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A multi-objective flexible manufacturing system design optimization using a hybrid response surface methodology

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Abstract

The present study proposes a hybrid framework combining multiple methods to determine the optimal values of design variables in a flexible manufacturing system (FMS). The framework uses a multi-objective response surface methodology (RSM) to achieve optimum performance. The performance of an FMS is characterized using various weighted measures using the best–worst method (BWM). Subsequently, an RSM approximates the functional relationship between the FMS performance and design variables. The central composite design (CCD) is used for this aim, and a polynomial regression model is fitted among the factors. Eventually, a bi-objective model, including the fitted and cost functions, is formulated and solved. As a result, the optimal percentage for deploying the FMS equipment and machines to achieve optimal performance with the lowest deployment cost is determined. The proposed framework can serve as a guideline for manufacturing organizations to lead strategic decisions regarding the design problems of FMSs. It significantly increases productivity for the manufacturing system, reduces redundant labor and material handling costs, and facilitates production.

Keywords Flexible manufacturing system · Response surface methodology · Central composite design · Best–worst method · Multi-objective optimization

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1 Introduction

FMSs were developed in response to the severity of competition in markets and the necessity of manufacturers to become more flexible in adapting to changes. An FMS is based on an integrated computer-controlled system that simultaneously processes numerous parts at middle-size volumes (Rifai et al. 2018). The eight main types of flexibility consist of routing, machine, operation, production, expansion, process, product, and volume (Yadav and Jayswal 2018; 2019). An FMS includes a set of machines and technologies that produces various products by performing different processes (Wang et al. 2018). Therefore, it is a computerized, high-tech, and automated manufacturing system that combines mass production efficiency with job shops' flexibility to improve productivity (Wang et al. 2016). In automated machining environments, minimizing the total time, decreasing the risk of tool breakdowns, and reducing tool switching are essential. However, some other factors can affect the performance of FMSs (Karimi et al. 2019). Decreasing setup time and equipment utilization and reducing and controlling work-in-process (WIP) directly impact manufacturing lead time (MLT). Hence, an

FMS and its related factors need optimal cycle times, equipment availability, and efficiency (Mahmood et al. 2017). These systems have a complicated design that deals with Distributed Data Processing (DDP) and Automated Material Flow (AMF) systems (Souier et al. 2019). Today, an FMS is a proper and prominent solution for industries to shift from a fixed type to a customized production (Silva et al. 2017).

The effects and importance of FMSs have been widely investigated. In this regard, the intelligence and flexibility of workstations are two critical factors. FMSs autonomously move material, WIPs, or production to enhance performance and efficiency. These systems should also be intelligent to respond to changes in the environment and customers' demands (Silva et al. 2017). FMSs are an essential solution for production systems to control and manage any changes required by the market and unforeseen demand (Yadav and Jayswal 2019). Due to the limited set of resources and influence on cost reduction and efficiency, optimizing FMSs scheduling is another essential part of the control that should be considered for these systems (Priore et al. 2018). Improving products' quality, work in process (WIP), lead times (LTs), reduction, and flexibility of operations are also considerable. Thus, flexible computerized manufacturing systems play a vital role in achieving them. Versatile machines used in the manufacturing system to perform multiple types of operations can reduce MLTs and WIPs (Zhengmin et al. 2019). FMSs are excellent production systems that have used and increased the development of computer-aided process planning (CAPP) techniques. FMSs can reduce gaps between process planning, production planning, timetabling problems, and scheduling (Pellegrinelli et al. 2018).

