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Procedia CIRP 72 (2018) 796–801

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51st CIRP Conference on Manufacturing Systems

Pilot To Full-Scale Production: A Battery Module Assembly Case Study

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Abstract

Electric vehicles are currently on the rise due to environmental and legal concerns. Furthermore, improvements made in battery assembly steadily boosts the efficiency of electric vehicles. A well-prevalent method to overcome the uncertainties that emerge from the ever-changing battery technology, is to assemble products using pilot production lines. However, literature pertaining to the scale-up of pilot production lines for full scale production is scarce. Therefore, in this paper, potential scale-up scenarios for battery module assembly line are proposed in a discrete event simulation software and results are compared. Furthermore, the benefits of the proposed method are discussed with a test case.

Peer-review under responsibility of the scientific committee of the 51st CIRP Conference on Manufacturing Systems.

Keywords: Cyber-Physical Systems; Battery module assembly; Pilot production.

1. Introduction

An important strategy adopted to ameliorate the undesirable effects of greenhouse gases and CO_2 emissions is power train electrification [1]. It is therefore predicted that the demand for electric mobility will slowly rise [2]. Consequently, it is essential for automobile industries to develop competencies in battery technology to remain competitive in the market. A well-prevalent strategy to fulfill this vision, is to build pilot lines to capture knowledge to be transferred for full-scale battery assembly [3]. A key aspect of battery manufacturing and assembly is that, it is currently facing multi-faceted problems arising from high manufacturing cost, unpredictable market, rapid changes in technology, increased number of variants and missing standardization of battery design [4].

Therefore, to overcome these challenges, various studies are being performed at WMG, as part of a suite of on-going research projects to capture knowledge from pilot production lines to support the early validation and verification capabilities for full-scale production, such that process optimisation and best-practice procedures for battery assembly can be quickly established.

With the advent of Industry 4.0, computer simulation is now an established way of improving the lifecycle management of the products by supporting decision-making, scheduling and cost analysis. Discrete-Event Simulation (DES), in particular, has been adopted to perform layout design, analyse operational performance [5] and has established its presence in the manufacturing domain [6]. In the context of battery module assembly, it is essential to simulate the product variants and its effect on material flow; discrete-event simulation can be used for this purpose [7]. Owing to the lack of implementation of such models in battery production, this paper discusses a case of battery module assembly, with the possible scenarios of scale-up for a mixed model assembly line. In this regard, the scale-up policies are integrated with two standard dispatching rules and the resulting scenarios are modelled using a DES software. Relevant statistical methods are used for comparison of the scenarios and the methodology is validated using a test case of two battery module variants. The impact of the product variety and system configuration on the pilot line and its potential scale-up scenarios and the support provided by Cyber-Physical Systems (CPS) in decision making are discussed.

2. Literature Review

In this section the research gap is highlighted by reviewing the available literature in three major areas namely: scale-up principles, battery module assembly and DES modelling. The research trend across these streams are discussed and summarized.

Manufacturing industries face several challenges during the transition of ideas and design from concept development to full-scale production. During this shift, unfavourable disturbances and challenges, such as the i) the inability to increase functionality of stations due to certain constraints ii) lack of knowledge regarding potential material flow issues iii) effect of scale-up on the labour and material feeding etc., can impact the performance of the system. Therefore, it is desirable to detect and prevent these disturbances as early as possible;

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10.1016/j.procir.2018.03.194

