{finish\_out,1} = T_{cycle}(P_{out}) \tag{2}$$

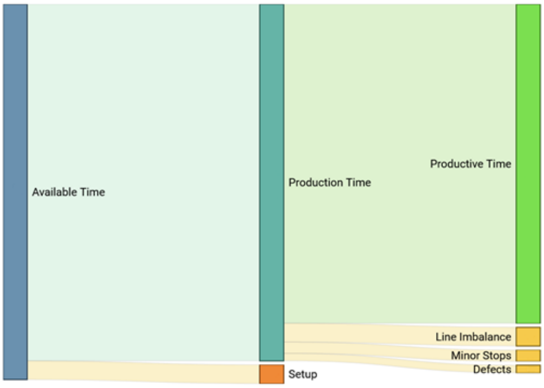

Fig. 2: Productivity losses in multi-product assembly lines considered in the parametric model.

$$t_{start\_out,i} = t_{finish\_out,i-1} \tag{3}$$

$$t_{finish\_out,i} = t_{start\_out,i} + T_{cycle}(p_{out}) \tag{4}$$

For each workstation i, the finishing time of the changeover is given by Equation 5.

$$t_{finish\_co,i} = t_{finish\_out,i} + T_{setup}(p_{out}, p_{in}) \tag{5}$$

For each workstation i, the start and finish times of the first unit of the incoming product are calculated using Equations 6-7.

$$t_{start\_in,i} = \max\left\{t_{finish\_co,i}\ ;\ t_{finish\_in,i-1}\right\} \tag{6}$$

$$t_{finish\_in,i} = t_{start\_in,i} + T_{cycle}(p_{in}) \tag{7}$$

In case $T_{cycle}(out) \geq T_{cycle}(in)$, the time lost on each station i is given by Equations 8-9.

$$\begin{aligned} &i \in \{1, N_{stations} - 1\}: T_{lost,i} = \\ &\max\left\{0\ ;\ t_{finish\_co,i+1} - t_{finish\_in,i} - WIP \cdot T_{cycle}(in)\right\} \end{aligned} \tag{8}$$

$$i = N_{stations}: T_{lost,i} = T_{setup}(p_{out}, p_{in}) \tag{9}$$

In case $T_{cycle}(out) < T_{cycle}(in)$, the time lost on each station i is given by Equations 10-11.

$$i = 1: T_{lost,i} = T_{setup}(p_{out}, p_{in}) \tag{10}$$

$$i \in \{2, N_{stations}\}: T_{lost,i} = t_{finish\_in,i-1} - t_{finish\_out,i} \tag{11}$$

Having calculated the time lost due to the changeover for each station, the total time lost is obtained with Equation 12.

$$T_{lost\_co} = \max\{T_{lost,i}\} \cdot N_{stations} \tag{12}$$

For each batch of products, a number of units have defects, depending on the product First Time Yield -see Equation 13-14.

$$N_{defects} = \lceil N_{batchsize} \cdot FTY \rceil \tag{13}$$

$$N_{conforming} = N_{batchsize} - N_{defects} \tag{14}$$

Equations 15-16 calculate the time employed to assemble defective and conforming units.

$$T_{defects} = N_{defects} \cdot N_{stations} \cdot T_{cycle} \tag{15}$$

$$T_{conforming} = N_{conforming} \cdot N_{stations} \cdot T_{cycle} \tag{16}$$

Therefore, the time needed to complete each batch of products is given by Equation 17.

$$T_{complete\ batch} = T_{conforming} + T_{defects} + T_{lost\_co} \tag{17}$$

Finally, for each batch, the recovered -productive- time is calculated using Equation 18.

$$T_{recovered} = WC \cdot N_{conforming} \tag{18}$$

The KPIs shown in Table 1 can be now calculated considering the full sequence of *NB* batches using Equations 19-23.

$$Output = \sum_{j=1}^{NB} N_{conforming,j} \tag{19}$$

$$Throughput = \frac{\sum_{j=1}^{NB} N_{conforming,j}}{\sum_{j=1}^{NB} T_{complete\_batch,j}} \tag{20}$$

$$LeadTime_{batch} = \max\left\{T_{complete\_batch}\right\}_{NB} \tag{21}$$

$$Throughput = \frac{\sum_{j=1}^{NB} T_{recovered,j}}{\sum_{j=1}^{NB} T_{complete\_batch,j}} \tag{22}$$

$$Prod_{line} = \frac{\sum_{j=1}^{NB} N_{conforming,j}}{N_{stations} \cdot \sum_{j=1}^{NB} T_{complete\_batch,j}} \tag{23}$$

2.3. Discrete Events Simulation Model

The second model employed to assess the performance of manual multi-product assembly lines uses Discrete Events Simulation (DES) implemented on the software FlexSim® (2021.0, FlexSim Software Products, Inc.). FlexSim® was chosen because it allows to recreate the changeover logic matching the mathematical model within the additional complexity of a DES model, as well as defining the KPIs to match the mathematical formulation ones.

The model developed, illustrated in Fig. 3, consists of 3 or 4 workstations with one operator each, organized in a sequential multi product assembly line. Each operator, using a workstation (coloured orange in Figure 3), processes the corresponding unit for a random period of time which follows a lognormal distribution governed by the mean -cycle time- and the standard deviation -expressed by the process variability parameter as a percentage of the mean: e.g. a process variability parameter value of 0.20 equals to the standard deviation being 20% of the cycle time. Once the unit has been processed, it can be placed in the WIP buffers between stations (coloured dark grey in Fig. 3) before being processed on the next station. The two quality control stations (coloured blue in Fig. 3) either reject or accept passing units. The probabilities of each result are governed by the First Time Yield (FTY) parameter. The changeover logic works so that once an operator has finished processing the last unit of a batch, it must set up its workstation for a duration given by a lognormal distribution of mean equal to the setup time parameter (which depends on the outgoing and incoming products) and standard deviation given by the setup variability parameter, similarly to the process variability. The numeric values of both parameters were estimated from real data gathered by the industrial partner, using the maximum likelihood estimators [13].

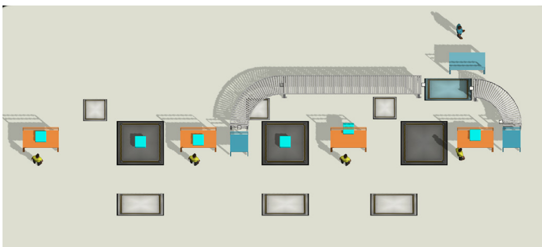

Fig. 3: Discrete Events Simulation model of Line 1.

2.4. Models features comparison

The two models described in Subsections 2.2 –parametric– and 2.3 –discrete events simulation– aim to calculate the same KPIs using the same input parameters. However, despite sharing some features, they differ in several aspects that make them behave differently under certain circumstances.

The first and most notable difference is that the parametric model does not consider the variability of process and setup times, while the DES model employs lognormal distributions for these times, governed by two variability parameters which express the ratio between the Standard Deviation and the Mean of the lognormal distribution.

The second difference is related to Quality: the parametric model considers an end-of-line quality control, while the DES model features two in-line quality control stations (one located in the middle and the other one located at the end of the assembly line).

The third difference is that the parametric model assumes the assembly stations are synchronous: they start and finish processing products in sync, which might not be the case in industrial environments. The DES model, on the other hand, does not force assembly stations synchronisation, and therefore reflects waiting or blocked times due to the effect of line imbalance, defects and variability.

The last point is changeovers. Both models take into account the workstations blocked and waiting times originated during a product changeover by the cycle time difference between outgoing and incoming products. However, the DES model also accounts for the combined effects of variability, quality issues and out-of-sync, which deteriorate productivity even more than these factors separately.

Having established the key differences, the next Subsection describes the cases used for verifying and validating both models.

2.5. Verification and Validation – an industrial real case

To validate the models described previously, they were employed on two scenarios from a global white goods manufacturer site located in the North of Spain, which will be named here as ‘Company B’. The scenarios consist of two different manual assembly lines (‘Line 1’ and ‘Line 2’) that have not been automated yet due to the substantial number of product variants they produce: around 50 references grouped into 6-8 families on each line. Each family of references has been considered as a single product because the Work Content and assembly sequence of the references within a product family are identical. The low order quantities of each reference and relatively high setup times relative to cycle times, make this case an example of high-mix low-volume demand.

The input data used for both scenarios are summarised in Table 2.

Table 2: Input data from an industrial real case for validating the models.

Variable	Units	Line 1	Line 2
No. workstations		4	3
No. product families		6	8
Batch size (avg.)	*units*	66	64
No. of batches		27	33
Total units ordered	*units*	1680	2116
Max. WIP between stations	*units*	1	1
Cycle time (avg.)	*min*	5.42	4.65
Work Content (avg.)	*min*	21.68	13.95
Line balance (avg.)	%	99.2	98.7
Setup time (avg.)	*min*	6.85	8.35
First Time Yield	%	99.2	99.8
Work Content ratio		1.33	1.41
Variability of process time	%	20	20
Variability of setup time	%	20	20

Both scenarios were calculated using the parametric and the DES models, and the results were compared against the actual KPIs obtained from the data gathered by the industrial partner.

To verify the models against each other (considering that the parametric model does not include variability of process and setup time), the DES model was used for each scenario with the Variability parameters set to zero.

The following Section 3 shows the results of the validation and verification against the industrial case described above.

3. Results

This section includes the KPIs resulting from simulating the two scenarios described in Subsection 2.5, named 'Line A' and 'Line B'. Figure 4 shows the resulting KPIs: Output, Throughput, Labour Productivity and Line Productivity.

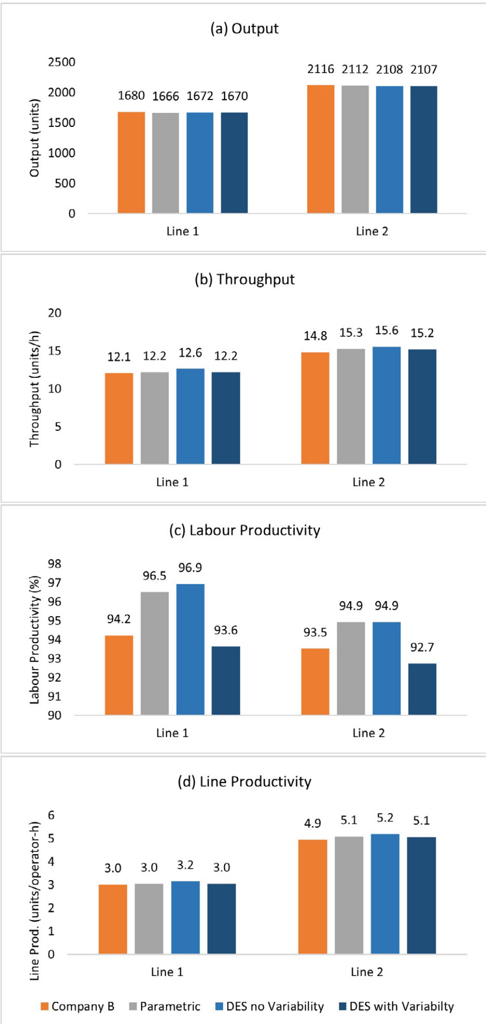

Fig. 4: Results of simulation using a parametric and Discrete events simulation model: (a) Output, (b) Throughput, (c) Labour productivity and (d) Line productivity.

Figure 5 below shows the relative error of each of the models when compared with the real industry data (column Company B) for each of the results from Figure 4.

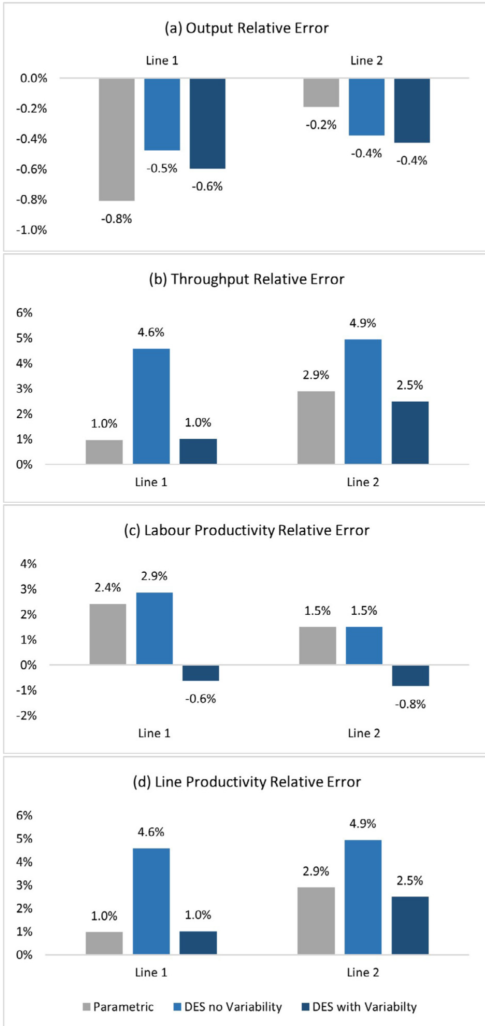

Fig. 5: Relative error of KPI results using a parametric and Discrete events simulation model: (a) Output, (b) Throughput, (c) Labour productivity and (d) Line productivity.

The relative errors between real industry data and the KPIs obtained using the models presented in this article are in all cases below 1% for Output, 5% for Throughput and Line Productivity, and 3% for Labour Productivity, which allows considering both models validated. In summary, the average relative error is 1.63% and the maximum relative error is 4.9%.

Moreover, the differences between the results of the parametric model and the DES model with no variability are consistent, not differing more than 3.5% in any KPI. This allows considering that the models are also verified.

It should be noted that both models overestimate Throughput and Productivity since they do not consider any constraints outside of the assembly line such as machine breakdowns, components quality or supply problems.

4. Discussion and Conclusion

The results shown in Section 3 allowed validating both models presented in Section 2 by comparison against real industry data which considers two scenarios. The results also allowed to verify the parametric model against the Discrete Events Simulation model with no variability, since their results differ less than 3.5% for any KPI.

The results show that both models underestimate Output and overestimate Throughput, Labour Productivity and Line Productivity. The mean relative error is 1.63% and the max relative error is 4.9%, which means that both models are reliable for high-mix low-volume demand scenarios similar to the ones considered here.

The sources of the errors could be (1) the simplifications that the models entail, such as the lack of process variability in the parametric model or the consideration of non-conforming units as scrap; (2) that constraints external to the assembly line take place: defective components, internal logistics service problems, or quality control equipment breakdown, among others.

Regarding the models limitations, the parametric model presents great ease of use and speed of calculations, so that it can be used as a preliminary ‘enhanced calculator’. Nevertheless, it lacks the complexity to take into account the combined effects of quality issues, variability, changeovers and minor stoppages. In consequence, it can be a useful, yet optimistic tool. The DES model, on the other hand, is already a powerful tool for examining theoretical situations, evaluating assembly line design alternatives, and answering specific questions within a given scenario. Moreover, the DES model can be easily expanded to include automated stations –e.g. collaborative robots [14]– or to take into account the effect of operator cognitive support technologies such as Augmented Reality [15].

Future lines of work would employ the parametric model presented here as a preliminary analysis tool, followed by a DES model expanded from the one described here, but adjusted to evaluate the impact of different digital technologies which would affect certain variables: for example, while employing collaborative robots would increase the line productivity, augmented reality for operator support would reduce the process time variability. Such a model would allow understanding how to maximise the effect of investments to achieve the desired operational or business goals. Finally, it remains an open topic comparing the estimated improvements to be obtained implementing Industry 4.0 digital technologies with the actual results in an industrial environment.

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B.5 Research Article: Processes (2023)

processes

Article

Parallel Walking-Worker Flexible Assembly Lines for High-Mix Low-Volume Demand

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Abstract: Demand trends towards mass customization drive the need for increasingly productive and flexible assembly operations. Walking-worker assembly lines can present advantages over fixed-worker systems. This article presents a multiproduct parallel walking-worker assembly line with shared automated stations, and evaluates its operational performance compared to semiautomated and manual fixed-worker lines. Simulation models were used to set up increasingly challenging scenarios based on an industrial case study. The results revealed that semiautomated parallel walking-worker lines could achieve greater productivity (+30%) than fixed-worker lines under high-mix low-volume demand conditions.