Since setting and designing an FMS is vital for a successful performance, this research uses and experimentally models the factors affecting the performance of an FMS and proposes an optimum configuration for these factors to attain the systems most effective and efficient performance. The paper, therefore, addresses a gap in the academic literature by proposing a formal hybrid framework using RSM to increase the productivity of FMSs at an optimal performance level. In this regard, while previous studies have characterized the performance of FMSs using a single measure or variable, e.g., routing and machine flexibility (e.g., Souier et al. 2019; Ghadirpour et al. 2020), in this study, a multi-dimensional perspective is followed to examine FMSs performance. Furthermore, the previous literature has focused on operational variables (e.g., layout, routing, and dispatching rules) and their effect on the performance of FMSs (e.g., Jerbi et al. 2019; Zhang et al. 2021; Shin et al. 2020). Nonetheless, the academic literature has not extensively considered the optimal level of multi-variables and how to apply FMS indicators. For example, some scholars have focused on the importance of influential factors in FMSs performance (e.g., Jain 2018; Jain and Soni 2019; Mishra 2020). The present study significantly contributes to these objectives by developing a hybrid framework that includes BWM, RSM, multi-objective optimization (MOO), and simulation. In this research, the RSM is also proposed to optimize the FMS performance of FMSs along with a nonlinear optimization method to tune the optimal set of parameters. In this regard, experiments based on a Central Composite Design (CCD) were conducted to investigate various component settings on an FMSs performance. Some primary indexes were considered to measure the performance of an FMS, and the final response variables were calculated based on the experimental results. The response variables were approximated by determining different inputs and running the designed experiments, and a mathematical model illustrating the relationship between input variables and system response was fitted. Since several performance factors were modeled using RSM to gain a multi-objective result, a weighting vector was obtained for different objectives using BWM. To this aim, a group of company experts initially determined the most important (best) and least important (worst) objectives (see Section 4 for details). Subsequently, they expressed their judgments regarding the pairwise preferences of the best objective regarding others and all objectives concerning the worst one. This information was then processed using the BWM model to determine the objective weights (Rezaei 2015). Ultimately, the fitted regression model was optimized, and the optimal designs of input variables were chosen.

The value of implementing a new and optimal technology-oriented framework is reflected in a positive impact on the efficiency and productivity of production systems. These improvements lead to better responses to customers and accelerate manufacturing processes. Achieving these results is often based on high investments in experiments or trial-and-error techniques. In this regard, applying simulation and experimental design reduces the costs of measuring each production equipment status. It determines the weights of the response levels as a significant input for better and more accurate analytics. These outputs are valuable for manufacturing companies to make better decisions with minimum cost and higher performance.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. FMS performance measures are reviewed in Section 3. The proposed methodology is described in Section 4, followed by its application in a real-world case study in Section 5. Finally, the paper is concluded in Section 6.

2 Basic concepts and literature review

This research is related to the production management field. The main components of FMSs are computer numerical control (CNC) machine tools loaded and unloaded by advanced industrial robots, automated material handling devices, storage and retrieval systems controlled by computer systems, and automated equipment (Kabir and Suzuki 2018). FMSs problems are classified into four areas, i.e., design, planning, scheduling, and control (Demesure et al. 2017). FMSs design problems include determining the appropriate number of machine tools of each type, the material handling system's capacity, and the size of the buffer. FMSs involve planning problems such as determining which parts should be machined simultaneously, optimizing machine tools into groups, allocating pallets and fixtures to part types, and assigning operations. Problems related to FMSs scheduling include determining the optimal input sequence of parts and the optimal sequence of machine tools. FMS control problems are those concerned with monitoring the system to ensure that requirements and due dates are met and that unreliability problems are considered (Demesure et al. 2017; Priore et al. 2018; Souier et al. 2019; Lee et al. 2020b). The proposed research in this paper is focused on addressing the design problem.

Previous studies have focused on routing and machine flexibility, which impact different performance parameters. FMSs problems are related to productivity improvement, selecting appropriate machines, number of allocated machines, material handling systems, capacity, buffers sizes, pallets allocations, FMSs planning, scheduling, jigs and fixtures allocations, limited resources optimization, and FMSs controls (Lee et al. 2020b; Bi et al. 2020). Table 1 presents a chronological overview of previous investigations regarding the performance of FMSs.

According to the studies above, scholars have considered several factors that significantly impact FMSs performance. Among them, authors refer to routing flexibility, sequencing flexibility, part sequencing, cutting conditions, skills and versatility of workers, type of machine, design changes required in the product, and determining the maximum number of routes. As Table 1 denotes, various studies have implemented MCDM approaches (e.g., Fuzzy MICMAC or ISM) to determine the importance of compelling factors and variables on FMSs performance. Furthermore, other studies have focused on optimization or simulation-based optimization methods to determine the optimal value of variables to increase the overall performance of FMSs. Other researchers have also focused on using the DoE and statistical analyses to assess the effects of variables and factors on the performance of FMSs. The proposed framework satisfies all these objectives through a hybrid framework that includes MCDM, RSM, MOO and simulation. This methodology is applied to a real-world industrial case to demonstrate the potential capabilities and desired objectives.

