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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.

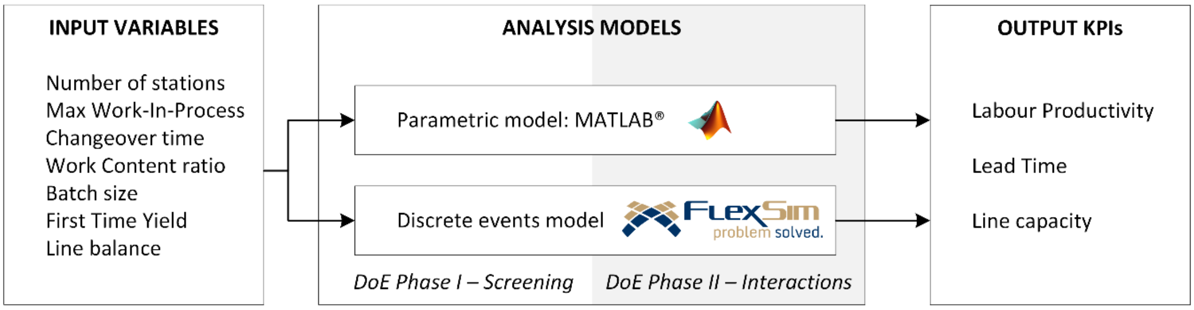

Figure 1. Diagram of Input factors and Output KPIs used for the analysis of mixed-model manual assembly lines.

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.

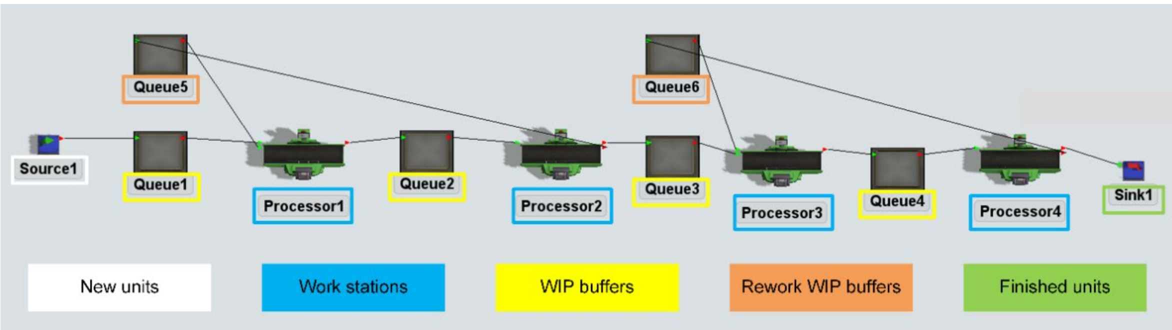

Figure 2. FlexSim® simulation model used for Configuration B.

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.

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 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.