Keywords: assembly lines; walking worker; multimodel; parallel stations; high-mix low-volume; simulation; flexible manufacturing systems

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1. Introduction

Mass customization and personalization demand trends drive production operations towards high product variability, smaller batch sizes, reduced inventory, and shorter lead times [1,2]. As a consequence, an increasing number of industries need to assemble a large number of similar products in small quantities each, which is called high-mix low-volume demand [1]. To succeed under such circumstances, productivity and flexibility are required at the same time, contrary to the existing dichotomy [3]. Reconfigurable assembly systems, first, followed by the cyberphysical or smart assembly systems of Industry 4.0 and the future adaptive cognitive assembly systems, aim to address it [4–6].

Current manual or semiautomatic serial assembly lines (ALs) present productivity limitations due to the inherent losses of frequent changeovers and the difficulties of balancing a large mix of different products on top of the constraints imposed by automated stations. Moreover, these conventional fixed-worker assembly lines (FWALs) are not highly responsive to demand volume changes since the number of operators cannot be modified without compromising line balance. Unbalanced assembly lines are an open issue [7], and mass personalization demand trends only aggravate the situation [8,9]. To address these problems, walking-worker assembly lines (WWALs) present benefits compared to FWALs. WWALs are line configurations in which operators move along the line, moving the products with them, so that each worker performs all assembly tasks on each station until the product is complete, and then starts over again. The benefits of WWALs versus FWALs are [10,11]: increased flexibility in production level by an easy modification of the number of workers, reduction of WIP inventory, and—most importantly—avoiding the negative effects of workstations imbalance, as long as the number of assembly stations exceeds the number of workers involved. However, WWALs may suffer from productivity losses when in-process waiting times occur because of the stations ahead of an operator being blocked by the other workers [12]. The inclusion of machines within the WWAL can cause additional bottlenecks [13], which can counter the benefits of process automation.

Another take on this problem is parallel assembly lines [14,15], which increase the reliability and flexibility of the lines, allow better balancing due to superior cycle times and lower number of operators and, therefore, increased productivity at the expense of larger equipment investments and space required. Combining both approaches—WWALs and parallel assembly lines—can provide important benefits in contexts of high-mix low-volume demand.

This article presents a multiproduct parallel walking-worker assembly line (PWWAL) with shared automated stations and evaluates its expected operational performance compared to semiautomated fixed-worker serial assembly lines when dealing with high-mix low-volume demand. The WWAL working logic was chosen due to its advantages over FWAL when dealing with stations balancing under high-mix demand conditions, despite the WWAL's intrinsic inefficiencies due to worker displacements. Additionally, parallel line configurations could prove useful when product changeovers are frequent due to smaller batch sizes, since the number of stations could be reduced, decreasing the changeover losses, which depend heavily on the number of stations when there are large cycle time differences between the models produced by the line.

Discrete events simulation (DES) models were used to perform this study due to their ease of implementation and the possibility to incorporate stochastic parameters [16–19]. FlexSim® was employed to develop the simulation models. An industrial study case from a global white-goods manufacturer was used to build the simulation models, provide input data, and allow validation using historical data. In this industrial case, which is common across many industries, the company goal is to improve the productivity of several manual assembly lines that had been optimized over the years. To achieve this goal, the lines could be merged and upgraded by introducing some automated stations to reduce the manual work content. However, productivity would increase at the expense of flexibility, since line balance deteriorates when increasing product variety. Thus, the motivation for this work is to gain insights into the productivity vs. flexibility trade-off of parallel walking-worker assembly lines in comparison to traditional fixed-worker lines.

The article is structured as follows: Section 1.1 offers a literature review on walking-worker assembly lines. Section 2 includes a description of the line configurations modeled, the models' inputs and outputs, and the simulation scenarios employed. Sections 3 and 4 present the results and discussion of the simulation scenarios, respectively.

1.1. Literature Review

Over the last 25 years, WWALs have been studied using analytical and simulation models, focusing on different aspects of this line configuration performance, and considering different combinations of factors. Table 1 summarizes the key aspects of the articles selected for this section. It is worth mentioning that none of the articles consider sequence-dependent setup times or automated stations in their WWAL models. Walking times are often considered negligible when the processing times are significantly larger.

Little had been written on walking (moving) worker assembly lines before D.P. Bischak's article in 1996 [10], which points out several advantages of unbuffered WW modules: flexibility in the production level; reduction in work-in-process inventories; avoiding the negative effects of AL imbalances produced by the frequent introduction of new products; and improving reported worker morale. On the other hand, the importance of operator cross-training increases as it becomes an enabler of this AL configuration. It was established that WWALs can improve system responsiveness in terms of throughput, and that they work well for unbalanced processing times. The simulation results show a reduced importance of WIP buffers for WWALs versus FWALs, that low variability systems require no WIP buffers, and that buffers would only increase lead time.

Table 1. Key aspects of selected research articles on walking-worker assembly lines (WWALs).

Author	Layout	Target	Method	Product	Setup	Walking Time	Automated Stations	Variability
Bischak [10]	U-cell	Max throughput	Simulation	Single-model	No	Negligible	No	Yes
Wang [11]	Linear	Max throughput & line productivity	Simulation	Single-model	No	Yes		
Lassalle [12]	Linear	In-process waiting time	Simulation	Mixed-model	No	Negligible	No	Yes
Wang [13]	Linear	In-process waiting time	Simulation & mathematical modeling	Single-model	No	Negligible	No	Simulation only
Al-Zuheri [20]	U-cell	Line productivity & er-gonomic perf.	Mathematical modeling	Single-model	No	Yes	No	Yes
Cevikcan [21]	Segmented rabbit-chase	Line balancing	Mathematical modeling	Mixed-model	No	Yes	No	No
Bortolini [22]	U-cell	Max line productivity	Simulation	Mixed-model	No	Negligible	No	Yes

Wang and Owen [11] presented a comparison between WWALs and FWALs in terms of line efficiency. Their DES model considered processing times variation and fixed walking times between stations in a linear single-model AL. It was concluded that the WWALs could provide higher output and efficiency than FWALs, and that it has greater tolerance to variations in processing time.

In a later article, Lassalle [12] looked into the details of the in-process operator waiting times of linear WWALs. Simulation was employed, considering negligible walking times and product changeovers. It was found that the productivity loss caused by in-process waiting times is predictable and adjustable, with the workers-to-workstations ratio being its main driver.

In their 2009 article, Wang et al. [13] studied linear WWALs using both simulation and mathematical modeling. They considered a mixed-model AL where workers may have unequal performance, leading to dynamic worker blockages due to the operational rule of not allowing faster operators to overtake slower ones.

Al-Zuheri et al.[20] looked into WWALs to understand their worker productivity and ergonomics performance. Mathematical modeling was used on a U-cell layout, considering process time variability, worker skill level, and walking speed, among other variables. It was found that increasing the workers' walking speed did not improve the productivity of the AL.

Cevikcan [21] presented a line balancing optimization methodology for multimodel WWALs based on a mathematical model. Bortolini [22] proposed a mixed-model sequencing algorithm for unpaced unbuffered WWALs on U-cell layouts, aiming to optimize line productivity.

In addition, a recent article from Hashemi-Petroodi et al. [23] presented a literature review of different assembly and manufacturing workforce reconfiguration strategies, including walking-worker assembly lines. The authors found that (1) little has been published on multimodel walking-worker assembly lines, and (2) that an open field of research is the consideration of different workforce reconfiguration strategies, including walking-worker assembly lines, in a human–robot interaction environment.

Our article aims to help close this gap by looking into multimodel WWALs, which include manual and automated workstations.

2. Materials and Methods

In this article, the performance of the proposed parallel walking-worker assembly line configurations is compared to two fixed-worker assembly line configurations. DES models were used to understand the behavior of the line configuration alternatives by simulating different scenarios. DES was chosen because it presents important advantages over mathematical modeling when stochastic elements are the main drivers of the system under study [19]. In the AL configurations considered here, the random nature of processing times is combined with random product arrival times to the automated stations. The simulation tool employed was FlexSim® (2022.0, FlexSim Software Products, Inc.). The scenarios are defined by a subset of the input parameters, design parameters. Fixed parameters are common to all models for all scenarios, as well as the disturbances, which govern stochastic features of the models. The performance of the AL configurations is evaluated using several key performance indicators (KPIs), as shown in Figure 1.

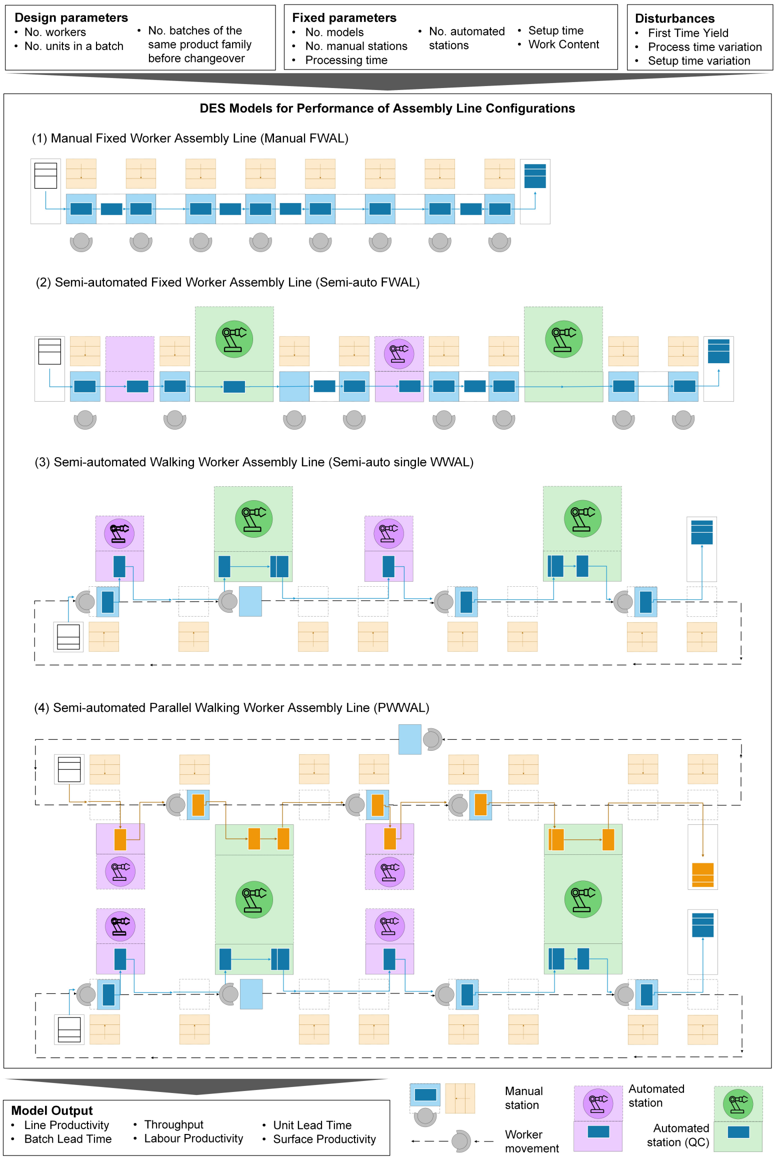

Figure 1. DES models for flexible assembly line configurations: (**1**) manual fixed-worker line (manual FWAL); (**2**) semiautomatic fixed-worker line (semiauto FWAL); (**3**) semiautomatic single walking

worker line (semiauto single WWAL); (**4**) parallel walking-worker assembly line (PWWAL). Design parameters are changed when analyzing the performance of assembly line configurations. Fixed parameters are based on industrial study case data. Variability of quality, manual assembly, and setup times are considered disturbances. Model output includes relevant KPIs for evaluation.

2.1. Assumptions

Figure 1 depicts the models employed in this study. All models feature the following general assumptions, following Boysen's classification [24]:

- The production systems are unpaced, buffered assembly lines.
- The number of workstations is constant, and they can only process one unit at a time. For the parallel line configuration, the number of stations refers to the number on each of the two lines.
- The model mix is known, and demand continues for the whole simulation horizon.
- They are multimodel assembly lines: they produce different models of products in batches. Setup is necessary before a batch of different products can be assembled, and it is performed by the operators as soon as possible, i.e., when the last unit of the previous batch has been processed. Setup time depends on the sequence of products, and it is lower when subsequent models are of the same product family.
- No component shortages: components being assembled onto the product are always available at the stations.
- The product sequence is governed by the parameter B_{CO}, which indicates the number of batches of the same family that are produced until a product family changeover occurs (which takes longer than a same-family model changeover).
- Processing and setup times are modeled stochastically using a lognormal distribution, which is governed by the average process/setup times and by a variability coefficient.
- Processing and setup times consist of smaller tasks, which are sufficiently small so that the line balance is not affected by a change in the number of stations.
- When converting manual work content (WC_m) into automated (WC_{auto}), WC_m can be reduced equally from all stations.
- WC_m transformed into WC_{auto} becomes 20% larger due to the inferior assembly speed of the automated stations compared to well-trained human operators.
- Two automated stations perform in-line quality control (QC) in the middle and at the end of the assembly process. Defective units are reworked out of line, which may cause idle time to downstream operators.

Figure 1(1),(2) depict manual and semiautomated FWALs, which feature the following specific assumptions:

- Fixed workers: the operators are assigned to workstations and they do not leave them.
- Serial layout: the stations form a line, and the work-in-process products travel along them sequentially.
- The line balance depends on the number of operators.
- The manual FWAL features manual stations only, while the semiautomated FWAL includes manual and automated stations.
- Workstation buffers have a maximum capacity of one product.

Figure 1(3) shows the semiautomated walking-worker single assembly line, and Figure 1(4) shows the proposed parallel walking-worker assembly line. In these line configurations presented here, operators walk along the line and pick the components to assemble for the in-process product on a mobile trolley, while automated stations process units (Figure 2a). When arriving at the automated stations, the operators leave their current product in the in buffer and take a processed product from the out buffer of the automated station (Figure 2b). The operators then resume their path (Figure 2c). When a product is finished, it is placed in the finished products buffer, and then the operator walks back to the starting point to resume production.

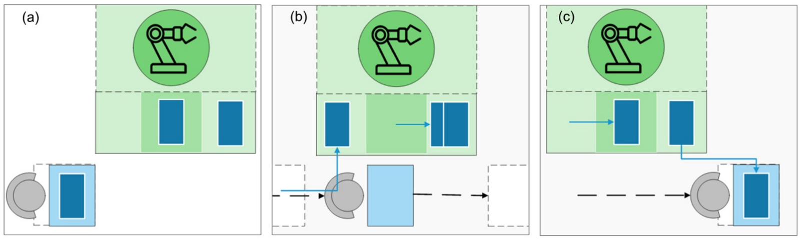

Figure 2. Operator–automated station interaction in semiautomated walking-worker assembly line. (**a**) Operator processes unit in a manual station. (**b**) Operator leaves unit on the automated station in buffer. (**c**) Operator takes ready unit from the automated station out buffer and moves to the next manual station to continue assembly.

Thus, both WWAL configurations were modeled under the following specific assumptions:

- The production system includes manual 'stations', which conform to one or two lines, and automated stations, some of which are shared by both lines for PWWAL.
- Despite the assembly being made on mobile trollies, it is the spaces by the picking shelves that are modeled as stations.
- There is a certain number (W) of operators working on the line, with a maximum equal to the number of stations.
- Operators move downstream, cannot overtake other operators, and can wait by a station in case it is not available when they arrive.
- The traveling time of the operators from one station to the next one is simulated considering a constant speed of 1 m/s.
- Automation stations in and out buffers' maximum capacity is one unit.
- Shared automated stations process products following an FIFO rule (first in, first out), and can only place processed units in the out buffer corresponding to the line of origin of the product.

The main objective of the analysis is to maximize line productivity, defined as the number of conforming units produced per operator-hour. In particular, the industry study case sets a line productivity target increase of +25% compared to the initial situation (manual FWAL). Minimizing production lead time is also considered important, but less so than line productivity maximization. The ability to modify throughput with ease is desirable as well. Consequently, a set of three 'main KPIs' (key performance indicators) was composed of line productivity, batch lead time, and throughput. A secondary set of three KPIs was used to understand what drives the main performance measures as well as find potential drawbacks. The 'secondary KPIs' are labor productivity, unit lead time, and surface productivity. Increasing labor productivity and surface productivity and minimizing unit lead time is also desirable if possible.