Moreover, as illustrated in Table 1, previous studies have focused on the performance of FMSs from a single point of view. For instance, some studies have investigated the productivity dimension, while others have studied the time flow as one criterion or dimension. However, the current study examines various performance measures simultaneously to optimize the performance of an FMS. Furthermore, previous studies have focused on operational variables and their effect on FMSs' performance, e.g., variables including layout, routing, and dispatching rules have been examined extensively. Nonetheless, the academic literature has not considered the optimal level of variables and how to apply FMS indicators. Thus, the present study also contributes to the FMSs body of knowledge by considering the design variables to provide manufacturing managers with an insight into how to apply FMS design.

3 FMSs performance measures

In the present research, the performance of an FMS is characterized by using (1) MLT, (2) production rate (R_p), (3) capacity, (4) productivity, (5) availability and (6) WIP. The improvement of automated equipment and manufacturing technologies efficiency is also illustrated based on these indexes. For instance, the MLT and production rate indexes illustrate how the automated manufacturing equipment and CNC machines may change the production duration or how the Automated Storage and Retrieval Storage (AS/RS) warehousing system can improve productivity and production flow. Besides, other factors such as product diversity and raw material ordering costs can be considered for this problem (Groover 2020). As FMSs offer a competitive and high-cost environment, internal and external factors should be considered (Edh Mirzaei et al. 2021). However, these performance indexes create a trade-off between efficiency and product characteristics (i.e., quality, variety, customization). This point should be considered during the optimization of an assembly line (Moretti et al. 2021). Table 2 presents the indexes for FMS performance measures.

Manufacturing lead time (MLT) or production period MLT is the time between production authorization and completion (Ivanov and Jaff 2017). MLT comprises queue, setup, run, delay and transport times (Jaff and Ivanov 2016). Accordingly, this study formulated MLT as follows.

$$MLT = \sum_{i=1}^{n_m} \left(T_{sui} + QT_{oi} + T_{noi} \right) \tag{1}$$

If the operation, non-operational processes and setting up times are considered equal in different workstations, the MLT formula is simplified as follows (Groover 2020).

$$MLT = n_m \times \left(T_{su} + QT_o + T_{no} \right) \tag{2}$$

Production rate (R_p). In job shop systems, if production unit per hour ($Q = 1$), then production time per unit is $T_p = T_{su} + T_o$. In mass production systems, the cycle time is defined as the sum of the longest operational and transportation time, excluding the setting time (Sprodowski et al. 2020). In this study, the production rate is measured as follows. First, the production time of each unit is estimated with Eq. (3).

Table 1 Relevant literature regarding FMS performance

Author(s)	Year	Research Objective(s)	Research Method(s)	Research Findings
Jain and Raj	2016	Extracting performance variables of FMS	Interpretive Structural Modelling (ISM) and Graph Theory and Matrix Approach (GTMA)	Identifying performance variables influential on FMS performance
Ali and Murshid	2016	Performance Evaluation of Flexible Manufacturing	Simulation and statistical analysis	The optimal routing flexibility level for a given material handling strategy is a determinant factor
Gothwal and Raj	2016	Performance evaluation of FMS	digraph and matrix/GTMA	Evaluation of the performance index for an organization, comparison of different industries, and ways to improve the performance
Mahmoud et al.	2017	Studying the performance factors of FMSs	hybrid application of process modeling, simulation, and fault tree analysis	Investigating the effects of changes in cutting conditions
Gothwal and Raj	2017	prioritizing the performance factors of FMSs	ISM	Twelve factors affecting the flexibility of FMSs were presented
Florescu et al.	2017	Determining Operational parameters estimation for an FMS	Case study and simulation	Extracting initial conditions or parameters on the behavior of the FMS
Florescu and Barabas	2018	Assessing the Performance of an FMS	Simulation	Effects of planning strategies in the use of system resources
Jain	2018	Prioritizing the performance factors of FMSs	Multi-Criteria Decision Making (MCDM), Multi-Objective Optimization based on Ratio Analysis (MOORA), and Parameter Space Investigation (PSI)	Productivity should be considered the most crucial factor
Jain and Soni	2019	Analyzing FMSs performance variables and interactions	ISM and Fuzzy Cross-Impact Matrix Multiplication Applied to Classification (MICMAC)	Automation, use of automated material handling, an effect on tool life, and rework percentage were identified as determinant factors of FMS performance
Yadav and Jayswal	2019	FMS performance improvement	Design of Experiments (DOE) and simulation	loop layout with many numbers batches is a determinant factor of FMS performance
Jerbi et al.	2019	Minimizing the mean flow time of an FMS	DOE and simulation	Optimization of FMS performance
Zhang et al.	2020	Performance modeling of an integrated FMS	Mathematical optimization and simulation	Investigating material handling processes
Mishra	2020	Verifying the enablers of volume flexibility and product-mix flexibility	Statistical Analysis	Enablers of volume flexibility and product-mix flexibility were confirmed
Nabi and Aized	2020	Performance evaluation of a multi-product FMS	MOO	Analyzing different production methods effects on FMS performance