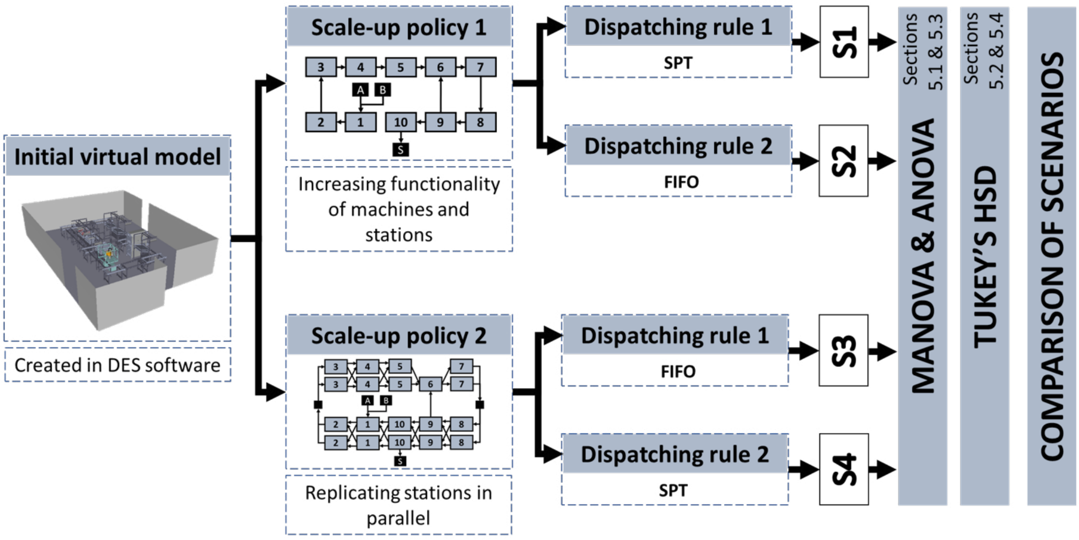

Fig. 1. The proposed methodology.

pilot production lines, which are considered as a training bed for full-scale production can be used for this purpose and, [8] in their research, highlight this issue. The transition from pilot to full-scale production, is not without challenges, hence, it is necessary to adopt strategies to enable and realise this transition. In this regard, [9] discuss two main principles for the implementation of scale-up in a manufacturing system. Moreover, [10], in their research, present a detailed account of the significant aspects and challenges faced in the scale-up of processes in the pharmaceutical industry. Scalability is considered as an important characteristic of Reconfigurable Manufacturing System (RMS); [11] consider an approach for the capacity scaling of RMS supported by optimization techniques to predict the time and extent of scaling necessary. The type of demand scenario that is considered can impact the strategy adopted for capacity scaling and this is discussed by [12]. [13] introduce a methodology to scale system capacity by reconfiguration of the system. Conclusively, studies and research works pertaining to provision of methodology or systematic approach to guide the process of scaling a pilot line are limited.

In the domain of battery assembly, notable research include modelling fault-tolerant control of the system [14], framework for automating the design process in the absence of standards for the battery components [15] and supporting decisions on assembly system design, equipment selection and task allocation [16].

Discrete-event simulation has seen its application in expediting the decision-making process in early production phase by utilizing pre-defined modules in power train electrification scenario [17]. [7] applies the concept of multi-scale simulation in task allocation, buffer size analysis and other operational elements in a battery module assembly case. According to [7], the concepts of simulation have been applied to battery electrode, cell and system modelling, however the realization of simulation in the domain of battery production process has not been well established.

2.1. Summary

Several studies have been conducted regarding the scalability of production lines under different demand scenarios. However, the concept of scaling up a pilot production line has not been widely researched in the context of manufacturing systems. Moreover, there is lack of a formal methodology for realizing a smooth transition from the pilot line to full-scale production. Simulation and modelling have established digitization of design data and hence provide basis for Industry 4.0 solution development. One such simulation approach, DES has been applied in several cases to optimize, decide and improve the operational performance of numerous production lines. However, limited models are available in literature to support battery production lines and therefore, in this paper, discrete event simulation is utilized to model a battery module assembly, with the intention to *i*) understand the best practice for scale-up of pilot line to full scale production, *ii*) comprehend the challenges imposed by the system configuration during scale-up, *iii*) integrate the principles of scale-up with scheduling policies and *iv*) compare potential scale-up strategies.

3. Methodology

The research focus is on the pilot line battery module assembly and their subsequent scale-up policies. Pilot production lines serve as a transition phase from concept development to full-scale production, wherein the validation of product and process is carried by pilot runs [8]. The plethora of data available from these production lines can serve as input for efficient identification of potential disturbances, comparison of scale-up strategies, fine tuning of process parameters and predictive maintenance of bespoke machines. Figure 1 shows the proposed methodology which is explained in detail further.