2.2. Notation

The following notations are introduced:

Design parameters:

W	Number of workers (index w).
Q	Number of units in a batch.
B_{CO}	Number of batches of the same product family before changeover.

Fixed parameters:

M	Number of models (index m).
K	Number of manual workstations (index k).
J	Number of automated workstations (index j).
T_p	Processing time.

T_s Setup time.
WC Work content (i.e., total process time).

Disturbances:

FTY First time yield.
CV_p Process time coefficient of variation: $CV_p = \sigma_{Tp} / \mu_{Tp}$.
CV_s Setup time coefficient of variation: $CV_s = \sigma_{Ts} / \mu_{Ts}$.

Key performance indicators:

P_{Line} Line productivity (units/operator-h): production rate of conforming units per operator.
LT_B Batch lead time (min): average time for a batch of units to be finished from the moment the last unit of the previous batch is finished.
Th Throughput (units/h): production rate of conforming units.
P_{Labor} Labor productivity (%): percentage of time that operators spend processing units. Setup and walking times are not considered productive.
LT_U Unit lead time (min): average time for a unit to be finished from the moment it starts being assembled.
P_S Surface productivity (units/operator-h-m^2): production rate of conforming units per operator and surface unit.

2.3. Input Data

The DES models employed data corresponding to the industrial case study. The parameter values are based on the industrial case data, as indicated in Table 2. The assembly operations considered in this article deal with three families of similar products. Although all product families share technological principles, core functionalities, and are subjected to the same QC tests, their dimensions, materials, and other secondary features are not the same. Batch sequencing is performed by grouping products of the same family together, which leads to the B_{CO} design parameter.

Table 2 includes the current state values for the design parameters, which define what are considered standard demand conditions. It also shows the fixed parameters and disturbances included in the models. They remain unchanged for all assembly line configurations on all demand scenarios.

Table 2. Design parameters, fixed parameters, and disturbances considered in the models.

Parameter	Units	Min	Max	Current State
W	Workers	2	10	8
Q	Units	12	48	48
B_{CO}	Batches	1	3	3
M	Models			3
K	Stations			8 (FWAL), 16 (PWWAL)
J	Stations			4
T_p	s			See Tables 3 and 4
T_s	s			See Table 5
WC	s			See Table 3
FTY	%			99
CV_p	%			15
CV_s	%			15

Processing times depend on the model (index m). The average values of manual processing times—for stations $k \in \{1, \ldots, 8\}$, along with the manual, automated, and walking work contents—are found in Table 3.

Note that, based on WC_m for manual FWAL, the automation of ca. 23% of the WC_m means to increase that WC by 20%, under the assumption that well-trained manual operators can assemble faster than a collaborative robot. It was deemed realistic to assume that both FWAL and WWAL process and setup times would have a similar distribution in terms of mean and variability values. It was also assumed that process times can be atomized because the individual (indivisible) tasks considered in the industrial case take, on average, between 7 and 20 s, which is significantly lower than the assembly stations process times (cf. Table 3).

Table 3. Manual processing times and work content input data.

Model, m	$T_{p_m}^{max}$ **(s)**	$T_{p_m}^{min}$ **(s)**	WC_m **(s)**	WC_{auto} **(s)**	WC_{walk} **(s)**	WC_{total} **(s)**
Manual FWAL						
1	158	146	1179	0	0	1179
2	129	119	962	0	0	962
3	100	92	745	0	0	745
Semiauto FWAL						
1	122	112	908	325	0	1233
2	99	92	740	266	0	1006
3	77	71	572	207	0	779
Semiauto PWWAL						
1	122	112	908	325	33	1266
2	99	92	740	266	33	1039
3	77	71	572	207	33	812

The average values of automated processing times for stations $j \in \{1, \ldots, 4\}$ are found in Table 5. In theory, none of the automated stations is the AL bottleneck. However, the processing times variability and the incoming units simultaneity calls for additional capacity. In the industrial study case presented here, automated stations $j = 1$ and $j = 3$ are duplicated (cf. Figure 1(3),(4)) because they are not QC stations, which reduces the investment requirements.

Table 4. Automated processing times input data.

	$T_{p_{m,j}}$ **(s)**			
Model, m	$j = 1$	$j = 2$	$j = 3$	$j = 4$
1	31	89	105	100
2	28	76	85	77
3	25	53	65	54

The first and second manual stations include tooling and fixtures that require lengthier changeovers than the rest, which consist of picking stations only. Moreover, the T_s base value is also altered depending on the preceding and subsequent model being produced. Table 5 shows the setup time average values. Automated stations do not require any setup time as it has been estimated to be of similar magnitude to same-product setup, therefore being included in the processing time.

Table 5. Setup time input data.

	T_s **(s)**	
Station	**Product Family Change**	**Same Product Family**
$k \in \{1, 2\}$	480	360
$k \in \{3, \ldots, 8\}$	48	36

The production sequence depends on the B_{CO} design parameter, as shown in Table 6. The sequence is repeated until the end of the simulation time. For semiauto PWWAL, model

1 (m_1) and model 3 (m_3) batches are assigned to one of the parallel lines, and model 2 (m_2) batches are assigned to the other one. In consequence, PWWALs benefit from performing fewer product family changeovers.

Table 6. Production sequence input data.

B_{CO}	Sequence (Batches of Q Units)									
1	m_1	m_2	m_3	⥁						
2	m_1	m_1	m_2	m_2	m_3	m_3	⥁			
3	m_1	m_1	m_1	m_2	m_2	m_2	m_3	m_3	m_3	⥁

The DES models consider the inherent variability of manual assembly processes by using a lognormal distribution for process and setup times, based on the recommendations by Banks and Chwif [25]. The mean (μ) for this distribution is the process standard assembly time for each—different for each product family—and the standard deviation (σ) is found as a percentage of the mean given by the parameters CV_p and CV_s. The values for these parameters were estimated from historical data from the industrial partner existing manual assembly lines, and found to be in the range of 15–20% for the assembly lines considered in this study case. To minimize the uncertainty of the results due to the stochastic nature of processing and setup times, each simulation scenario was run 20 times.

To calculate P_S, the surface requirements for each assembly line configuration were measured—manual AL configuration—or estimated from the study case preliminary line designs, resulting in the surface requirements shown in Table 7. Note that the greater WWAL lengths, compared to semiautomated FWAL, are due to the increased WIP and operator buffers.

Table 7. Shopfloor surface requirements for different assembly line configurations.

Configuration	Depth (m)	Length (m)	Shopfloor Surface (m^2)
Manual FWAL	4	16	64
Semiautomated FWAL	4	23	92
Single WWAL	5	33	165
Parallel WWAL	10	33	330

The simulation time is 60 h, with a 1 h warmup time. At the start, buffers between manual stations are empty (FWAL models), and automated stations are full.

2.4. Validation

The manual fixed-worker assembly line configuration (Figure 1(1)) was simulated using input parameter values from the industrial study case from a global white-goods manufacturer site located in the north of Spain. The simulation output was compared against the company's operational KPIs collected in January 2021. The average relative error of the KPI estimations was 1.8%, and the maximum error was 4.9%. This error magnitude was deemed satisfactory for the scope of this work. Thus, the DES model was validated, and the same simulation methodology was used to build the semiautomated FW and the parallel walking-worker assembly line configurations (Figure 1(2)–(4)).

2.5. Performance Comparison for Different Demand Scenarios

The performance of the different line configurations was assessed under different demand conditions. The standard demand conditions, *scenario i*, were created by setting the design parameters to 8 operators, a batch size of 48 units, and a product family changeover frequency of 3 batches, as shown in Table 8. This scenario represents the performance of the line configurations if the demand remains stable and does not change towards mass customization. The results from this *scenario i* set the baseline performance of each line configuration.

Table 8. Simulation scenarios and design parameters analyzed.

Scenario	W (Operators)	Q (Units)	B_{CO} (Batches)
i. Standard demand	8	48	3
ii. High-mix (1)	8	$\{12, 24, 48\}$	3
iii. High-mix (2)	8	48	$\{1, 2, 3\}$
iv. Low-volume	$\{2, 4, 8\}$	48	3
v. High-mix low-volume	8	12	1
vi. Degree of automation	$\{4, 6, 8\}$	$\{12, 48\}$	$\{1, 3\}$

To adapt to increasingly challenging demand conditions, assembly operations flexibility in terms of reduced lead times, smaller batch sizes, and more frequent rotation of product families are critical. To understand the performance of the different assembly line configurations under such conditions, simulation *scenarios ii–v* were set up, as shown in Table 8. *Scenarios ii–iv* look into how the performance of each line configuration is affected by the change of the three design parameters individually. *Scenario v* considers the most severe demand conditions at the same time and compares the performance against the base scenario. Finally, *scenario vi* analyzes the effect of automation in terms of percentage of work content automated, under either standard or high-mix low-volume demand conditions, and for a varying number of manual operators. On the other hand, the effect of the automation layout structure (i.e., the number of shared automated stations) would be hardly observed and analyzed using the industrial study case presented here because none of the automated stations are the AL bottleneck. Therefore, in this particular case, the number of automated stations would not significantly impact the AL operational KPIs. The following section, Section 3, includes the outcome of the simulations.

3. Results

This section includes the models' outputs (KPIs) for each *scenario i–vi* shown in Table 8. The results shown in this section are the average KPI values of 20 simulation runs. The maximum standard deviation of the results, as a percentage of the average value, is 1.1%. This indicates that the results are relatively stable with respect to the models' disturbances. For each scenario, the simulation results are shown in tables including the three AL configurations. The main KPIs (P_{Line}, LT_B, Th) improvements for the semiautomated FWAL and PWWAL configurations are then evaluated compared to the manual FWAL configuration. Note that Th (units/h) and P_{Line} (units/oper-h) variations with respect to manual FWAL are the same because the number of operators remains constant.

3.1. Base Scenario: Current-State Demand

The results of simulating the base scenario demand on the four assembly line configurations are shown in Table 9. Firstly, P_{Line} increases as a result of automation for semiautomated FWAL and WWAL configurations. It is important to note that the manual work content reduction obtained by introducing automation was ca. -23%.

Table 9. Operational KPIs for manual FWAL, semiautomated FWAL, semiautomated single WWAL, and parallel walking-worker assembly line configurations under standard demand conditions (*scenario i*).

			Manual	Semiauto	Semiauto Single WWAL					
KPI	**Units**	**Goal**	**FWAL**	**FWAL**	$W = 8$	$W = 7$	$W = 6$	$W = 5$	$W = 4$	**PWWAL**
P_{Line}	u/oper-h	↗	3.19	3.98	3.48	3.70	3.93	4.03	4.28	4.23
LT_B	min	↘	132	111	138	145	156	176	200	203
Th	u/h	↗	25.5	31.9	27.9	25.9	23.6	20.1	17.1	33.8
P_{Labour}	%	↗	87.0	83.3	71.6	75.7	79.3	82.9	85.6	85.6
LT_U	min	↘	20.5	23.4	25.4	25.0	26.3	20.1	27.5	27.9
P_S	u/oper-h-m^2	↗	0.050	0.043	0.021	0.022	0.024	0.024	0.026	0.013

The eight workers semiautomated single WWAL improves the performance compared to the manual FWAL. However, it presents worse performance than semiauto FWAL in terms of each and every one of the KPIs considered because there are not more stations than workers. This means that the single WWAL suffers from both line unbalancing and walking inefficiencies. Progressively reducing the number of workers in this configuration increases P_{Labor}, P_{Line}, and P_S, at the cost of a sharp reduction in Th. Adding a second walking-worker line and sharing some of the existing automated stations leads to increased productivity and throughput, transforming the semiautomated single WWAL into the parallel WWAL shown in Figure 1(4). It is very significant that the walking-worker way of working allows duplicating the throughput—from 17.1 to 33.8 units/h—by duplicating the number of workers while maintaining very high labor productivity (85.6%). Since the single WWAL presents no critical productivity advantages over the PWWAL, the following subsections omit the results of the single WWAL and focus on the semiauto FWAL vs. PWWAL comparison.

The semiautomated FWAL configuration achieves a +25% increase in PLine (see Figure 3). On the other hand, the PWWAL P_{Line} rises by +33% despite the walking time losses since there are no line balancing losses in this configuration. This is particularly remarkable when considering that WWAL configurations present an additional walking WC of 33 s per unit and 33 s return time to the first station (see Tables 3 and 7).

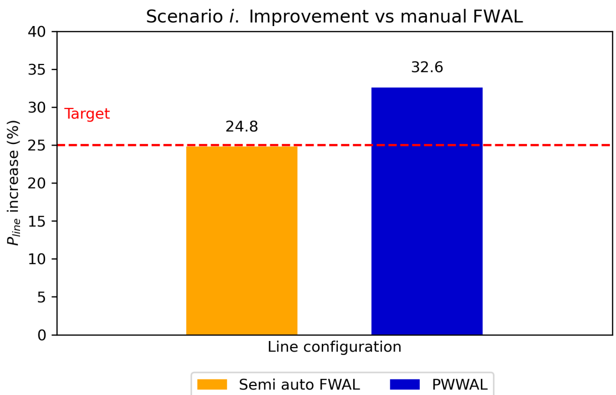

Figure 3. Line productivity increase of semiautomated FW and parallel walking-worker with respect to manual FW line configuration under standard demand conditions (*scenario i*).

On the other hand, batch lead time follows different trends: it improves for semiautomated FWAL (-16% LT_B reduction) but it worsens significantly for PWWAL (+54% LT_B increase) compared to manual FWAL. Semiauto FWAL LT_B improves despite the increased line length—eight manual stations plus four automated stations—due to the increased Th (+25%). Contrarily, PWWAL LT_B increases greatly despite its total Th increase (1) due to the walking-worker logic; (2) because each one of the parallel lines consists of only four operators—cf. LT_B for single WWAL with $W = 4$ and LT_B for PWWAL on Table 9; and (3) because the total work content increases by ca. 7–9% when taking into account manual, automated, and walking WC (see Table 3).

Unit lead time increases as a result of introducing automated stations, but less so for semiauto FWAL (+14% LT_U increase) than for PWWAL (+36% LT_U increase vs. manual FWAL). Once again, note that the LT_U of single WWAL with four operators is approximately the same as the LT_U of PWWAL.

Finally, the surface needed for the PWWAL is much greater than for manual or semiautomated FW lines (see Table 7), resulting in a significant P_S decrease.

As shown in Figure 3, the main KPI improvements (P_{Line} increase) meet the industrial case study target under standard demand conditions. The next section, Section 3.2, analyzes how the AL configurations deal with more challenging demand conditions.

3.2. High-Mix and Low-Volume Demand Scenarios

Simulation *scenarios ii* to *iv* test the line configurations under tougher demand conditions than *scenario i*. The performance of the assembly systems is expected to deteriorate for all AL configurations, but the focus here is the performance of semiautomated FWAL and PWWAL compared to manual FWAL.

Scenario ii: High-mix presents the necessity of reducing batch sizes due to increasingly atomized demand trends. Table 10 shows the KPIs resulting from simulating the different line configurations under a gradually smaller batch size (Q). The PWWAL configuration is best in terms of P_{Line}, Th, and P_{Labor} at all levels of Q, and is the worst in terms of LT_B, LT_U, and P_S. For the three line configurations, all KPIs deteriorate as a result of reducing Q.

Note that line productivity for semiautomated FWAL with $Q = 24$ units is still greater than for manual FWAL with $Q = 48$ units, and that the line productivity for PWWAL with $Q = 12$ units is still significantly superior to manual FWAL with a Q of 48 units. A key driver for this is that setup time losses are smaller for PWWAL than for FWAL because PWWAL employs fewer operators per AL branch.

Table 10. Operational KPIs of manual FWAL, semiautomatic FWAL, and PWWAL for reduced batch size (Q, *scenario ii*), reduced no. of batches until product family changeovers (B_{CO}, *scenario iii*), and reduced no. of workers (W, *scenario iv*).