Table 2 FMS Performance Indexes

Index	Description
I	Operation sequence $i = 1, 2, \ldots, n_m$
n_m	Separated machines used in the production line or operation sequences
Q	Quantity of products in each batch
T_{oi}	The time of each operation in the machine or workstation i
T_{noi}	The time of each non-operational process in the machine or workstation i
T_{sui}	The time of setting the workpiece, tools and jigs and fixtures in the machine or workstation i
W	The number of workstations
H	The number of shifts in each workstation (Hours per day in each shift)
S_w	The number of shifts in each Week
MTBF	Mean time between failure
MTTR	Mean time to repair
WIP	Work-in-Process
U	Productivity
P_C	Production Capacity
R_p	Production Rate

$$T_p = \frac{T_{su} + QT_o}{Q} \tag{3}$$

Then, the production rate is defined as follows (Groover 2020).

$$R_p = \frac{1}{T_p} \tag{4}$$

Capacity Capacity is the maximum output rate a production system can produce in a given period. In this study, capacity is calculated based on the number of shifts and workstations (Elmaghraby 2011), see Eq. (5). This factor aims to reach a time-related production demand (Lee et al. 2020a).

$$P_C = WS_w \times HR_p \tag{5}$$

where P_C is the production capacity for each group of working stations.

Productivity Productivity is commonly defined as the ratio of a system or machines output quantity (value) to its capacity (Grifell-Tatjé and Knox Lovell 2015). Productivity is calculated based on Eq. (6).

$$\text{Productivity} = \frac{Output}{PC} = U \tag{6}$$

Availability or machine reliability This vital index affects the performance measurement of the considered system and includes two factors (i) mean time between failures (MTBF) and (ii) mean time to repair (MTTR). MTBF is calculated by dividing the "Total Time" by the "Number of Failures" and MTTR by dividing the "Total Time" by the "Number of Units Under Test". The machine availability value measures automated manufacturing systems performance as follows (He et al. 2017).

$$\text{Availability} = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} \tag{7}$$

Work-in-process WIP refers to partially finished goods waiting for completion. WIP handling cost is one of the manufacturing costs. WIP products commonly have some of the below statuses (Chattinnawat 2013).

(a) Their production process has not been started yet;
(b) Some stages of their processes have already started, or
(c) They are finished and are being prepared for delivery.

Therefore, the completion statuses of WIP products are various. The equation below shows this index (Groover 2020).

$$WIP = \frac{UP_C}{HS_w} \times MLT \tag{8}$$

The best status for WIP is that all products in the production line have been processed. Thus, the ratio is 1:1 in mass production systems, while in batch production systems, the WIP ratio is 1:50 or higher. However, this depends on the average batch size and other production factors (Khan et al. 2017).