3.1. Overview

From Figure 1, the operational performance of an initial virtual representation of the system is analysed in a DES software. Data obtained from the pilot production line, such as the process and setup time, available space, material feeding etc., is used in this stage to develop the model. This initial model is subjected to two scale-up strategies. Strategy 1, which will henceforth be referred to as INC referring to the increase in functionality, involves decreasing the process time by increasing the efficiency and performance of various machines such that the required demand can be met. Strategy 2, which will henceforth be referred to as REP referring to replication, involves addition of stations with similar functionality in parallel, thereby increasing resources to meet the demand. Two dispatching rules are assigned to INC and REP. One of the rules is First In First Out (FIFO) and the other is Shortest Processing Time (SPT). This combination generates four scenarios as follows

- S1 INC with SPT
- S2 INC with FIFO
- S3 REP with FIFO
- S4 REP with SPT

The criteria for comparison of the scenarios depends upon the throughput. The threshold is set as x products of type A and y products of type B; scenarios or replications of scenarios that result in throughput less than this number are not considered for comparison. From literature, two statistical techniques that are used to compare the scenarios generated in DES are Ranking and Selection and Multiple Comparison techniques [18]. In this study, Multiple Comparison Procedures are identified as the most suitable approach as they provide information about the differences between the different scenarios in comparison. Therefore, the selected scenarios are subjected to statistical analysis as seen from Figure 1; MANOVA and ANOVA are explained in sections 5.1 and 5.3 respectively following which the results are discussed.

It is to be noted that, although the same methodology might be applicable to different production systems, the results and behaviour obtained and discussed in this study are a consequence of the initial system configuration in consideration. The following sections explain the reasoning behind selection of the policies and rules for scale-up and scheduling.

3.2. Scale-up

The concept of pilot production line has been briefly discussed earlier. Pilot production phase is usually followed by a ramp-up and/or full-scale production. Therefore, it is essential that the most suitable strategy for full-scale production to be identified well in advance to reduce the time to market. Virtual engineering toolsets, in particular, discrete-event simulation models are capable of providing support in this decision making. Based on the two principles provided by [9], station replicating and increasing functionality have been chosen. In REP, the stations that are over-utilized are identified by running experiments in the software and additional stations that serve the same functionality are added to the system. This, however, results in an increase in the number of operators if the added stations are manual. Additional floor space is required for this expansion as well. Therefore, more operators are assigned to the stations inside the cyber model. Although there is cost associated with this, it has not been quantified in this research. The comparisons have been made from an operational behaviour point of view. On the other hand, in INC, the identified stations are assessed for potential functional improvements and by increasing the functional characteristics, the new demand is met without any addition of stations. The process and setup times of the stations in the software model are reduced to represent this increased functionality. However, this is not discussed in detail in this study since this required immense amount of data regarding the details of the proposed improvement which is hard to establish in the concept stage. It is to be noted that the number of stations remains the same as the initial model, hence there is no necessity to add more operators to the system. The next section explains the scheduling policies adopted.

3.3. Scheduling and dispatching rules

In a production environment, scheduling and sequencing of jobs can be done at various phases. Static schedules are generated at the start of the production run and are not changed, whereas, dynamic schedules are generated whenever a disturbance occurs during production that demands a change in the existing schedule. Several dispatching rules are applied during production scheduling to select products according to certain established priorities. For the purpose of this study, two dispatching rules, namely First In First Out (FIFO) and Shortest Processing Time (SPT) are selected and their combination with the above-mentioned scale-up principles generates the four scenarios which will be discussed in the following sections.

4. Case study initial model

Battery module assembly is performed prior to the pack assembly, wherein cylindrical batteries are arranged in a pre-determined pattern to obtain the required energy and power. During this process, various components for module framework, cooling system, electrical connections etc. are fitted. A schematic diagram of the initial system configuration is shown in Figure 2. The key features of the system in discussion are as follows. The cylindrical 18650 Li-ion cells that are assembled, have to be accessed from both directions, the top and the bottom, to achieve the joining process. Therefore, there is need for a reorientation operation after which the joining process has to be repeated. In order to realise this, the conveyor system is provided with a loop as shown in Figure 2. The two sources A and B generate the two variants respectively.

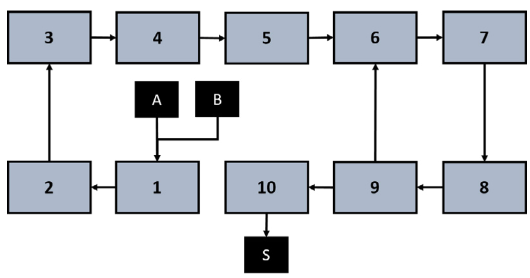

Fig. 2. Initial model representation.