		Batch Size, Q (Units)			**B_{CO} (Batches)**			**W (Operators)**		
KPI	**AL Configuration**	**12**	**24**	**48**	**1**	**2**	**3**	**2**	**4**	**8**
P_{Line} (u/oper-h)	Manual FW	2.73	3.04	3.19	3.19	3.20	3.19	3.60	3.45	3.19
	Semiauto. FW	3.07	3.64	3.98	3.91	3.97	3.98	-	-	3.98
	PWW	3.56	3.97	4.23	4.14	4.18	4.23	4.45	4.42	4.23
LT_B (min)	Manual FW	50	77	132	131	131	132	416	225	132
	Semiauto. FW	51	70	111	112	111	111	-	-	111
	PWW	73	124	203	209	206	203	704	366	203
Th (u/h)	Manual FW	21.9	24.4	25.5	25.5	25.6	25.5	7.2	13.8	25.5
	Semiauto. FW	24.5	29.1	31.9	31.3	31.8	31.9	-	-	31.9
	PWW	28.5	31.7	33.8	33.1	33.4	33.8	8.9	17.7	33.8
P_{Labor} (%)	Manual FW	73.2	82.0	87.0	85.8	86.6	87.0	96.2	93.0	87.0
	Semiauto. FW	63.4	75.0	83.3	80.5	82.6	83.3	-	-	83.3
	PWW	72.9	80.9	85.6	85.0	85.6	85.6	90.9	90.2	85.6
LT_U (min)	Manual FW	18.5	19.4	20.5	20.1	20.3	20.5	18.8	19.7	20.5
	semiauto. FW	24.0	23.5	23.4	23.4	23.3	23.4	-	-	23.4
	PWW	33.2	29.7	27.9	28.5	28.2	27.9	66.6	40.1	27.9
P_S (u/oper-h-m^2)	Manual FW	0.043	0.048	0.050	0.050	0.050	0.050	0.056	0.054	0.050
	Semiauto. FW	0.033	0.040	0.043	0.043	0.043	0.043	-	-	0.043
	PWW	0.011	0.012	0.013	0.013	0.013	0.013	0.013	0.013	0.013

Figure 4 shows that manual FWAL deals with reduced batch sizes worse than semiautomated AL since the P_{Line} of semiauto FWAL and PWWAL shows improvements for all levels of batch size. It can be seen that PWWAL maintains an improvement of ca. +30 to +33% P_{Line} compared to manual FWAL for all Q levels. On the other hand, semiautomated FWAL improvements vs. manual FWAL decrease as Q decreases. This leads to the conclusion that PWWAL deals with reduced batch sizes better than semiautomated FWAL. This is a key finding since maintaining high line productivity, even when significantly reducing the batch size, is the main goal of the PWWAL.

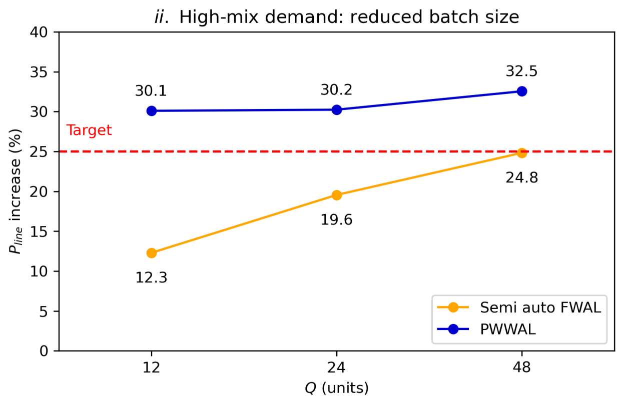

Figure 4. Line productivity improvement of semiautomated FW and parallel walking-worker with respect to manual FW line configuration for reduced batch size (Q, *scenario ii*).

Scenario iii also considers a high-mix demand situation, in this case by requiring more frequent changeovers, i.e., the number of batches before product family changeover, B_{CO}, decreases. The KPI results of *scenario iii* are shown in Table 10. The only performance indicator that is significantly affected is P_{Labor}, which decreases for semiautomated FWAL by ca. 2 percent points. However, this decrease in P_{Labor} is not large enough to drag down P_{Line} significantly, as shown in Figure 5.

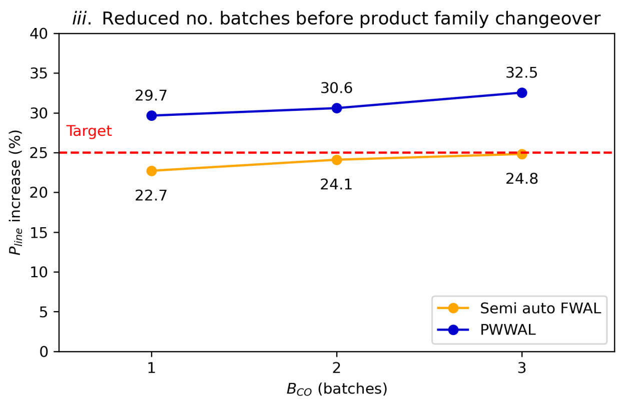

Figure 5. Line productivity improvement of semiautomated FW and parallel walking-worker with respect to manual FW line configuration for reduced no. of batches until product family changeovers (B_{CO}, *scenario iii*).

Simulation *scenario iv* considers a situation where the demand levels drop, and the throughput of the AL must be adjusted accordingly. To achieve this, the number of workers, W, is reduced. Note that the semiautomated FWAL is not able to modify this parameter under the constraints presented in Section 2. In reality, the production level of the semiautomated line could be adjusted by modifying other factors, such as the number of shifts, which are outside the scope of this work. Table 10 shows the simulation results for each line configuration when changing the parameter W.

Firstly, Th decreases as W decreases for manual FWAL and PWWAL configurations, but it does not decrease equally, due to line and labor productivity. P_{Labor} increases significantly for manual FWAL (from 87 to 96.2%) but not so much for PWWAL (from 85.6% to 90.9%) when W is reduced from eight to two workers. The P_{Labor} increase is due to the better line balance in the case of manual FWAL; and due to the reduction in in-process operator idle time for PWWAL—consistent with the conclusions by Lassalle et al. [12]—and the reduction in automated station saturation caused by the lower Th. Consequently, P_{Line} increases when W decreases.

Lead times, however, behave quite differently. LT_U decreases slightly for manual FWAL but increases sharply for PWWAL because of its production logic, by which operators leave units in the automation queues upon arrival, and then take a unit already processed by the automated stations. Since the number of WIP buffers before automations remains constant regardless of W, when $W << K$, the lead time increases. On the other hand, LT_B increases as W is reduced since its main contributor is the cycle time, which is inversely proportional to W. This trend affects both manual and PWW line configurations.

Finally, P_S increases very slightly when W is reduced, as a consequence of the increased P_{Line}. It is important to note that the PWW line configuration is the only one that allows introducing more operators if needed—until the automations are saturated—which allows increased throughput even further at the cost of reducing productivity.

Figure 6 shows that PWWAL performs better than manual FWAL in terms of P_{Line} at all levels of W. However, with $W = 2$ operators it is no longer possible for PWWAL to achieve the target +25% increase in P_{Line} compared to manual FWAL.

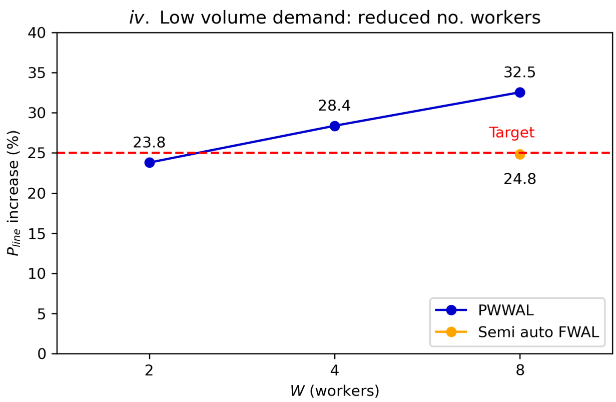

Figure 6. Line productivity improvement of semiautomated FW and parallel walking-worker with respect to manual FW line configuration for reduced no. of workers (W, *scenario iv*).

3.3. High-Mix Low-Volume Demand Scenario

Simulation *scenario v* considers a combination of *scenarios ii* and *iii* demand conditions: small batch size ($Q = 12$ units) and frequent product family changeovers ($B_{CO} = 1$ batch). Table 11 shows the KPIs resulting from *scenario v*.

Table 11. Operational KPIs for manual FWAL, semiautomated FWAL, and parallel walking-worker assembly line configurations under high-mix low-demand demand conditions (*scenario v*).

KPI	Units	Manual FWAL	Semiauto FWAL	PWWAL
P_{Line}	u/oper-h	2.63	2.82	3.42
LT_B	min	51	53	88
Th	u/h	21.0	22.6	27.4
P_{Labor}	%	70.3	58.0	70.4
LT_U	min	18.6	24.8	34.5
P_S	u/oper-h-m^2	0.041	0.031	0.010

P_{Line} and Th for semiautomatic FW and PWW lines are greater than those of manual AL configuration. However, only the PWWAL configuration allows a similar P_{Labor} under high-mix low-volume conditions. P_{Labor} decreases sharply under high-mix low-volume demand compared to standard conditions (cf. results of *scenario i* on Table 9), which affects semiautomated FWAL more intensely than PWWAL. This explains why PLine improves only by +7% for semiautomated FWAL, compared to +30% for PWWAL, as shown in Figure 7.

On the other hand, LT_B is worse for semiautomated than for manual lines. LT_B for PWWAL is significantly greater than for FWAL. This is deduced from the fact that LT_U almost doubles for PWWAL compared to manual FWAL (34.5 min vs. 18.6 min). This also indicates that the WIP levels of PWWAL must be superior to those of FWAL lines. Finally, P_S shrinks slightly under high-mix low-volume demand conditions compared to *scenario i*.

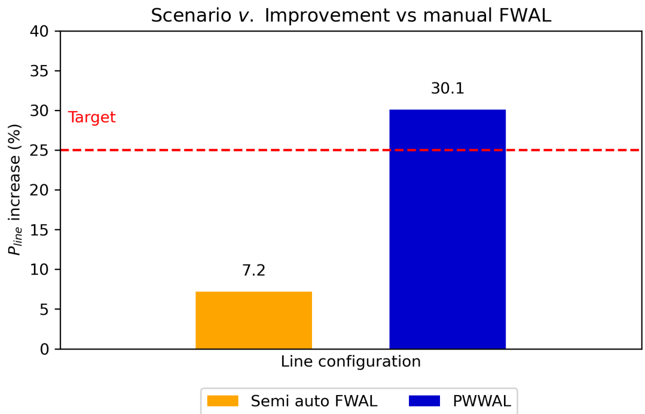

Figure 7. Line productivity improvement of semiautomated FW and parallel walking-worker with respect to manual FW line configuration under high-mix low-volume demand conditions (*scenario v*).

In summary, under both standard (*scenario i*) and high-mix low-volume demand conditions (*scenario v*), the parallel walking-worker line configuration achieves greater line productivity, which is the main goal of the industrial case presented. However, parallel walking-worker lines suffer from a higher batch lead time than fixed-worker line configurations. The parallel walking-worker configuration allows meeting the target line productivity improvement of 25% even under the most challenging conditions simulated. In contrast, the semiautomated FWAL presents perform better on secondary KPIs, such as lead time and surface productivity.

3.4. Degree of Automation

Simulation *scenario vi* tests the performance of semiautomated AL configurations for varying degrees of automation, in terms of the percentage of manual work content that has been assigned to automated stations. *Scenario vi* also considers the influence of demand conditions (Q, B_{co}) and number of manual operators (W). The results of *scenario vi* simulations are shown in Table 12, with the behavior of the most significant KPIs depicted in Figure 8.

Table 12. Operational KPIs of semiautomated FWAL and PWWAL for varying degrees of automation and number of workers (W), under base or high-mix low-volume demand conditions (Q, B_{co}).

KPI	AL Configuration	W (Oper)	Degree of Automation (%)					
			10	20	23	30	40	50
Standard Demand ($Q = 48$ Units, $B_{co} = 3$ Batches)								
P_{Line} (u/oper-h)	PWWAL	4	3.89	4.29	4.42	4.78	5.55	5.04
		6	3.81	4.21	4.34	4.64	4.23	3.38
		8	3.66	4.10	4.23	4.12	3.19	2.54
	Semiauto FWAL	8	3.52	3.86	3.98	3.89	2.96	2.35
LT_B (min)	PWWAL	4	411	375	366	338	298	320
		6	290	261	254	239	258	321
		8	232	209	203	208	260	327
	Semiauto FWAL	8	122	113	112	121	157	196
Th (u/h)	PWWAL	4	15.6	17.2	17.7	19.1	22.0	20.2
		6	22.8	25.3	26.0	27.8	25.4	20.3
		8	29.3	32.8	33.8	33.0	25.6	20.3
	Semiauto FWAL	8	28.2	30.9	31.9	31.1	23.6	18.8
P_{Labor} (%)	PWWAL	4	84.9	83.1	82.5	80.7	77.0	64.6
		6	80.9	78.6	77.8	74.6	62.3	44.6
		8	74.8	71.7	70.4	64.6	49.3	33.7
	Semiauto FWAL	8	63.2	59.3	58.0	54.9	44.4	32.1
LT_U (min)	PWWAL	4	45.7	41.4	40.1	37.1	32.2	35.2
		6	36.2	32.7	31.7	29.7	32.6	40.9
		8	32.2	28.7	27.9	28.6	37.0	46.8
	Semiauto FWAL	8	23.5	23.4	23.4	29.9	38.4	46.8
P_S (u/oper-h-m^2)	PWWAL	4	0.012	0.013	0.013	0.014	0.017	0.015
		6	0.012	0.013	0.013	0.014	0.013	0.010
		8	0.011	0.012	0.013	0.012	0.010	0.008
	Semiauto FWAL	8	0.038	0.042	0.043	0.042	0.032	0.026
High-Mix Low-Volume Demand ($Q = 12$ Units, $B_{co} = 1$ Batch)								
P_{Line} (u/oper-h)	PWWAL	4	3.53	3.88	4.02	4.31	4.80	4.83
		6	3.36	3.68	3.78	3.99	3.88	3.34
		8	3.11	3.36	3.42	3.45	3.04	2.53
	Semiauto FWAL	8	2.63	2.77	2.82	2.94	2.76	2.41
LT_B (min)	PWWAL	4	151	137	133	124	112	110
		6	111	102	99	95	96	110
		8	96	89	88	87	96	115
	Semiauto FWAL	8	56	54	54	55	63	75
Th (u/h)	PWWAL	4	14.1	15.5	16.1	17.3	19.2	19.3
		6	20.2	22.1	22.7	23.9	23.3	20.0
		8	24.9	26.9	27.4	27.6	24.6	20.2
	Semiauto FWAL	8	21.0	22.2	22.6	23.5	22.1	19.2
P_{Labor} (%)	PWWAL	4	84.9	83.1	82.5	80.7	77.0	64.6
		6	80.9	78.6	77.8	74.6	62.3	44.6
		8	74.8	71.7	70.4	64.6	49.3	33.7
	Semiauto FWAL	8	63.2	59.3	58.0	54.9	44.4	32.1
LT_U (min)	PWWAL	4	50.5	45.8	44.3	41.2	37.0	36.8
		6	41.1	37.5	36.5	34.6	35.5	41.4
		8	38.1	35.2	34.5	34.2	38.5	47.0
	Semiauto FWAL	8	25.1	24.9	24.8	25.7	30.7	38.7
P_S (u/oper-h-m^2)	PWWAL	4	0.011	0.012	0.012	0.013	0.015	0.015
		6	0.010	0.011	0.011	0.012	0.012	0.010
		8	0.009	0.010	0.010	0.010	0.009	0.008
	Semiauto FWAL	8	0.029	0.030	0.031	0.032	0.030	0.026

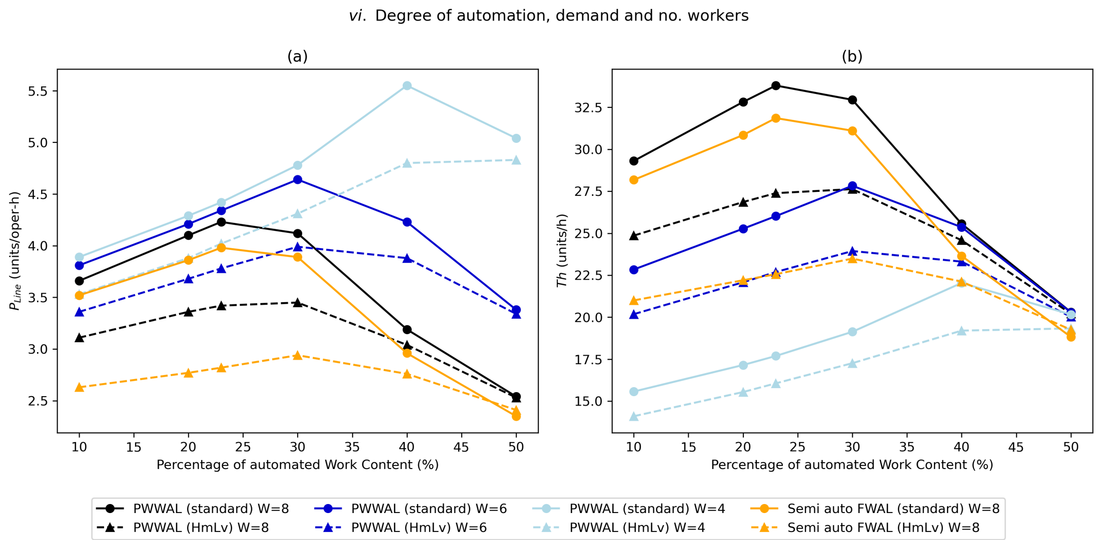

Figure 8. Performance of semiautomated FW and parallel walking-worker line configurations, for different number of manual workers, under standard and high-mix low-volume demand conditions (*scenario v*): (**a**) line productivity (P_{Line}), (**b**) throughput (Th).

