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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.

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.

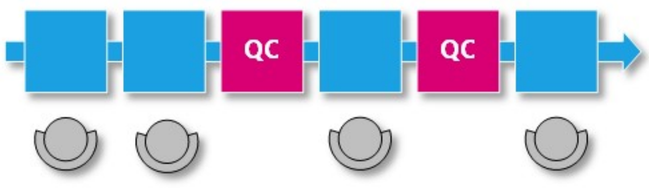

Fig. 1: Multi-product assembly line with quality control stations.

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.

$$t_{finish\_out,1} = T_{cycle}(P_{out}) \tag{2}$$

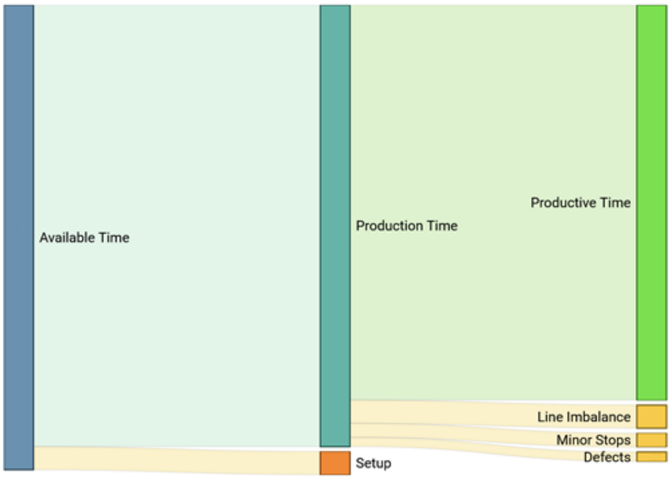

Fig. 2: Productivity losses in multi-product assembly lines considered in the parametric model.

$$t_{start\_out,i} = t_{finish\_out,i-1} \tag{3}$$

$$t_{finish\_out,i} = t_{start\_out,i} + T_{cycle}(p_{out}) \tag{4}$$

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.

$$i \in \{1, N_{stations} - 1\} : T_{lost,i} = \max\left\{0\ ;\ t_{finish\_co,i+1} - t_{finish\_in,i} - WIP \cdot T_{cycle}(in)\right\} \tag{8}$$

$$i = N_{stations} : T_{lost,i} = T_{setup}(p_{out}, p_{in}) \tag{9}$$

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].

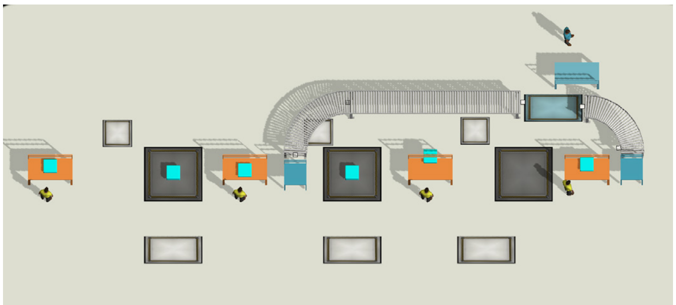

Fig. 3: Discrete Events Simulation model of Line 1.

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.