Table 1 shows the process sequence for the two product variants that are assembled on the line. It can be seen that, when a product variant does not need processing at a station, it can bypass the station with the help of RFID (Radio Frequency IDentification) tags. For instance, product *B* does not need to be plastic welded and hence it bypasses station 5. Similarly, product *A* does not require ultrasonic welding and hence it does not need to be operated at station 6. The aspect of the case study which needs to be highlighted is the presence of the loop/shuttle from station 9 to station 6 which provides some routing flexibility. Product *B* does not have the need to travel the loop, however, product *A* is subjected to pulse arc welding on both cell terminals and hence travels through the loop and gets processed in station 8 twice. The production system has a throughput of 55 products per day with automated stations of 2, 6 and 8. Six operators work on 7 manual stations and travel to a station on a requirement basis.

Table 1. Process sequence for the two product variants.

Station number	Product A	Product B
1	Assemble carrier tray	Assemble carrier tray
2	Cell loading and testing	Cell loading and testing
3	Install cooling system	Inspection
4	Assemble top tray	Install busbar
5	Plastic weld housing	-
6	-	Ultrasonic wire bonding
7	Install busbar	Install busbar
8	Pulse arc welding	Pulse arc welding
9	Assemble insulation cover (top)	Weld inspection
10	Assemble insulation cover (bottom)	Assemble cover plate

4.1. DES model parameters

The scale-up model creation process exacts various parameters to be defined. The new demand is assumed to be twice that of the initial one and this is reflected by an increase in the inter-arrival time for products *A* and *B*. The product mix ratio is 70% product *A* and 30% product *B* and batching is not considered. Each station has a setup time which will be considered when product type changes. A warm-up time of 10000 seconds is considered to allow the system to reach steady state for performing statistical analysis. The simulation is run based on a shift time of 28800 seconds and stochasticity is introduced into the model using statistical distributions. For instance, mean time to failure values are modelled using the exponential distribution. 100 replications are performed for each of the scenarios. The presence of the loop/shuttle in the model can result in unprecedented behavior of the system with respect to product flow time. However, no buffer stations are considered in the model. A schematic representation of the REP scenarios (S3 and S4) is shown in Figure 3. Since the INC scenarios (S1 and S2) do not have a change in their configuration they look identical to the initial model shown in Figure 2. Although, there are several performance measures that arise from quality and operational domain, the key performance indicator that is considered for this study is the mean flow time of products A and B.

5. Results and discussion

A comparison of the operational performance of the four scenarios is performed by Multivariate ANalysis Of VAriance (MANOVA) and ANalysis Of VAriance (ANOVA) to statistically identify the existence of significant difference between the scenarios. For both tests, the four scenarios represent the independent variable.

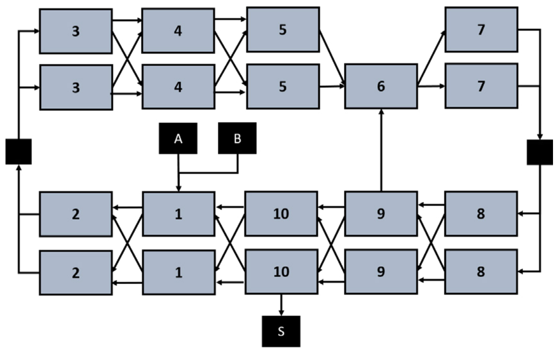

Fig. 3. Schematic representation of scenarios 3 and 4.

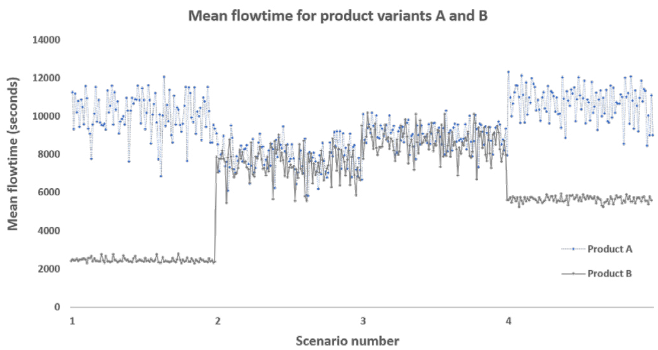

Fig. 4. Mean flowtime for the two product variants.