Figure 8a shows the assembly line productivity as the degree of automation increases. Note that the *base scenario* corresponds to 23% automated WC. The simulation results show that the productivity is at a maximum for the base scenario with eight manual operators ($W = 8$). This is coherent with the number of manual and automated stations being chosen, aiming for line balance. From this point, decreasing the degree of automation reduces the line productivity, since the manual labor becomes the bottleneck. Increasing the degree of automation while keeping W constant also reduces the line productivity, due to the automated stations becoming the bottleneck. Note that this trend is maintained for both standard demand conditions (solid line series) and high-mix low-volume conditions (dashed line series). Productivity falls because the workers are increasingly idle and the output does not increase. The assumption that manual WC can be automated, increasing the processing time by 20%, plays an important role here. The study case assumes that this is reasonable since a well-trained operator assembles faster than a regular collaborative robot (see Section 2.3). Therefore, reducing W should increase the line productivity when the degree of automation is high. Unfortunately, for traditional FWAL lines (yellow), this change cannot be carried out without degrading the line balance. On the other hand, walking-worker lines can reduce the number of manual operators without incurring any penalty. This situation was simulated for $W = 6$ and $W = 4$ total manual operators (medium and light blue series, respectively, in Figure 8a. By decreasing W, PWWALs allow to achieve an even greater line productivity with a higher degree of automation. This is due to the fact that the manual and automated process times are being balanced.

However, this productivity increase comes at the expense of reducing the throughput of the assembly line, since W has been reduced, as shown in Figure 8b. Note how a smaller W results in gradually lower Th for all levels of automation and for all demand conditions. The Th of both line configurations (PWWAL and semiauto FWAL) for all levels of W tends towards a common point as the degree of automation increases, because Th is governed by the process time of the bottleneck.

In conclusion, PWWALs offer greater flexibility than fixed-worker lines in terms of benefiting from an increased degree of automation because they allow to easily rebalance the manual/automated workload by seamlessly removing operators, thus achieving greater line productivity. On the other hand, this comes at the expense of reducing the throughput and significantly increasing the batch lead time.

4. Discussion

Simulation results indicate that PWWALs have better operational performance than semiautomated or manual FWALs in terms of line productivity, throughput, and labor productivity, especially when facing high-mix low-volume demand, which makes it necessary to perform frequent family product changeovers, use small batch sizes, or use a reduced number of assembly operators. On the other hand, PWWALs present longer batch and unit lead times and require additional WIP stock and shopfloor space.

Automation-driven reduction of the products' manual work content by −23% leads to a productivity increase of +33% for PWWAL (vs. +25% increase for semiautomated FWAL) compared to manual AL configuration under standard demand conditions. Under high-mix demand conditions, PWWAL achieves a +30% productivity increase, significantly superior to the +7% productivity increase for semiautomatic FWAL—compared to manual FWAL, as shown in *scenario v*. In conclusion, the main goal of a +25% line productivity increase when producing small batches of highly mixed products can be achieved by the PWWAL, and not by the FWAL.

The PWWAL configuration suffers less from line unbalance caused by automated stations and product variety, provided that the workers-to-stations ratio remains low and that each worker moves through all the assembly stations. The WWAL cells within a line [21] reintroduce the problems of line balancing, but they reduce the need for operator training. Note that although total *WC* increases for WWAL compared to FWAL due to operator walking times, these losses are offset by superior labor productivity. PWWAL configuration also suffers less from setup time losses because each AL branch has fewer workers, which minimizes the waiting/blocking time losses caused by cycle time differences between the products involved in the changeover.

Introducing automated stations does not improve the average batch lead time, since the increased throughput is offset by the increased total work content and the superior number of workstations. PWWAL configurations present significantly worse batch lead times than semiauto or manual FWALs under any demand situations. It is also important to note that the average unit lead time to complete a unit increases for semiautomated FWAL, and especially for PWWAL configurations, compared to manual FWAL, which means that the WIP stock held at the line at any given moment would be greater. This is caused by the capacity buffers placed before and after the automations, which are required to hold twice as many WIP units in the PWW line since each automated QC station is served by two (slower) assembly lines which could have different cycle times.

Labor productivity decreases due to the introduction of automation and the reduction of batch sizes—which increases the percentage of time dedicated to setups. The PWWAL configuration is less affected than semiautomated FWAL by frequent changeovers since shorter ALs suffer less from operator idle times generated by cycle time differences between incoming and outgoing products. These idle times increase as the number of operators increases. Nonetheless, labor productivity losses are offset by the reduction in work content caused by automation.

Lastly, PWWAL presents high requirements in terms of shopfloor space compared to the fixed-worker assembly lines. PWWAL surface productivity is, under high-mix low-volume conditions, 0.010 units/operator-h-m^2, which is considerably lower than that of manual (0.041) or semiautomated configurations (0.031). The higher surface needs derive from the additional WIP and operator space buffers that the PWWAL needs to operate efficiently.

Increasing the degree of automation creates an imbalance between manual and automated work content that requires adjusting the number of workers. PWWALs offer greater flexibility than fixed-worker lines because they can seamlessly adjust the number of manual operators. However, the increased line productivity resulting from simultaneously increasing the degree of automation and decreasing the number of operators reduces the line throughput and increases significantly the batch lead time.

Besides the KPIs already exposed, PWWAL presents other advantages in terms of flexibility and reconfigurability. Production level changes are made simple by modifying the number of operators working on each AL branch independently—within the limits imposed by the capacity of the automated stations—without changes in the operators work organization. In fact, the number of workers could be temporarily increased beyond the designatedfour operators per AL branch at the expense of productivity. A parallel line configuration also brings additional sequencing possibilities, for example, being able to assemble a batch of products in both lines simultaneously to reduce the batch lead time—effectively working with half the batch size—at the cost of line productivity. Finally, the introduction of products to the PWWAL would present fewer drawbacks due to the reduced sensitivity of this line configuration to work content differences and poor line balance.

In conclusion, PWWAL configurations would be particularly beneficial in assembly operation situations where line productivity needs to be maximized under high-mix low-volume demand conditions, and when batch lead times are not a critical factor.

5. Conclusions

To address the need for more flexible and more productive assembly operations brought about by mass customization demand trends, this article presented a concept of a multimodel parallel walking-worker assembly line with shared automations. Based on an industry real-study case, discrete events simulation was utilized to model this assembly line concept, along with manual linear and semiautomated fixed-worker assembly lines. The models were used to compare the performance of the different line configurations under standard demand as well as different scenarios of increasingly challenging conditions in terms of reduced batch sizes and more frequent product changeovers. To evaluate efficiency, a set of six key performance indicators (KPIs) were employed: line productivity, batch lead time, throughput, labor productivity, unit lead time, and surface productivity.

It was found that under high-mix low-volume demand conditions requiring small batch sizes and frequent product family changeovers, the parallel walking-worker line configuration achieves greater line productivity and throughput than the semiautomated or manual fixed-worker line configuration. On the other hand, semiautomated fixed-worker assembly lines present better batch lead time, unit lead time, and surface productivity. Manual fixed-worker configuration productivity is inferior to the semiautomated alternatives according to all KPIs except for surface productivity. Increasing the degree of automation allows to increase the line productivity under all demand conditions, only if the number of workers can be reduced smoothly—which is the case for walking-worker configurations but not for fixed-worker lines. However, this comes at the expense of reducing the line throughput and increasing the lead time.

A key current research limitation lies in considering multiple layouts and shared automation configurations in order to find optimal line configurations or the performance of reconfigurable systems over long periods of time.

Areas for future work include (1) optimizing the actual layout of the parallel walking-worker configuration, to minimize the surface footprint; (2) the actual implementation of the parallel walking-worker concept in an industrial setting, which would enable validating the parallel walking-worker assembly line model; (3) expanding the simulation models to include machine breakdowns and quality problems, in terms of rework times and scrap products; and (4) a supply chain simulation layer feeding parts to the assembly lines. Future developments based on current research limitations would include assessing the operational performance of different line configurations in terms of both automation and layout.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AL	Assembly line
DES	Discrete events simulation
FWAL	Fixed-worker assembly line
PWWAL	Parallel walking-worker assembly line
QC	Quality control
WIP	Work in process
WWAL	Walking-worker assembly line

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B.6 Research Article: Machines (2023)

machines

Article

Multi-Model In-Plant Logistics Using Milkruns for Flexible Assembly Systems under Disturbances: An Industry Study Case

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Abstract: Mass customisation demand requires increasingly flexible assembly operations. For the in-plant logistics of such systems, milkrun trains could present advantages under high variability conditions. This article uses an industrial study case from a global white-goods manufacturing company. A discrete events simulation model was developed to explore the performance of multi-model assembly lines using a set of operational and logistics Key Performance Indicators. Four simulation scenarios analyse the separate effects of an increased number of product models and three different sources of variability. The results show that milkruns can protect the assembly lines from upstream process disturbances.

Keywords: milkrun; in-plant logistics; flexible assembly; simulation; high-mix low-volume; lean manufacturing

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1. Introduction

Since the end of the 20th century, it is considered that demand trends are shifting from mass production towards mass customisation [1] and mass personalisation [2]. To address this situation, manufacturing companies need to produce an increasing number of different products, in smaller quantities each, without compromising on quality or price [3]. For consumer goods manufacturers, this means shifting from large batches of very similar products towards high-mix low-volume production. To gain an advantage or simply remain competitive, production flexibility, reconfigurability and resilience are key [4].

In a typical discrete production process—e.g., automobiles, white goods, home electronics, furniture, toys—the assembly stage taking place after manufacturing is also of capital importance [5]. Traditional assembly operations are performed in manual or semi-automated lines or cells, which are usually dedicated to one product or a small family of products closely related [6]. These products are assembled in batches to minimise the losses incurred due to product changeovers [7,8]. Looking at existing assembly operations approaches to build upon, Lean Manufacturing [9] proposes a methodology inherently oriented towards reduced batch sizes, frequent product changeovers, multi-product assembly cells and cross-functional operator teams [10,11]. In this context, it seems clear that traditional assembly lines face serious threats when confronted with the high-mix low-volume demand brought by the mass customisation paradigm. The main challenges include dealing with complexity, uncertainty and disturbances, successfully deploying disruptive digital technologies [12]—i.e., Industry4.0 [13] or smart manufacturing [14]—and further integrating the sub-systems related to assembly: supporting functions such as internal logistics [15], maintenance [16] or quality control [17].

Internal logistics is the supply chain function most closely related to the assembly operations since it is tasked with feeding components to the assembly line or cell without introducing production constraints [18,19]. Flexible assembly lines driven by mass customisation and featuring mixed- or multi-model production pose additional challenges to internal logistics [20], which impact directly on the classic Lean supply performance indicators [21]. In-plant milkruns [22] (*misuzumashi* [23], *tow-train* [18]) are one of the best available Lean tools for efficiently supplying parts to flexible multi-model assembly lines [24].

The brief literature review that will be presented in Section 2 shows that despite an increasing research depth on the topic of milkrun logistic systems for flexible assembly lines, there are still limited published works which include variability. Two papers are very closely related to our research topic: Korytkowski et al.'s [25] is great but features a single-model assembly line, while Faccio et al.'s [26] article considers mixed-model assembly lines, but the sources of variability considered there are limited to milkrun train capacity and refilling interval. This connects with the key avenues for future work identified by Gil-Vilda et al. [19], which point to including variability and disturbances to the study of milkrun systems.

In consequence, the goal of this article is to continue exploring the use of milkrun trains for the internal logistics of flexible assembly operations featuring multiple manual assembly lines. In particular, we aim to look at scenarios where demand presents mass customisation characteristics (i.e., high-mix low-volume). The work presented here aims to evaluate the performance of milkrun trains and assembly lines in this demand context by focusing on two main aspects, following the lines for further investigation detected by Gil-Vilda et al. [19], namely the product mix (multi-model in opposition to single-model assembly) and the impact of variability and stochastic disturbances.

To address the aforementioned objectives, the following research questions are formulated:

1. What is the effect on the operational and logistics Key Performance Indicators (KPIs) of producing multiple models in an assembly line compared to single-model production? Are there significant differences between mixed-model and multi-model production from the milkrun internal logistics point of view?
2. How is the milkrun-assembly lines system affected by variability? In particular, to what extent is it impacted by assembly process variability and supply chain disturbances?

To carry out this research, Discrete Events Simulation (DES) was the chosen tool. A real industrial study case from a global white-goods manufacturer site located in northern Spain is presented and used to provide the foundations of the different simulation scenarios analysed to address the research questions.

The structure of this article is the following: Section 2 presents a brief literature review on the topic, highlighting the key findings made by previous research and the open lines of research derived from them. Section 3 Methodology introduces the assumptions used to build the simulation model, details the study case data and the parameters as well as the performance indicators selected to define and assess the simulation scenarios. Section 4 Results presents the outcome of the simulation, which is then discussed in Section 5.

2. Literature Review

Feeding the components to assembly lines requires complex in-plant logistics to do so in an efficient, flexible and responsive manner. Although many feeding policies could be used [27], some have clear advantages when facing a demand situation of mass customisation or mass personalisation.

In the context of Lean logistics, milkruns (also named 'tow-trains' or shuttles) are defined as '*pickups and deliveries at fixed times along fixed routes*' [18]. Inbound and outbound milkrun delivery systems work analogously, sharing a key aspect: '*milkruns are round tours on which full and empty returnable containers are exchanged in a 1:1 ratio*' [22].

Several authors have proposed different approaches for classifying milkrun systems. For instance, Kilic et al. [28] proposed that the main problem for milkrun design is to determine the routes and time periods aiming to minimise total cost, which are composed of transportation and Work In Process (WIP) holding costs. Their framework classifies milkrun problems depending on the need to determine the time periods, the routes or both; for one- or multiple-routed milkruns; and considering either equally or differently timed routes. On the other hand, Mácsay et al. [29] described four milkrun-based material supply strategies, while Klenk et al. [30] modelled milkrun systems using Methods-Time Measurement (MTM) parameters and explored six major milkrun concepts.

Alnahhal et al. conducted a literature review in 2014 [31] that found a scarcity of studies looking at in-plant milkrun systems as a whole, and that there was a research tendency to drift away from Lean goals to look for optimality based on restrictive objectives in its stead. Later articles, however, addressed in-plant milkruns from multiple angles; in particular, for mixed-model assembly systems closely related to multi-model systems, which are the focus of this article. A plethora of study cases have also been published in recent years, helping to illustrate the benefits of milkruns and the production challenges they help to overcome. The following subsections look into some of them in further detail.

2.1. In-Plant Milkruns for Mixed-Model Assembly Lines

Alnahhal et al. [32] looked into using milkruns for mixed-model assembly lines from decentralised supermarkets. Variables such as train routing, scheduling and loading problems were considered, aiming to minimise the number of trains, loading variability route length variability and assembly line inventory costs. Different analysis tools were employed: analytical equations, dynamic programming and Mixed-Integer Programming (MIP). On the other hand, Golz et al. [33] used a heuristic solution in two stages to minimise the number of shuttle drivers, focusing on the automotive sector.