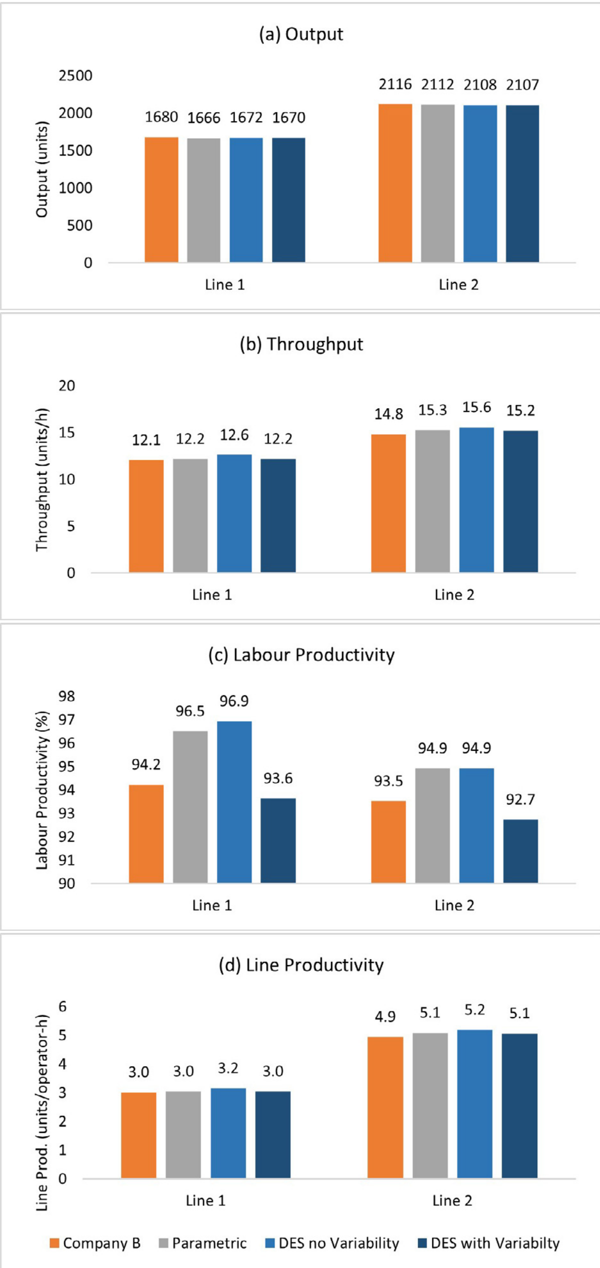

Fig. 4: Results of simulation using a parametric and Discrete events simulation model: (a) Output, (b) Throughput, (c) Labour productivity and (d) Line productivity.

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.

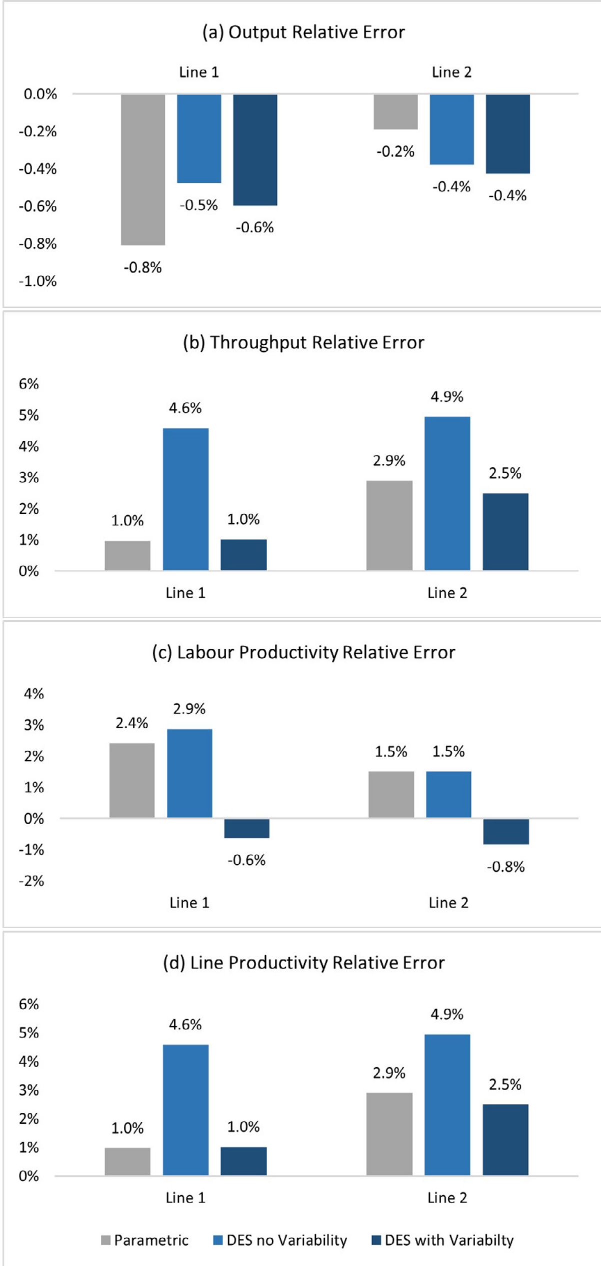

Fig. 5: Relative error of KPI results using a parametric and Discrete events simulation model: (a) Output, (b) Throughput, (c) Labour productivity and (d) Line productivity.

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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