4 Methodology

RSM is an effective solution for modeling and analyzing variables effects on a particular response(s) of interest. In this case, the goal is to optimize the response(s) (Lalwani et al. 2020). Suppose a system operating under a set of controllable variables $\mathbf{x} = \left(x_1, x_2, \ldots, x_k\right)$ and uncontrollable variables $\mathbf{z} = \left(z_1, z_2, \ldots, z_p\right)$ that result in a response variable y. It is assumed that a function of type $y = f(\mathbf{x}, \mathbf{y})$ is established according to some physical and chemical underlying relations. RSM aims to approximate the above function using a polynomial function of the least significant order (Myers et al. 2011; Zhang et al. 2020). de Oliveira et al. (2019) proposed a nine-step roadmap to perform an RSM.

- (1) Identifying the parameters, influencing factors and response(s).
- (2) Analyzing the impacts of the identified factors on the response variable(s).
- (3) Designing an experiment of a linear polynomial model to examine the main and interaction effects of factors.
- (4) Performing the designed experiments, and (5) evaluating the existence of curvature. (6) If no curvature exists, the stationary point is determined. (7) Otherwise, a new set of experiments adding axial points (three-level factorial designs like central composite or Box-Behnken designs) is designed and performed.
- (8) Designing a model in the form of $y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \sum_{j=i+1}^{k} \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \varepsilon$, for each response ($\varepsilon$ the error), where β_0, $\left(\beta_1, \ldots, \beta_k\right)$, $\left(\beta_{12}, \ldots ., \beta_{k-1,k}\right)$, $\left(\beta_{11}, \ldots, \beta_{kk}\right)$ are the intercept, the main effect or first order, the interaction and pure-quadratic term coefficients, respectively.
- (9) Optimizing the designed model.

The methodology was designed based on the nine steps to conduct the RSM analysis proposed by de Oliveira et al. (2019) in Fig. 1. Each step is described in the subsequent sections. The first step of the proposed methodology (i.e., factor identification and DoEs) corresponds to steps 1–3 of de Oliveira et al. (2019) methodology. This step identifies and measures the considered response variables (i.e., productivity). Then, a two-block CCD design is scheduled. Afterwards, the experiments were implemented using simulation to measure the response variables. The FMS productivity factors such as MLT, production rate, WIPs, capacity, productivity and availability are considered to reach the optimized combination of equipment. Hence, the calculated simulation results reached from these factors are the input or response level of the CCD design for each run. The third step of the proposed framework (i.e., metamodel building and optimization) deals with designing the model as explained in steps 5–8 of de Oliveira et al. (2019). Step 4 of the proposed framework (i.e., model optimization) corresponds to the optimization of the developed model according to step 9 of de Oliveira et al. (2019). This step determines the weight of productivity measures using the BWM method. Then, the overall performance function is determined, and the final aggregated model is designed and optimized.