This sector was also the focal point of Faccio et al.'s work [26], in which they proposed a general framework using short-term (dynamic) and long-term (static) sets of decisions allowing to size up the feeding systems for mixed-model assembly lines composed of supermarkets, kanbans and tow-trains. In another article [34], Faccio et al. dived deeper into the subject by investigating kanban number optimisation. It was highlighted that traditional kanban calculation methods fell short under a multi-line mixed-model assembly systems.

Emde et al. also looked at optimising some aspects of mixed-model assembly lines, namely (1) the location of in-house logistics zones [35] and (2) the loading of tow-trains to minimise the inventory at the assembly and to avoid material shortages, using an exact polynomial procedure [36]. Discrete Events Simulation was used by Vieira et al. [37] in an automated way (using a tailored API on top of a DES commercial software) to model and analyse the costs of mixed-model supermarkets.

2.2. Other Aspects of In-Plant Milkruns

A few articles examined the performance evaluation of milkrun systems. Klenk et al. [38] evaluated milkruns in terms of cost, lead time and service level. Their article used real data from the automotive industry with a focus on dealing with demand peaks. Bozer et al. [39] presented a performance evaluation model used to estimate the probability of (1) exceeding the physical capacity of the milkrun train and (2) exceeding the prescribed cycle time. This model assumed a basic, single-train system and that assembly lines are never starved of components. It highlighted some of the milkrun advantages: low lead times, low variability and low line-side inventory levels. Other articles describe milkrun systems evaluation methods which employ cost efficiency [29] or the required number of tow-trains [40]. Many authors used discrete event simulation to evaluate the potential performance of milkrun systems as a tool for milkrun design [41], evaluating dynamic scheduling strategies [42] or digital twin verification and validation [43].

The Association of German Engineers (VDI—*Verein Deutscher Ingenierure*) proposed the standardisation guidelines VDI 5586 [44] for in-plant milkrun systems design and dimensioning. Schmid et al. [45] discussed the draft VDI norm and found several drawbacks. Their article states that algorithms can support the milkrun design process; however, this system's design cannot be formulated as a regular optimisation problem. In a later article, Urru et al. [46] highlighted that VDI 5586 was the only norm for milkrun logistics systems design and that it is only applicable under severe restrictions. A methodology was then proposed to complement the VDI guideline. Kluska et al. proposed a milkrun design methodology which includes the use of simulation as supporting tool [41].

Gyulai et al. [47] provided an overview of models and algorithms for treating milkrun systems as a Vehicle Routing Problem (VRP). This article introduced a new approach with initial solution generation heuristics and a local search method to solve the VRP.

Gil-Vilda et al. [19] focused on studying the surface productivity and milkrun work time of U-shaped assembly lines fed by a milkrun train using a mathematical model. This article established promising avenues for future research: (1) assessing the impact of the number of parts per container and (2) analysing the impact of variability.

On the topic of variability, two articles stand out. Korytkowski [25] posed the research question about *'how disturbances in the production environment and managerial decisions affect the milkrun efficiency'*. This work analyses a single-model assembly line by employing discrete events simulation including three variability parameters—assembly process coefficient of variability, probability of a delayed milkrun cycle start and the magnitude of such delay—in addition to other three parameters: WIP buffer capacity, TAKT time synchronisation, and the milkrun cycle time. The KPIs used were throughput, WIP stock, milkrun utilisation and workstation starvation. The key conclusions were that TAKT sync does not affect the KPIs, even in conjunction with limited WIP buffer capacity. It was also found that a higher milkrun cycle time decreases the milkrun utilisation and increases the assembly line stock. Finally, this article concluded that milkrun systems mitigate the impact of production variations, which implies that they do not require large safety times built into them. Faccio et al. [26] also introduced variability sources in their dynamic milkrun framework for mixed-model assembly lines. In particular, this article includes tow-train capacity variability (related to the number of parts per kanban container, which is linked to the stochastic demand considered) and refilling interval variability.

2.3. In-Plant Milkrun Study Cases

There is no scarcity of published articles featuring study cases of in-plant milkrun systems. However, there are not so many articles specifically focusing on milkruns feeding multi-model assembly lines, and only a few articles consider stochastic variables. It is also noteworthy that the majority of study cases on the topic belong to the automotive industry. Table 1 summarises the study case articles found in this brief review, which includes the articles mentioned previously as well as a few additional documents [48–52] which specifically present milkrun study cases.

Table 1 shows some noteworthy points. First of all, no article specifically shows study cases of multi-model assembly lines, although there are some articles on mixed-model systems. Secondly, very few articles present real industrial study cases outside of the automotive sector. Finally, variability has not been commonly considered by research articles on the topic so far. The work presented here aims to cover the three highlighted shortcomings.

Table 1. Key aspects of selected research articles on in-plant milkrun systems which include study cases.

Article	Analysis Tool	Objective	No. Lines	No. Vehicles	Product Mix	Variability	Real Industry Case	Sector
Aksoy [51]	MILP and heuristics	MR route optimisation	Multi	Multi	Single	No	Yes	Automotive
Alfonso [53]	Simulation	Ergonomy and material flow improvement	Multi	Single	Single	No	Yes	Automotive
Alnahhal [32]	MIP, DP and math modelling	Min WIP, variability, handling cost	**Multi**	Multi	**Mixed**	No	No	NS [1]
Coelho [43]	Simulation	Verify and validate digital twin framework for in-plant logistics	Multi	NS	NS	**Yes**	Yes	Automotive
Costa [52]	Simulation	Train loading	Multi	Single	Single	No	Yes	Electronics
Emde [48]	MIP and heuristics	Min WIP	**Single**	Single	**Mixed**	No	No	Automotive
Faccio [26]	Math model	Min no vehicles and WIP	**Multi**	Multi	**Mixed**	**Yes**	Yes	Automotive
Faccio [34]	Math model	Optimal no. kanbans	**Multi**	Multi	**Mixed**	**Yes**	Yes	Automotive
Gil-Vilda [19]	Math model	Max surface productivity	Single	Single	Single	No	Yes	Unknown
Golz [33]	MILP and heuristics	Min no. trains	**Multi**	Single	**Mixed**	**Yes**	No	Automotive
Gyulai [47]	Heuristics and local search method	Min no. vehicles	Multi	Multi	NS	No	NS	Automotive
Kilic [28]	Mixed Integer Programming (MIP)	Min cost (no vehicles × distance travelled)	Multi	Multi	NS	No	Yes	Automotive
Klenk [38]	Math model	Handling demand peaks	Multi	Single	NS	**Yes**	Yes	Automotive
Korytkowski [25]	Simulation	Effect of disturbances and management decisions	Single	Single	Single	**Yes**	No	NS
Pekarcikova [54]	Simulation	Improve logistic flows	Single	Single	Single	No	NS	Automotive
Rao [42]	Simulation	Improve material flow, reduce no. vehicles	Multi	Multi	Single	No	NS	NS
Satoglu [50]	Math model and heuristics	MR route to minimise handling and stock costs	Multi	Single	Single	No	Yes	Electronics
Simic [49]	Particle swarm optimisation	Min stock costs	Single	Single	Single	No	No	Automotive

[1] NS: Not Specified.

3. Materials and Methods

In this article, the operational performance of two assembly lines and the milkrun train that feeds them is evaluated under different conditions. The system consisting of assembly lines and internal logistics was studied by considering a set of inputs, a Discrete Events Simulation model and a set of output KPIs, as depicted in Figure 1. The model consists of two main parts: the assembly lines and the supply chain feeding the components to the Assembly Line (AL) in containers using a milkrun train. Simulation was chosen for building this model because it allows the introduction of stochastic elements [55], such as process or logistics variability, which is necessary to achieve this work's goals. The simulation tool employed was FlexSim® (2022.0, FlexSim Software Products, Inc., Orem, UT, USA). Several simulation scenarios are created by modifying different parameters and disturbances values to analyse desired aspects of the system behaviour. Section 3.1 details the modelling assumptions. Section 3.2 includes the notation and definitions employed, and Section 3.3 includes the input data used in the models, which are used for validation (Section 3.4) and the experiment design (Section 3.5).

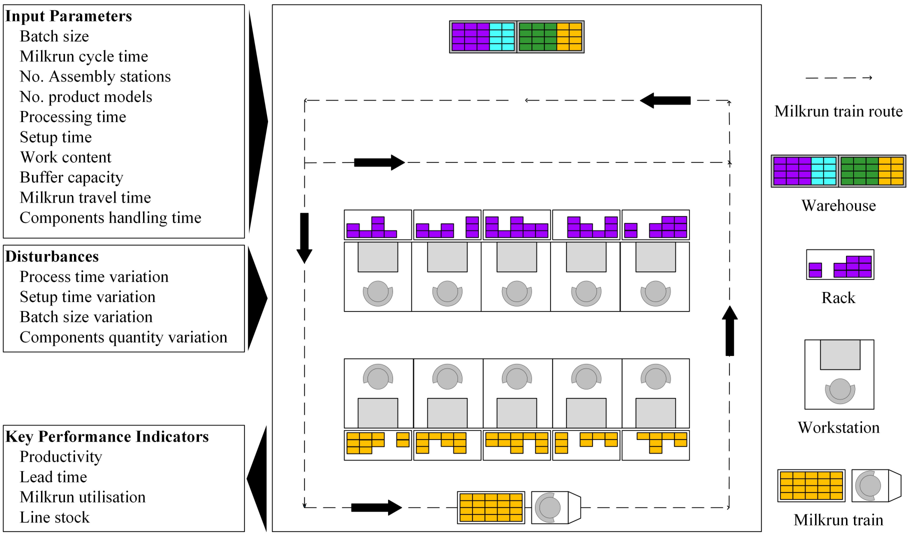

Figure 1. In-plant milkrun for multi-model assembly lines. Input parameters and disturbances are changed when analysing the performance of the system using simulation. Model output includes relevant operational and logistics Key Performance Indicators (KPIs) for evaluation.

3.1. Assumptions

The simulation model depicted in Figure 1 is made of two main subsystems: (1) two manual assembly lines, which feature operators, workstations, product buffers and components racks; and (2) internal logistics, which include a milkrun train, the components Points Of Use (POUs), a warehouse and the information flow necessary to ensure the assembly line receives the required components on time; see Figure 2.

Assembly lines: Figure 2a,b show the elements of the assembly lines used in this model, which feature the following assumptions following the classification of assembly systems by Boysen et al. [6]:

- The assembly systems are unpaced, buffered lines.
- These are fixed-worker assembly lines: operators are assigned to stations.
- There is manual assembly only (no semi- or fully automated work content).
- The number of workstations is constant. Each station can process only one product unit at a time.
- Operators need to gather all components specified by the Bill of Materials (BOM) to proceed to assemble at their stations; see Figure 2a.
- The demand mix is known and it continues for the whole simulation horizon.
- The assembly lines can be single-model, mixed-model or multi-model. Single-model lines only produce one product variant per AL. Mixed-model lines can produce more than one model, but there is no setup time between products. Multi-model lines are similar to mixed-model lines but they do incur setup time losses when changing over from one product model to another.
- Setup times, where present, are not dependent on the product sequence.
- The product sequence consists of an alternating pattern of batches of products. The batch size is stochastic, based on a discrete uniform distribution to represent the probability of a batch being released to the assembly line with fewer units than standard. This represents the disturbances caused by upstream manufacturing processes. The probability distribution is governed by the batch size coefficient of variability (CV_q).

- Processing and setup times are stochastic. They follow a lognormal distribution based on mean values and standard deviations, which are expressed by the coefficients of variability (CV_p, CV_s).
- Slightly different processing times on each station mean that these are unbalanced assembly lines, as shown in the 'Input' subsection.

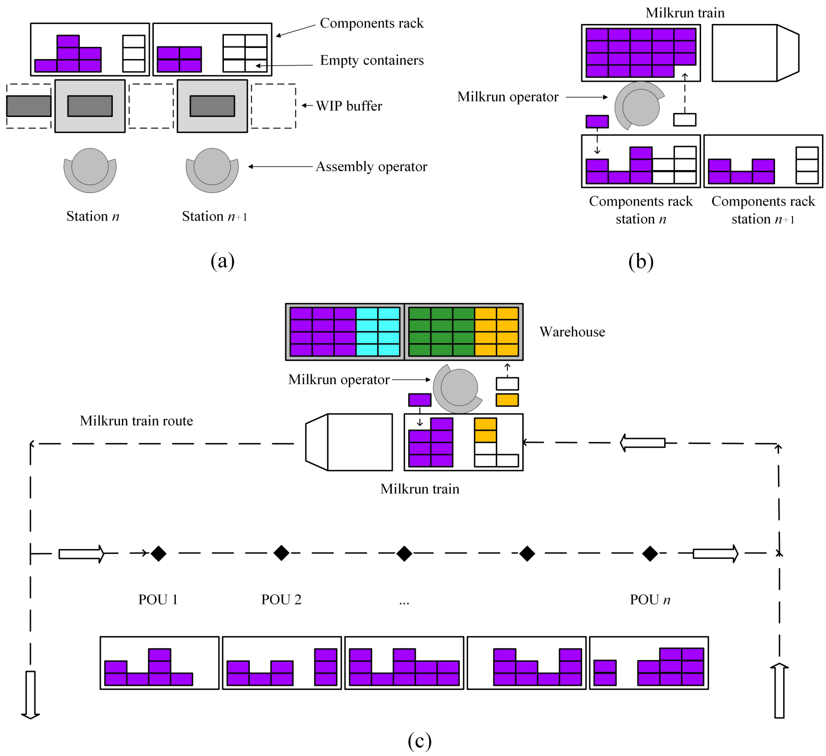

Figure 2. Simulation model subsystems interaction. (**a**) Assembly line stations; (**b**) Milkrun operator loading and unloading containers to assembly station; (**c**) Milkrun train picking at the warehouse, followed by the components replenishment cycle across all Points Of Use (POUs) of the route.

Internal Logistics: Figure 2 shows the main components of the internal logistics, which consists of four subsystems:

- Information flow between the assembly lines and the milkrun train, so that the milkrun picks up the right components for the product models that will be needed in the AL. This includes the calculations of the number of containers of each component N_i. This is worked out based on the expected consumption over the milkrun cycle time (d), the no. of pieces of component i per product unit (n_i) and the no. of pieces per container (q_i), with a minimum of 2, as shown in Equation (1). This minimum of 2 containers is required to prevent assembly line starvation, which could occur otherwise since the milkrun logic implies taking empty containers and replacing them with full ones on the next cycle.

$$N_i = \max\left(\left\lceil \frac{d_i \cdot n_i}{q_i} \right\rceil, 2\right) \tag{1}$$

- The number of pieces in each component container is stochastic, based on the standard number of pieces per container and a coefficient of variability (CV_c). A discrete uniform distribution is employed, which uses CV_c as the lower limit and the standard no. of pieces as the upper limit. This represents the probability of a certain number of pieces being non-conforming due to quality problems, inaccurate counting at the external suppliers' production site or incorrect re-packing at the in-plant warehouse, especially for components packed in bulk, such as nuts and bolts.

- Milkrun train picking at the warehouse (see Figure 2c) is modelled as a single POU. The milkrun train is emptied upon arrival, and it is thereafter filled again with the required containers for the next supply cycle.
- The milkrun transportation time from/to all POUs (Figure 2c) is based on historical time measurements from the industrial study case. Since the data show very little variability, the model assumes a deterministic transportation time given by the input parameter T_t.
- Supply chain operator loading and unloading of component containers to the assembly lines at each POU, as shown in Figure 2b. There are two possible situations: (1) Regular cycle (same product model): the operator replaces the empty boxes in the 'returns rack' with full boxes of the same component. The handling time is different for full and empty containers; see the input subsection. (2) Product changeover cycle (before the assembly line changeover): in which the milkrun operator firstly replaces any current product empty container to ensure that the current batch can be finished and then loads the next containers of the next product components so that they are available to the assembly operators when they finish the stations' changeover.