5.1. MANOVA testing

The two dependent variables required for MANOVA are the mean flow time for products *A* and *B* respectively. There are several assumptions that need to be satisfied to run the tests and this was performed in SPSS. Few assumptions were violated, however, it is expected that the effect of this violation will be negligible due to the sample size considered. Subsequently, Pillai's trace values in the multivariate test results were considered for analysis. P-value less than the significance level of 0.001 is obtained.

5.2. MANOVA results

The null hypothesis H_0 in MANOVA states that all the scenario means are equal

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 \tag{1}$$

Where μ_1, μ_2, μ_3 and μ_4 are the means of the respective scenarios. Since the p value is less than the significance level, null hypothesis is rejected and at least one set of means is significantly different from another. To understand more about this difference, a multiple comparison procedure called Tukey's Honest Significant Difference (HSD) test is considered. A comparison of mean flowtime for products *A* and *B* for four scenarios is shown in Figure 4. Figures 5 and 6 show the results obtained from Tukey's HSD test. From Tables 2 and 3, the values in the subset column represent the mean flowtime for the scenarios and it can be seen from both tables, that none of the scenarios share a subset; the mean flowtime of all the scenarios are significantly different from each other for both products.

Table 2. Homogenous subset output for MANOVA testing of product A

Scenario No.	Subset 1	Subset 2	Subset 3	Subset 4
2	7842.24			
3		9053.77		
1			10096.25	
4				10708.55

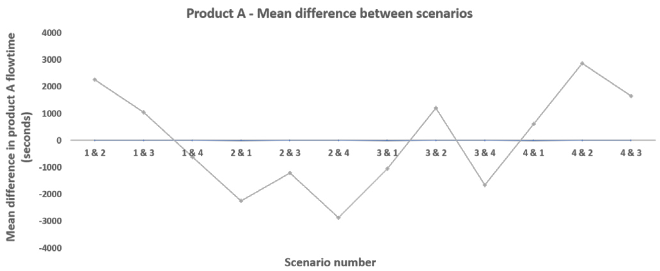

Fig. 5. Mean difference between scenarios for product A flowtime.

Table 3. Homogenous subset output for MANOVA testing of product B

Scenario No.	Subset 1	Subset 2	Subset 3	Subset 4
1	2453.68			
4		5639.33		
2			7473.13	
3				8646.28

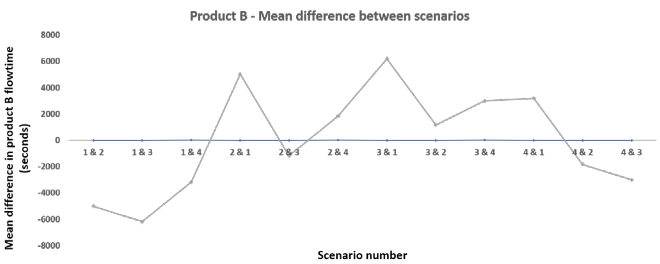

Fig. 6. Mean difference between scenarios for product B flowtime.

5.3. ANOVA testing

The MANOVA test was conducted considering the two product flow times as different dependent variables. Although, the results provide valuable data, the effect of combining flowtime of both products is not perceivable from the obtained results. Hence ANOVA was performed by considering the flowtime as one dependent variable by adding the mean flowtime of products *A* and *B* for each replication of each scenario. Assumption tests were conducted identical to the previous case. P-value of less than 0.001 was obtained and hence the null hypothesis that the scenario means are equal can be rejected.

5.4. ANOVA results

The rejection of null hypothesis implies that at least one set of means is significantly different from another. The total flowtime (mean flowtime *A* + mean flowtime *B*) for the 100 replications in each scenario is shown in Figure 7 and the mean difference between the scenarios is shown in Figure 8. From Table 4, the total mean flowtime for the scenarios are in different subsets; the mean flowtime for all four scenarios are significantly different from each other.

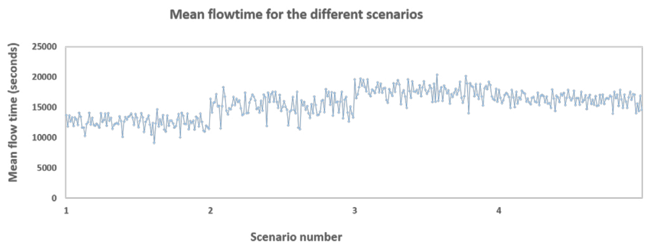

Fig. 7. Total mean flowtime for different scenarios.