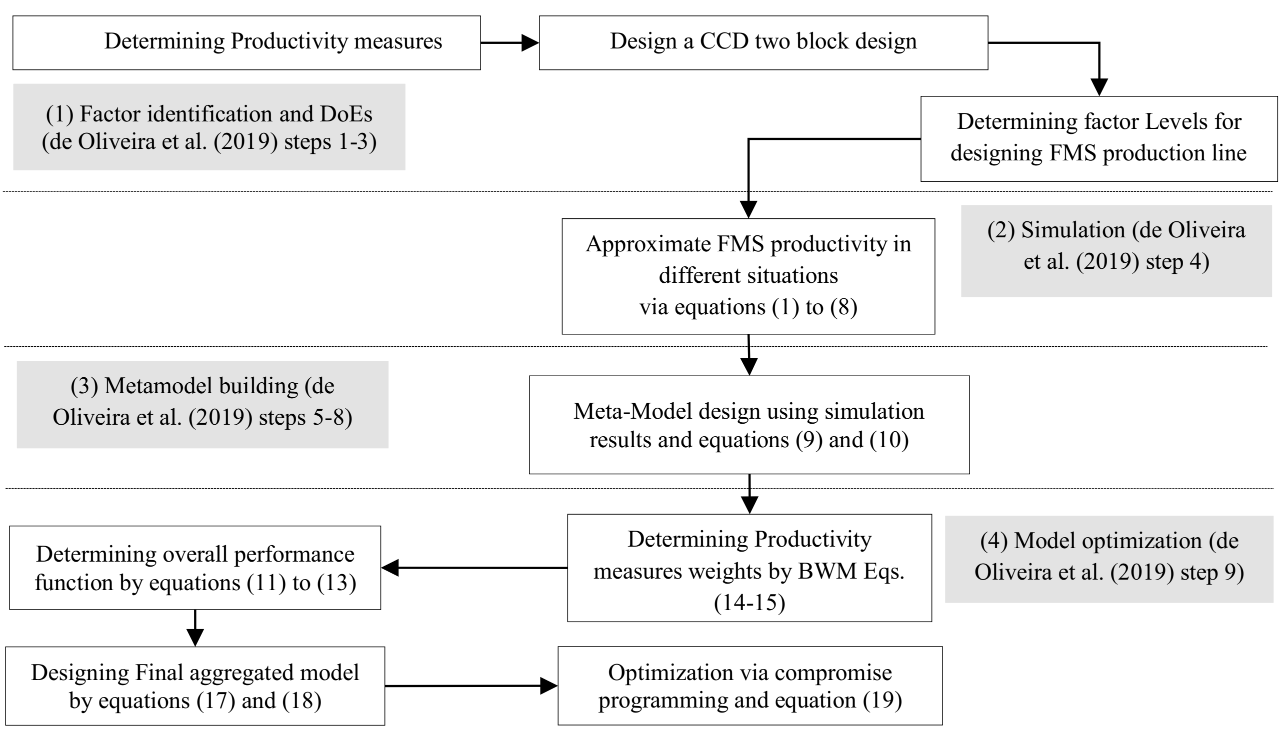


Fig. 1 The framework of the current study

4.1 Factor identification and DoEs

The first step involves defining an FMSs productivity index and identifying the variables affecting these measures. The primary assumption is investigating production productivity by considering various factors and equipment compositions in the automated manufacturing system. In dealing with the problem of FMSs productivity, different variables are introduced as essential factors affecting FMSs performance. This research evaluated various equipment compositions affecting the FMS productivity indices. The critical factors are as follows.

- Computer-Aided Design/Manufacturing/Engineering (CAD/CAM/CAE) plans to design and locate the automated assembly workstations along with CNC machines.
- Programmable Logic Controller (PLC).
- AS/RS and Automated Guided Vehicles (AGV) for storage and material handling system.
- Jigs and Fixtures, including a funnel, power supply, etc.
- Group Technology (GT) implementation with determined cell. The problem framework is illustrated in Fig. 2. The main objective is to determine how to set different factors to maximize FMSs productivity.

To calculate the response surface "y" for each experiment, these factors and measures are aggregated using the BWM weights. A CCD in two blocks was designed to analyze the illustrated problem in Fig. 2. In a CCD, each factor is evaluated at two factorial levels, indicated with (-1, 1), two axial levels $\pm\alpha$, and a central level, indicated with 0. A complete CCD with k factors is composed of a set of 2^k factorial points, $2k$ axial points and n_c the central point, a total of $2^k + 2k + n_c$ experiments (Myers et al. 2011). For $k = 5$, a complete CCD includes more than $42 + n_c$ experiments. To decrease the number of required experiments, a half-CCD plan was used that included $2^{k-1} + 2k + n_c$ experiments in each iteration. Therefore, for $k = 5$, the designed experiment included $26 + n_c$ experiments in each replication. Using Minitab Statistical Software (MINITAB) to design the experiments, the optimal value of α for five factors was determined to equal 2. The factor levels are illustrated in Fig. 3. This figure sets the factor levels according to their settlement amount in the production line.

4.2 Simulation

To represent the studied FMS with different factor combinations (treatments), a discrete-event simulation using the AnyLogic software has been employed. Discrete event simulation captures different systems performances under various situations (Choi and Kang 2013; Rao and Naikan 2016). Simulation provides an easier way of dealing with sources of variations. The present study aims to analyze the effects of designing factors on FMS productivity. Since six different productivity measures represented the performance of the FMS, as described in Section 4, simulation was used to approximate the FMS productivity in different situations.