3.2. Notation

The following notations are introduced:
Input: Parameters

Q	Batch size
CT	Assembly cycle time
CT_{MR}	Milkrun cycle time
L	No. of assembly lines, index l.
K	No. of assembly workstations (no. POUs) per assembly line, index k.
M	No. of product models, index m.
T_p	Processing time
T_s	Setup time
WC	Work content (i.e., total process time)
WIP	No. of work in progress units between workstations
T_t	Milkrun transportation time to/from assembly line
T_h^e	Milkrun operator container handling time, empty container
T_h^f	Milkrun operator container handling time, full container

Input: Disturbances

CV_p	Process time coefficient of variation: $CV_p = \sigma_{Tp}/\mu_{Tp}$
CV_s	Setup time coefficient of variation: $CV_s = \sigma_{Ts}/\mu_{Ts}$
CV_c	Conforming units per container coefficient of variation
CV_q	Batch size coefficient of variation

Output: Key Performance Indicators

P	Productivity (units/operator-h): production rate of conforming units per assembly operator.
LT	Lead Time (min): average time for a batch of units to be finished from the moment the last unit of the previous batch is finished.
U	Milkrun Utilisation (%): fraction of total available time that the supply chain operator is busy (picking components at the warehouse, driving the milkrun train and handling containers to load/unload the components at the POUs).
S	Stock in the assembly line (units): average stock of components held in the assembly line measured in equivalent finished product units.

3.3. Input Data

The simulation model uses data provided by the industrial study case, which presents a common situation faced by plenty of manufacturing businesses globally. Table 2 shows the model parameters base, min and max values.

Table 2. Input parameters and disturbances base and range values.

Parameter	Units	Min	Max	Base Value
Q	units			48
CT	s			see Table 3
CT_{MR}	min			140
L	lines			2
K	stations			5
M	models	2	4	4
T_p	s			see Table 3
T_s	s			480
WC	s			see Table 3
WIP	units			1
T_t	min			4
T_h^e	s			1
T_h^f	s			2
CV_p		0	0.50	0.15
CV_s		0	0.50	0.15
CV_q		0	0.50	0.10
CV_c		0	0.20	0.00

The operations considered in this model include two manual assembly lines which assemble four product models, two on each line. The mean processing times for each model and station along with work content and cycle time is summarised in Table 3. These processing times were obtained from the industrial company standard operating procedures, which in turn are calculated using MTM.

Table 3. Product processing time input data.

Line	m	T_p (s)					CT (s)	WC (s)
		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$		
1	1	192.8	187.5	185.5	188.2	190.1	192.8	944.1
	2	214.3	210.2	215.4	212.0	210.7	215.4	1062.6
2	3	237.6	238.5	236.7	233.0	232.1	238.5	1177.9
	4	176.1	176.1	175.1	173.2	173.0	176.1	873.5

The products within a line share materials, technological features and general purposes, but they require different components, assembly fixtures and tooling. This calls for changeovers to adjust the workstations when a batch of a different product model is required. The parameter governing setup times is T_s, which takes each operator approximately 6 min (see Table 2), independently of the product sequencing.

Each product unit consists of many different components, as shown in Table 4. Most components are required only once per finished product unit, although some components, especially the smaller ones, may be required in larger numbers.

Table 4. Bill Of Materials summary data.

m	No. Components					Total No. Components	Total Pieces
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$		
1	16	6	10	11	4	47	62
2	28	4	14	13	13	72	132
3	20	7	20	18	21	86	160
4	16	9	9	24	14	72	105

Components are transported to the POUs and then presented to the assembly operators in containers, i.e., boxes, trays or small trolleys. Each container carries a certain number of pieces of one component, typically a few dozens for middle- and large-size components, and about one hundred pieces for small components, such as bolts, screws and washers.

In this particular study case, an important number of components are packed in very large quantities per container compared to the number of pieces needed to feed the assembly line for the duration of the milkrun cycle. Note that the the milkrun cycle time is approximately similar to the time required to complete a production batch. To illustrate this fact, Table 5 shows the number of components of each product model that are packed in *large quantities*. Here, *large quantities* refers to the case in which one single container includes a number of pieces allowing to assemble more than two full batches of products—i.e., it is equivalent to the assembly line consumption of two milkrun cycles.

Table 5. Details of the high number of components served in large quantities [2] to the assembly lines.

Number of Components	Product Model				Avg
	$m = 1$	$m = 2$	$m = 3$	$m = 4$	
Total no. components	47	72	86	72	69
Packed in large quantities [2]					
No. components	13	25	29	37	26
Percentage components	28%	35%	34%	51%	28%

[2] Containers including a no. of pieces equivalent to the consumption of more than two milkrun cycles.

When the milkrun operator arrives at each POU, the containers are handled between the train and the back side of the POU racks. Based on measurements at the industrial partner facility, one second was estimated for handling empty containers and two seconds for containers full of components, as shown in Table 2. When walking from the milkrun train to the POU, the milkrun operator's speed was considered 1 m/s. The milkrun train speed in the assembly line area was found to be around 1 m/s, and the POU positions are separated approximately 2 m from each other, resulting in a 12 m long assembly line. Regarding the milkrun train travel from the warehouse to either assembly line, the industrial partner measurements showed little variability for an average travel time of approximately 4 min each way. The milkrun preparation time at the warehouse (picking time) was simulated considering the warehouse as a single picking point and treated as any POU of the assembly line.

The DES model takes into account the inherent variability of manual assembly operations by using lognormal distributions for processing and setup times, following the recommendations of [56]. The lognormal distribution is generated using the mean (μ) values of T_p and T_s—see Table 3—and the standard deviation (σ), which is given as a percentage of the mean by the coefficients of variation CV_p and CV_s. The base values for the coefficients were estimated from historical data provided by the industrial partner of this study case. The data allowed estimating CV_p and CV_s to be in the range of 0.15–0.20 for manual assembly lines. Note that since one of the goals of this work is to analyse the influence of processing and setup times variability on the internal logistics performance, CV_p and CV_s will take a range of values in certain simulation scenarios. Another two sources of variability, introduced in Section 3.1, are considered: the conforming units per container variability (CV_c) and the batch size quantity variability (CV_q). They are relevant along with the processing and setup variability because the logistic performance of the milkrun system is directly related to them.

3.4. Verification and Validation

The validation and verification of the simulation models were performed separately for assembly operations and internal logistics.

For the assembly operations section, historical production KPIs data were gathered and compared against the results of a simple parametric model and a discrete events simulation model. The results presented by the authors in [57] allowed the validation of both models by comparison against real industry study case data. It was also possible to verify the parametric model against the simulation model (considering no variability) because their results difference was smaller than 3.5% for any considered performance metric. In summary, the results indicated that both parametric and simulation models slightly underestimate total output and that they overestimate the production rate, labour productivity and line productivity. Both models were found to be reliable for the context considered here since the mean relative error was 1.63% and the max relative error was 4.9%.

Regarding the internal logistics part of the simulation model, the validation was carried out using measurements at the industrial partner assembly lines from June 2022. A total of 18 milkrun cycle measurements were registered, finding an average milkrun utilisation of 78.4%. This was compared with the equivalent simulation model results (U = 71.6%) to calculate a relative error of 8.7%, slightly below 10%, which was considered satisfactory for the scope of this work.

3.5. Experiment Design

To address the research questions laid out in Section 1, several simulation scenarios were designed and then implemented on the simulation model by modifying the model's parameters. Table 6 summarises the parameters and range of values used to set up the simulation scenarios.

Table 6. Simulation scenarios.

Scenario	Parameter	Units	Range
i. Product mix	M	models	$\{2, 4\}$
	T_s	s	$\{0, 480\}$
ii. Process variability	CV_p, CV_s	per unit	$[0, 0.50]$
iii. Batch size variability	CV_q	per unit	$[0, 0.50]$
iv. Components quantity var.	CV_c	per unit	$[0, 0.20]$

The first research question—'*(1) What is the effect on the operational and logistics KPIs of producing multiple models in an assembly line compared to single-model production? Are there significant differences between mixed-model and multi-model production from the milkrun internal logistics point of view?*'—is examined by changing the number of product models under demand (one model per assembly line for single-model, $M = 2$; two models per assembly line per mixed- and multi-model, $M = 4$) and the setup time duration parameter (T_s set to 0 s for mixed-model, 480 s for multi-model). For this *scenario i.*, process and batch quantity coefficients of variability take their base values (T_p and T_s 0.15, CV_q 0.10), and the conforming units per container coefficient of variability is set to 0, as stated in Table 2.

The second research question—'*(2) How is the milkrun-assembly lines system affected by variability? In particular, to what extent is it impacted by assembly process variability and supply* *chain disturbances?'*—will be decomposed into the three variability sources considered in the simulation model. Firstly, process variability is governed by parameters CV_p (assembly processing time variability) and CV_s (setup time variability). These parameters will take values ranging from 0 (no variability at all) up to 0.50 (high variability), making up *scenario ii.* Secondly, the batch size variability coefficient will be used to represent in-plant manufacturing issues leading to smaller-than-standard batches of products being released for assembly. Similarly to the previous scenario, in *scenario iii.* CV_q values will range from 0 to 0.50, covering from no disturbances up to half of the batches having fewer units than it was intended. Finally, *scenario iv.* looks into external supplier perturbations which are simulated using the components quantity coefficient of variability. CV_c will take values in the range of 0 to 0.20, meaning that each components container can have up to 20% fewer valid pieces in the less favourable case. The effect of the interactions between the variability parameters was not analysed because a preliminary two-level full factorial design of experiments showed that two-factor interactions were not significant for the KPIs under study in comparison to the effects of the variability parameters by themselves.

The following Section 4 Results shows the outcome of the simulation scenarios introduced here.

4. Results

This section includes the outcome of the simulations corresponding to *scenarios i.-iv*. Section 4.1 addresses the first research question, and Section 4.2 includes *scenarios ii.-iv.*, which jointly address the second research question.

The results shown here are obtained with a simulation horizon of 74 h with a warm-up time of 2 h (i.e., nine production shifts after the warm-up is finished). To account for the stochastic nature of the results, each simulation scenario is run 20 times. This number was chosen because it was found that using a larger number of runs did not affect the resulting output in a statistically significant manner. At the start of each simulation run, all assembly stations and buffers between them are empty as well as all the components racks and the milkrun train.

The results shown in this section are presented in boxplots where the upper and lower limit of the boxes corresponds to the first and third quartiles. The coloured line is the mean and the whiskers limits are set to 1.5 times the interquartile range. Outlier data points (beyond the whiskers) are marked by a circle. The charts scale has been kept constant across all simulation scenarios to facilitate comparison.

4.1. Single-Model vs. Mixed-Model, Multi-Model Assembly

The selected operational KPIs comparing the performance of the assembly lines under *scenario i.* demand conditions are shown in Figure 3 and summarised in Table 7.

The productivity of single- and mixed-model lines is significantly superior to multi-model lines, as is expected considering that the setup time becomes zero (from 480 s per batch of 48 units, which represents just below 5% of the time needed to complete the batch on average). The difference in productivity between single- and mixed-model lines is related to operator idle and blocked times following product model changeovers as a result of cycle time differences between the incoming and outgoing products. Said difference does not account for significant productivity results in this case. Batch lead time, as expected, is slightly larger for mixed- and multi-model lines compared to single-model lines.

On the internal logistics KPIs side, milkrun utilisation and assembly line stock show a clear differentiation between single-model assembly lines and the other two. Incorporating multiple product models increases greatly the utilisation (from 51% to 72%, a +44% increment). Note that this steep increase could be linked to the high percentage of components packed in large quantities. This will be examined in the next Section 5 Discussion.

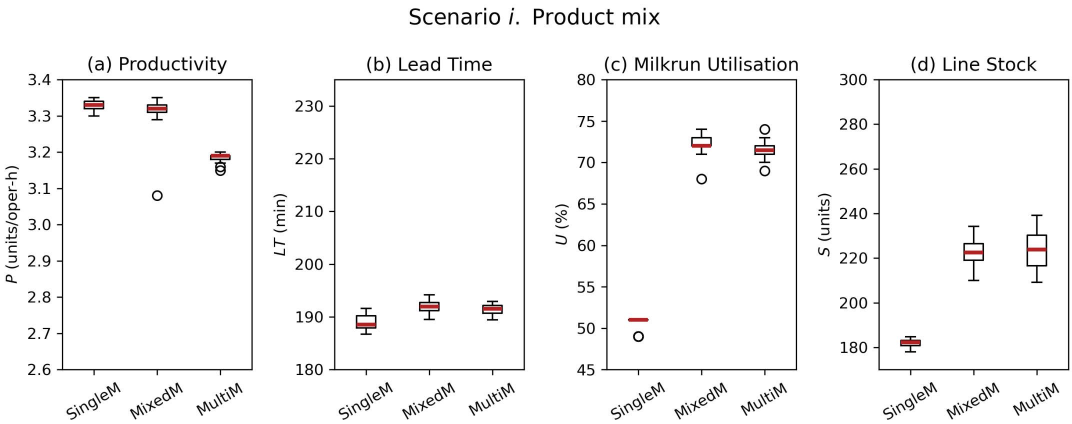

Figure 3. *Scenario i.*: Mean and deviation values of KPIs for single-, mixed- and multi-model assembly lines. (**a**) Line productivity, (**b**) batch lead time, (**c**) milkrun utilisation and (**d**) assembly line stock levels.

The component stock in the assembly line also suffers an increase for mixed- and multi-model lines driven by the same reason: single-model assembly lines see their average component stock decrease as the containers with very large quantities of pieces are consumed over time. Contrarily, mixed- and multi-model lines are constantly fed with small component boxes full of pieces. In the case shown here, the difference is significant but not dramatic, at an approx. +22% increase (from 182 to 223 units).

In summary, increasing product mix negatively affects operational KPIs (reduces productivity, increases batch lead time), which was expected. It also increases greatly supply chain operator utilisation (+44% rise), although the magnitude of this sharp increase could be attributed to the high percentage of components packed in large quantities.

Table 7. *Scenario i*: Mean and standard deviation (SD) of main KPIs for single-, mixed- and multi-model assembly lines.

Product Mix	*P* (u/oper-h)		*LT* (min)		*U* (%)		*S* (u)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Single-model	3.33	0.015	188.9	1.5	50.60	0.82	181.7	1.9
Mixed-model	3.31	0.006	192.0	1.4	72.05	1.23	222.8	6.2
Multi-model	3.19	0.013	191.4	1.1	71.50	1.24	223.2	8.4

4.2. Variability and Disturbances

This subsection looks at how increasing levels of variability affect the operational (P, LT) and internal logistics KPIs (U, S). As described in Section 3.5, simulation experiments were set up to independently analyse the influence of assembly line process variability (CV_p and CV_s, *scenario ii.*), batch size variability (CV_q, *scenario iii.*) and conforming components variability (CV_c, *scenario iv.*).

4.2.1. Process Variability

To analyse the impact of the assembly line process and setup variability, the respective coefficients were modified increasingly from 0 up to 0.50 (the base value for the industrial case study is 0.15; see Table 2). Figure 4 shows the results of this simulation scenario, and Table 8 includes the results' numeric values for average and standard deviation.

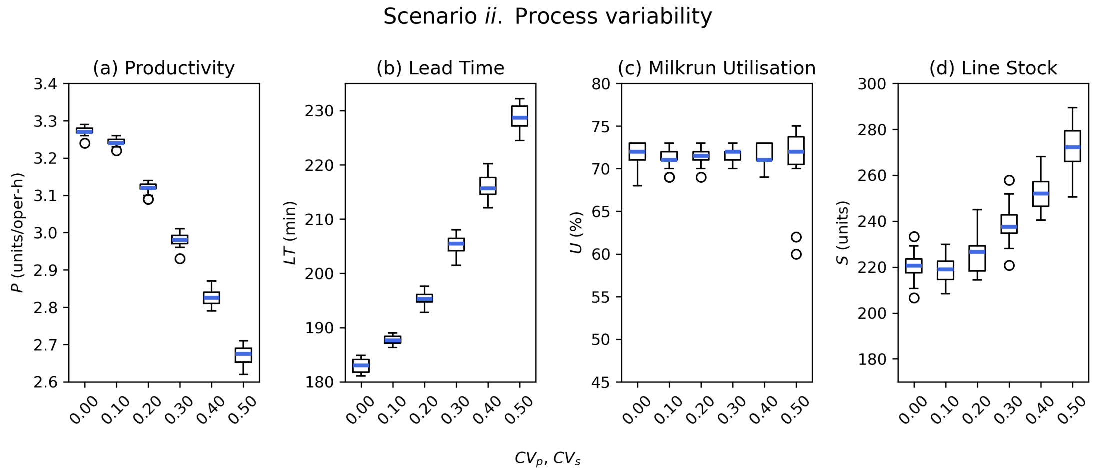

Figure 4. *Scenario ii.*: Mean and deviation values of KPIs for varying levels of process and setup coefficients of variation. (**a**) Productivity, (**b**) batch lead time, (**c**) milkrun utilisation, and (**d**) assembly line stock level.