Table 4. Homogenous subset output for ANOVA test

Scenario No.	Subset 1	Subset 2	Subset 3	Subset 4
1	12549.94			
2		15315.38		
4			16347.88	
3				17700.06

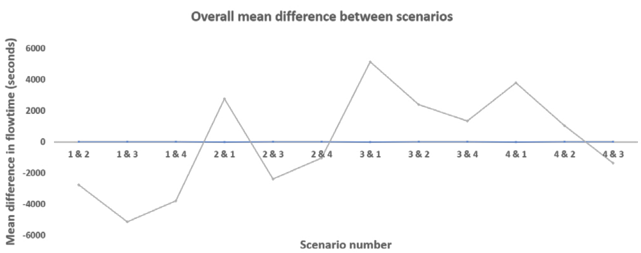

Fig. 8. Mean difference between scenarios for total mean flowtime.

5.5. Discussion

Comparisons of the mean flowtime of products *A* and *B* as seen from Figure 4, reveals that the flowtime of product *B* is influenced heavily by the type of dispatching rule considered. From Tukey's test (Figure 5), the mean difference between S2 and S4 is approximately 3000 seconds. Therefore, INC with FIFO dispatching rule allows product *A* to be assembled much faster than other scenarios. It is to be noted that REP with SPT dispatching rule increases the overall processing time of product A. On the other hand, INC with SPT dispatching rule reduces the mean flow time of product *B* considerably, whereas REP with FIFO increases the mean flowtime of product B. The comparisons performed so far, have considered the flowtime of the product variants separately. However, considering the total flow time of products *A* and *B*, from Figure 7, it is evident that INC with SPT dispatching rule reduces the total assembly time. Another trend that can be identified is the relative increase in flowtime for scenarios adopting the REP scale-up strategy when compared to INC scale-up strategy. Therefore, it is safe to assume that for the considered performance measure, initial system configuration, product variants and processing times, a scale-up strategy which involves improving performance of machines/stations by increasing their functionality integrated with the SPT dispatching rule provides good results. The proposed approach can be useful for decision making with the caveat being the inability to compare the prediction results from a cyber model with actual results from a physical model.

6. Conclusion and future work

In this study, two distinct scenarios for scale-up have been proposed. However, a hybrid strategy that combines the INC and REP could possibly be considered for future purposes. The data regarding processing time has been obtained from the pilot line for creating the DES models. However, quality data that can be inferred from the setup time change has not been considered for analysis. Moreover, there is possibility to feed data to machine learning algorithms to better predict scale-up strategies. In this research, only two of the many available dispatching rules have been compared. There is also potential of considering scheduling at different phases of production. For instance, when a disturbance such as machine breakdown occurs, a change in dispatching rule to reduce the effect of disturbance could be considered. Throughout the study, a particular initial system configuration has been considered, however, many such experiments can be conducted using different initial system configurations of battery module assembly and the obtained data could help predict best practice scale-up strategy for full-scale production.

This research highlights the importance of battery manufacturing and assembly in current industrial scenarios. Consequently, best practice for development and assembly of battery modules and packs is the need of the hour. Therefore, it is essential to validate products and processes in pilot production lines, which ultimately must be scaled-up for full scale production. The profuse quantity of data generated in such lines can support the creation of virtual models to understand scale-up strategies. Data regarding the operational performance and routing of the stations is fed into DES model and integrated with scale-up policies and dispatching rules to generate four different scenarios. The performance of the scenarios is compared statistically to support decision making. Although the proposed methodology is implemented in a system that assembles battery modules, it is possible to extend this approach to other manufacturing systems. It is, however, necessary to check the availability of sufficient space for adding new processing units, the possibility of increasing the functionality of a machine, etc. prior to the implementation. Additionally, the potential benefits of this implementation to a specific application or scenario, could be ascertained with the help of experiments.The authors believe that this research study proposes a methodology to i) guide good practice scale-up from pilot production line, and ii) develop cyber-physical architecture at the pilot line level, by using DES as a tool for decision making and guiding the smooth transition from pilot line to full-scale production.

Acknowledgements

The authors acknowledge the support of Innovate UK through the AMPLiFII project (ref: 102490), and UK EPSRC through KDCM (ref: EP/K018191/1).

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