4.3 Metamodel building

While simulation represents an illustration of the considered system, a metamodel develops a mathematical model of the behavior of a system using the simulation results for further analysis (Chen et al. 2019). Two general types of methodologies are used to build metamodels. First, if the underlying relationships among variables are known and perceptible, mathematical modeling translates the interrelation among variables into corresponding mathematical equations. On the other hand, when these relationships are complex and unknown, building an empirical model would be appropriate (de Oliveira et al. 2019). Empirical model-building techniques are usually based on regression analyses to fit a polynomial regression model. The degree of this polynomial depends on the significance of the corresponding term in the statistical analysis phase. To this aim, DoE is used to test the significance of the related terms and then to fit the suitable form of the meaningful polynomial of the required order. Considering $\left(x_1, x_2, \ldots, x_k\right)$ as the impacting factors on the response y, the first-order (linear) model is as follows.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \tag{9}$$

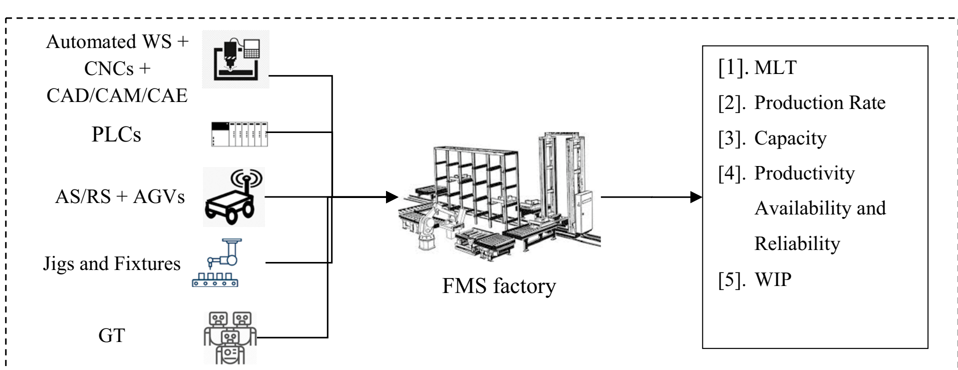
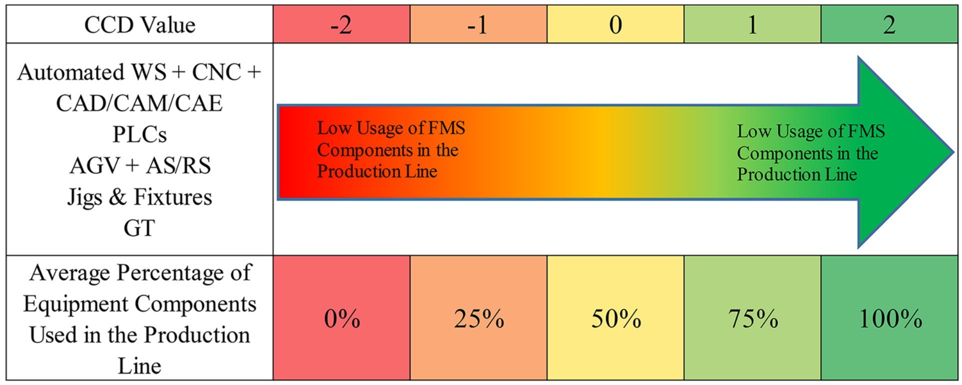


Fig. 2 The design FMS problem framework

Fig. 3 Factor levels used for designing FMS production line



The second-order metamodel of the form in Eq. (10) is more popular.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \sum_{j=i+1}^{k} \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \varepsilon \tag{10}$$

Higher-order terms are usually insignificant due to the sparsity of effects, meaning that higher-order interactions are scarcely significant and neglected. The sparsity of effects is studied and approved by Bergquist et al. (2011). Six main manufacturing factors, including MLT (x_1), production rate x_2, capacity x_3, productivity x_4, availability x_5 and WIP x_6, were used in the experiments to measure the response level for the manufacturing system, as discussed in Section 3.