In terms of operational KPIs, Figure 4a,b show that, as expected, an increase in process variability negatively the performance of the assembly line, especially considering that this lines' number of work-in-process units is limited to one. In particular, it can be seen that the productivity deteriorates greatly when CV_p and CV_s are greater than 0.20 both in terms of mean and standard deviation. Batch lead time follows the same trend.

Figure 4c shows that U does not suffer any changes, although its standard deviation increases slightly. On the other hand, the assembly line components' stock levels are severely impacted, rising from approx. 220 units for none or very small variability (CV_p and CV_s at 0–0.10) up to an average of approx. 270 units for CV_p, CV_s 0.50, which represents a noticeable +23% increase. Standard deviation also rises, but it remains small compared to the mean values of S, as shown in Figure 4d. In summary, only AL stock levels are affected by in-process variability, while the milkrun driver's workload remains unaffected.

Table 8. *Scenario ii.*: Mean and standard deviation of main KPIs for increasing values of process variability.

CV_p, CV_s	P (u/oper-h)		LT (min)		U (%)		S (u)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
0.00	3.27	0.012	183.0	1.2	71.75	1.33	220.4	4.9
0.10	3.24	0.011	187.8	0.8	71.25	1.16	218.7	5.8
0.20	3.12	0.015	195.4	1.1	71.45	1.05	238.5	7.6
0.30	2.98	0.019	205.2	1.8	71.30	0.99	238.1	8.8
0.40	2.83	0.021	216.0	2.2	71.45	1.23	252.6	7.8
0.50	2.67	0.025	228.7	2.3	71.28	4.06	272.1	10.7

4.2.2. Batch Size Variability

To understand the impact that upstream manufacturing process issues would have on the assembly operational and internal logistics performance, *scenario iii.* was set up by changing the value of CV_q, which determines the probability of an assembly production batch smaller than standard. CV_q takes values between 0 (no disruption) and 0.50 (meaning that on average, half the batches released to the assembly lines have between 36 and 48 units.

The simulation results of *scenario iii.* are summarised in Figure 5, and average and standard deviation data are shown in Table 9.

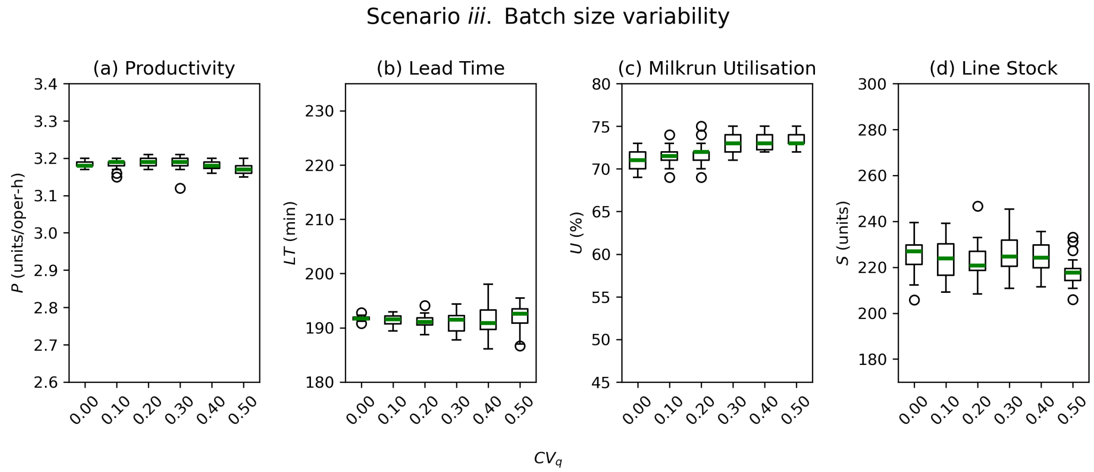

Figure 5. *Scenario iii.*: Mean and average values of KPIs for varying levels of batch size coefficients of variation. (**a**) Productivity, (**b**) batch lead time, (**c**) milkrun utilisation, and (**d**) assembly line stock.

Figure 5a,b shows that the average of both line productivity and lead time remains constant despite changes in CV_q. Although P standard deviation increases slightly, it remains very low at about 0.25–0.43% of the average value. The lead time StDev, on the other hand, does increase more than five-fold while remaining very low compared to average values (StDev of 0.24–1.39%). Therefore, the data show that batch size variability has no significant impact on the operational KPIs. Although variability rises as CV_q grows, it remains at very low levels in relative terms.

Figure 5c,d show very little impact on internal logistics KPIs as a result of an important rise in batch size variability. The milkrun utilisation average does increase slightly (from 71 to 73%, c.+4% rise), but the StDev reduction (from 1.25% to 0.82%) is not statistically significant. In a similar fashion, assembly line components stock decreases slightly in both average and standard deviation values, but none of these changes are statistically significant.

Table 9. *Scenario iii.*: Mean and standard deviation of main KPIs for increasing values of batch size variability.

CV_q	***P* (u/oper-h)**		***LT* (min)**		***U* (%)**		***S* (u)**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
0.00	3.18	0.008	191.7	0.5	70.68	1.25	225.6	8.0
0.10	3.19	0.013	191.4	1.1	71.50	1.24	223.2	8.4
0.20	3.19	0.012	191.1	1.2	71.74	1.37	222.6	9.1
0.30	3.19	0.019	191.0	2.0	72.84	1.07	225.8	8.5
0.40	3.18	0.011	191.1	2.8	73.17	0.92	224.7	6.7
0.50	3.17	0.014	191.9	2.7	73.32	0.82	218.1	6.8

4.2.3. Components Quantity Variability

The goal of this subsection is to analyse the impact of the components quantity coefficient of variability CV_c. This coefficient is employed to represent disturbances within in-house or external suppliers' processes, resulting in a lower-than-standard number of conforming pieces in each component container. As explained in Section 3, the number of conforming pieces per container is simulated using a discrete uniform distribution which has the inferior limit set to CV_c percent of the nominal value. *Scenario iv.* considers CV_c values from 0 to 0.20, as shown in Table 10.

Figure 6a shows that productivity is affected negatively by an increase in CV_c, although the magnitude of the impact is very limited: only a −2.2% reduction from the base scenario when components containers have up to 20% less conforming pieces than expected. Similarly, lead time is impacted negatively by CV_c increase, as depicted in Figure 6b. The *LT* average rises slightly (c.+2%) and suffers a greater dispersion of results (StDev increases by +54%). All in all, even a substantial increase in components quantity variability does not affect the assembly lines' operational KPIs severely.

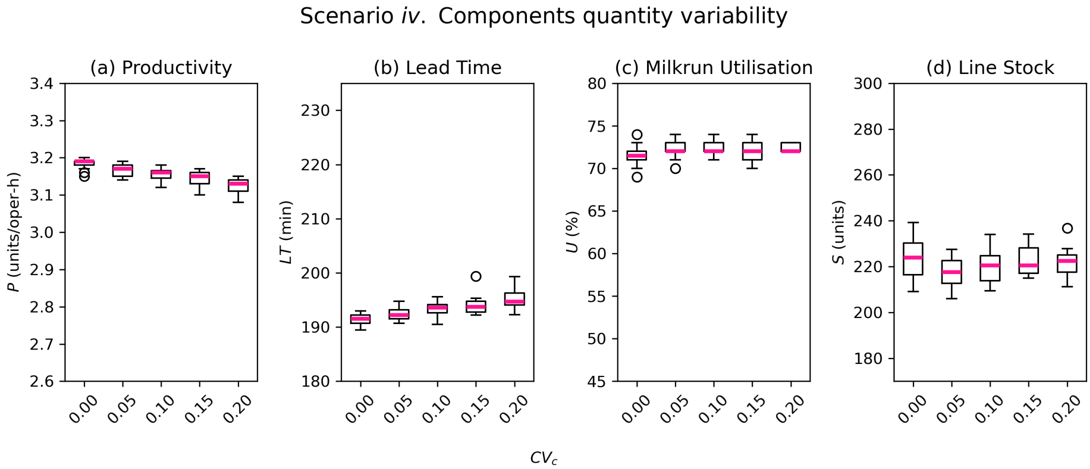

Figure 6. *Scenario iv.*: Mean and deviation values of KPIs for varying levels of components quantity coefficients of variation. (**a**) Productivity, (**b**) batch lead time, (**c**) milkrun utilisation, (**d**) assembly line stock.

Regarding internal logistics KPIs, Figure 6c,d show that an increase of CV_c has no significant impact on either milkrun utilisation or assembly line component stock levels.

Table 10. *Scenario iv.*: Mean and standard deviation of main KPIs for increasing values of component quantity variability.

CV_c	*P* (u/oper-h)		*LT* (min)		*U* (%)		*S* (u)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
0.00	3.19	0.013	191.4	1.1	71.50	1.24	223.2	8.4
0.05	3.17	0.015	192.4	1.2	72.17	0.99	217.5	6.2
0.10	3.16	0.016	193.5	1.2	72.26	0.81	220.0	6.8
0.15	3.15	0.019	194.0	1.6	72.00	1.05	222.0	5.6
0.20	3.12	0.019	195.2	1.7	72.40	0.50	221.9	5.9

5. Discussion

The results shown in the previous section have been summarised in Table 11.

Table 11. Summary of KPI change trends resulting from each scenario considered.

Scenario	Productivity	Lead Time	Milkrun Utilisation	Line Stock
Goal	↑	↓	↓	↓
i. Product mix	↘	↗	↑↑	↑↑
ii. Process variability: CV_p, CV_s ↑	↓↓	↑↑	=	↑↑
iii. Batch size variability: CV_q ↑	=	=	≈	≈
iv. Components quantity variability: CV_c ↑	↘	↗	≈	≈

Increasing the product mix from single- to mixed- and multi-model assembly lines results in a moderate impact on operational performance (P, LT) but a very significant negative effect on internal logistics KPIs, which could have further implications. For instance, the rise of assembly line component stock would increase the required floor space and decrease the assembly line surface productivity.

It is important to note that according to the results shown in Section 3.1, the greatest factor affecting U is the product mix, with a remarkable +44% increase resulting from changing from single- to multi-model assembly.

This sharp increase in U is caused by the rising number of containers that need to be handled, which is due to two main reasons.

(1) First of all, the number of component containers to be handled is larger every time there is a product changeover, which is the case for almost every milkrun cycle under the assumption that the milkrun cycle time is approximately similar to the time required to complete a batch of products (cf. CT_{MR}, Q in Table 2 and CT in Table 3). The increased number of containers to be handled is due to the fact that the supply chain operator needs to take all the containers of the outgoing model from the POU racks regardless of how many component pieces are left and replace them with components for the incoming product model. During regular supply cycles, on the other hand, containers are only replaced if needed (empty boxes work as kanban signals).

(2) The second reason is related with the compound effects of the first reason and the fact that in this particular study case, we find a large number of components packed in large quantities (see Table 5). This fact means that for a significant percentage of the components, each milkrun train carries enough pieces to assemble more than four times the required amount of pieces. Furthermore, the milkrun train will need to take back to the warehouse a full container and a half-empty container every time a changeover is needed.

Thus, it seems reasonable to conclude that milkrun utilisation is higher on mixed- and multi-model lines compared to single-model assembly lines. However, the magnitude of the increase shown in the Results must be considered carefully, since it it would be strongly related to the container quantities of this particular industrial study case.

As a closing remark on this subject, two aspects could be looked at in order to reduce the milkrun utilisation for multi-model assembly lines. Firstly, if enough shop-floor space is available, small components packed in large quantities could be left by the workstations, forming an assembly line supermarket, independent of the regular milkrun cycles. For larger components, relaxing the rule of minimum two containers (see Equation (1)) could be considered. Secondly, packing components in smaller quantities (so that two containers cover approximately the consumption of a milkrun cycle) could also reduce the milkrun workload so that it is only slightly higher than for single-model assembly lines.

Production variability (CV_p, CV_s) is the most important disturbance factor affecting productivity, lead time and assembly line components stock. However, it does not affect supply chain operator utilisation because the productivity reduction implies a reduction of output rate (which slows down components consumption). The reason behind this is that the milkrun work logic establishes a fixed replenishment frequency (milkrun cycle time), resulting in a supply chain operator workload effectively unaffected by several minor variations over the course of a full replenishment cycle.

Despite the previous expectation that variability would always impact performance negatively, results from Sections 4.2.2 and 4.2.3 show that the internal logistics KPIs are not sensitive to disturbances originated by batch size and components quantity variability (CV_q and CV_c respectively). This implies that employing milkruns for the internal logistics of flexible multi-model assembly lines under high-mix low-volume demand is a way to shield this part of the supply chain from upstream disturbances, arriving from either external or internal processes.

It was also found that variability regarding batch size (CV_q) does not have any noticeable negative impact on operational performance, as shown in Figure 5c.

Note that as mentioned in Section 2, this article addresses a gap in the literature by specifically addressing in-plan logistics for multi-model assembly operations, including variability, and using a real study case—specially from an industry sector other than automotive.

The fact that the simulation model used in this work is based on a real industry study case provides valuable insight into the behaviour of similar assembly operations—internal logistics systems under increasingly hard conditions in terms of variability and product mix. However, it is important to note that this also limits the generalisation extent of the results obtained due to certain aspects listed below.

First of all, the case employed here considers only a relatively small product variation within each assembly line (ΔWC 13% and 34% for AL no.1 and AL no.2, respectively) and almost no difference in terms of average WC per model when comparing both lines (ΔWC c.2%). Understanding how much product variability affects the operational and internal logistics KPIs could be a potential avenue for further research to understand the extent of the potential benefits of employing milkruns for high-mix low-volume assembly.

Secondly, it could be argued that the number of conforming components coefficient of variability (CV_c) only modifies the number of pieces per container available to the assembly operator, but it does not realistically capture the possibility of components actually arriving at the assembly line and then causing quality control failures or unexpected assembly process time increases, which would imply additional productivity losses due to reasons such as product rework and idle/blocked assembly operators.

Thirdly, milkrun transportation time was considered deterministic because the industry case measurements indicated this time were consistent. However, for multi-train production sites, variability caused by occasional milkrun train traffic jams could be considered.

Finally, modelling the milkrun train as a single wagon could be slightly underestimating its utilisation despite the satisfactory validation results. Specifically, in potential scenarios featuring longer milkrun cycle times—note that the CT_{MR} parameter was unchanged through scenarios *i.* to *iv.*—this would entail a greater number of component containers and therefore potentially a greater number of required wagons leading to an increased walking time for the supply chain operator, which the current simulation model would not capture.

6. Conclusions

To address a mass customisation demand context that drives high-mix low-volume assembly operations, this article studied the implications of using milkrun trains for the internal logistics of multi-model assembly lines. Based on a real industrial study case from the white-goods sector, a discrete events simulation model was employed to set up four different scenarios which evaluate the effect of product mix and three different sources of variability. To measure such impact, a set of four Key Performance Indicators (KPIs) were used, two corresponding to assembly operations and two corresponding to supply chain efficiency.

It was found that multi-model lines increase significantly the milkrun utilisation and the assembly line components stock compared to single-model lines. However, the magnitude of this large increase could be partially attributed to particularities of the study case. Operational KPIs were also affected negatively but to a much lesser extent. Internal logistics performance is greatly affected by the variability of assembly line processing time, especially in terms of component stock. Other sources of variability, such as the ones affecting the number of units per production batch or the components quantity per container, have very limited impact on the selected KPIs. This would imply that employing milkruns for the internal logistics of flexible multi-model assembly lines under high-mix low-volume demand is a way to shield this part of the supply chain from upstream disturbances, arriving from either external or internal processes.

Two key limitations of this work are the relatively low product variability in terms of work content and the milkrun train physical features simplification.

Further research paths include exploring the implications of much greater product work content variability, incorporating more detailed physical models of the milkrun train and expanding the simulation model to include adjacent layers that could constrain the performance of the assembly system as a whole, such as quality (defects, reworks, quality controls) or breakdowns and maintenance.

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Abbreviations

The following abbreviations are used in this manuscript:

AL	Assembly Line
BOM	Bill Of Materials
DES	Discrete Events Simulation
KPI	Key Performance Indicator
POU	Point Of Use
WC	Work Content
WIP	Work-In-Process

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