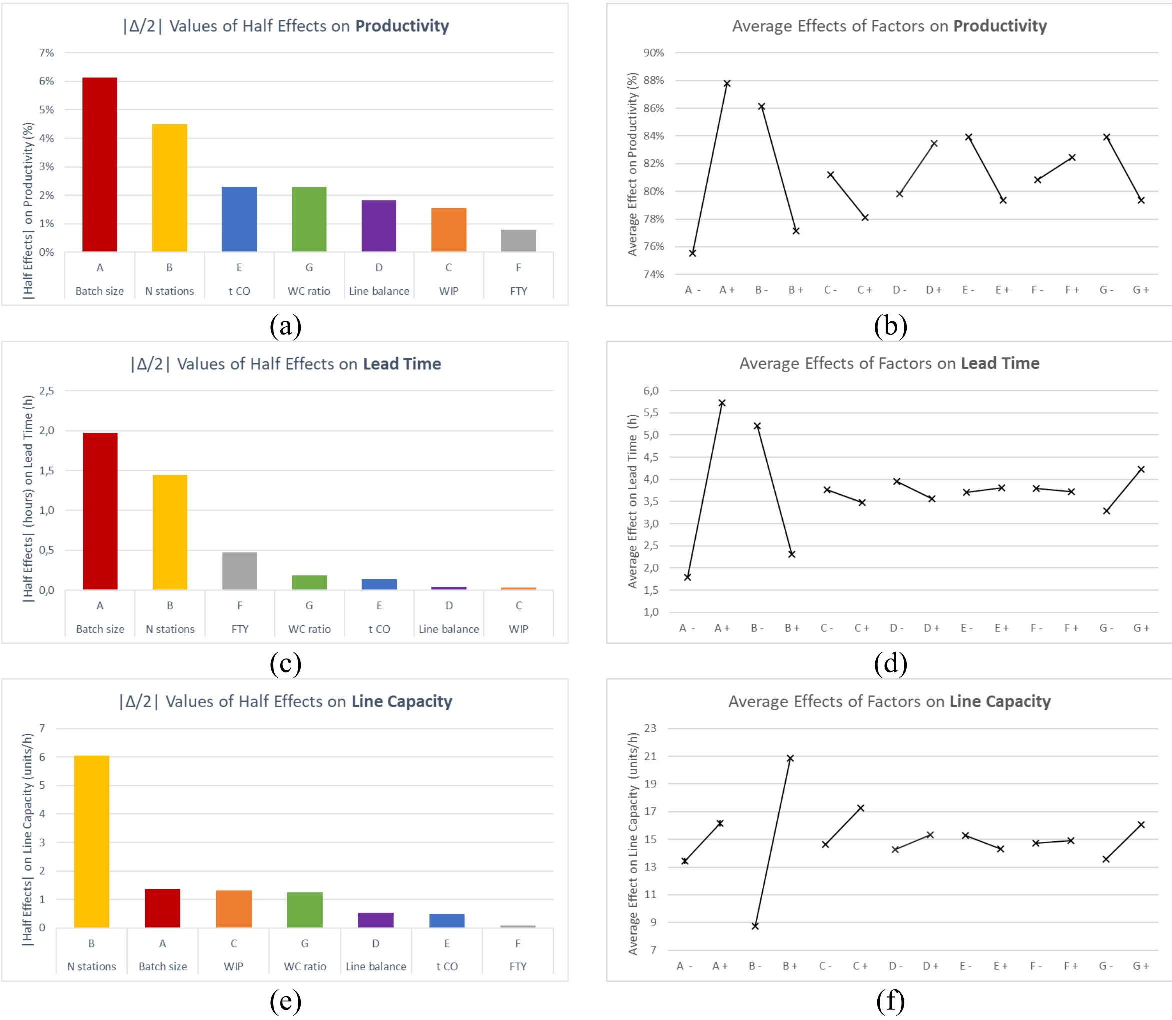

Figure 3. Left: bar charts for values of half-effects of Input factors on **(a)** Productivity, **(c)** Lead Time and **(e)** Line Capacity in a Fractional Factorial experimental design. Right: average effects of input factors on **(b)** Productivity, **(d)** Lead Time and **(f)** Line Capacity in a 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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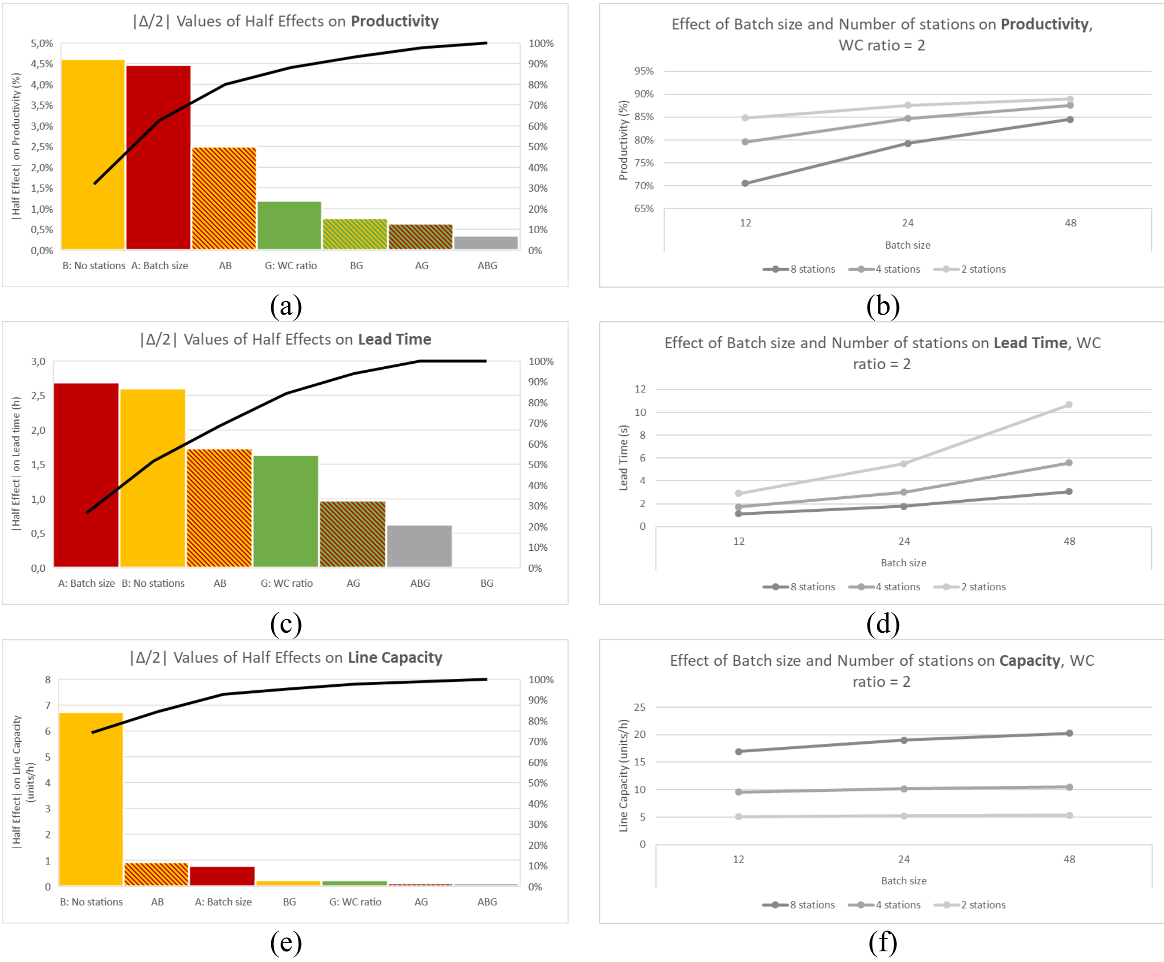
specifically to analyse these interactions.



(a) (b) (c) (d) (e) (f)

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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