4.4 Model optimization

As described in Section 3, six measures were used to evaluate the performance of the studied FMS. Suppose that $y_1(k)$ is the approximated performance for the MLT measure; $y_2(k)$ the model fitted for production rate; $y_3(k)$ the model developed for capacity under treatment k; $y_4(k)$ the model developed for productivity; $y_5(k)$ the model obtained for availability or machine reliability, and $y_6(k)$ is the model developed for WIP under treatment k. Consequently, the overall performance function under treatment k is obtained to optimize the FMS performance.

$$\mathrm{y(k)} = \sum_{\mathrm{i=1}}^{6} \mathrm{w_i} \times \mathrm{y\prime_i(k)} \tag{11}$$

where $W = (w_1, w_2, \dots, w_6)$ is the performance measures weight vector and $y\prime_i(k), i = 1, 2, \dots, 6$ are the normalized performance of i^{th} measure under treatment k. For the first MLT and sixth WIP measures, Eq. (12) is estimated.

$$\mathrm{y\prime_i(k)} = \frac{\min\limits_{\mathrm{k}} \mathrm{y_i(k)}}{\mathrm{y_i(k)}} \tag{12}$$

While for the second (production rate), third (capacity), fourth (productivity), and fifth (availability) measures, Eq. (13) is employed as follows.

$$\mathrm{y\prime_i(k)} = \frac{\mathrm{y_i(k)}}{\max\limits_{\mathrm{k}} \mathrm{y_i(k)}} \tag{13}$$

Considering the six performance criteria for the FMS performance, a criteria weight vector $W = (w_1, w_2, \dots, w_6)$ is required. In this regard, the BWM method was implemented. BWM is commonly employed to extract criteria weights (Rezaei 2015). Further developments of this method have been designed for specific and uncertain circumstances (Mahdiraji et al. 2020). In this paper, the nonlinear approach of BWM was used as follows (Rezaei 2015).

1. Determine the set of decision criteria known as $(\{\mathrm{C_1, C_2, \dots, C_n}\})$.
2. Define the best (most important) and worst (least important) criteria using experts opinions. The best criteria is known as (B) or (b), and the worst criteria is denoted as (W) or (w). Subsequently, determine the preference of the best criteria over other criteria by a number between 1 and 9, known as $\mathrm{A_B = (A_{b1}, A_{b1}, \dots ., A_{bn})}$.
3. Measure the importance of other criteria over the worst criteria on a scale between 1 and 9, denoted by $\mathrm{A_W = (A_{1w}, A_{2w}, \dots ., A_{nw})}$ by each expert through a designed questionnaire.
4. Determine the optimal weights by solving the NLP model as (14) via GAMS software. The results are emanated as $W_j^k = \{W_1^k, W_2^k, \dots, W_n^k\}$ for the $\mathrm{k^{th}}$ expert. Then, these weights are aggregated via arithmetic mean to measure the final weight of each FMS performance indicator.

$$
\begin{aligned}
&\min \xi \\
&\mathrm{St}: \\
&\left|\frac{W_B}{W_j} - A_{bj}\right| \le \xi; \quad \text{for all j} \\
&\left|A_{jw} - \frac{W_j}{W_w}\right| \le \xi; \quad \text{for all j} \\
&\sum W_j = 1, \\
&W_j \ge 0
\end{aligned}
\tag{14}
$$

5. To check the reliability of the extracted weights, the compatibility ratio (CR) for each expert is investigated via Eq. (15), where CR^k is the consistency ratio for k^{th} expert. In this research, CR less than 0.1 is acceptable. CI determines the consistency index adopted by Rezaei (2015).

$$CR^k = \frac{\xi^*}{CI} \tag{15}$$

Using $y(k)$ as the aggregated response variable, the first objective of the problem is formulated as follows.

$$\mathrm{Max}\,y = \max_{x_1,x_2,\ldots,x_5} f\left(x_1, x_2, \ldots, x_5\right) = \mathrm{Max}\, f_1(x) \tag{16}$$

where $f\left(x_1, x_2, \ldots, x_5\right) = f_1(x)$ is a polynomial metamodel, as discussed in Section 4.3. However, an additional objective function is also considered since deploying these factors requires infrastructure investment. If a one-percent increase in the level of factor $x_i, i = 1, 2, \ldots, 5$ needs a cost of $c_i, i = 1, 2, \ldots, 5$, then the cost-related function is formulated as follows.

$$\mathrm{Min}\sum_{i=1}^{5} c_i x_i = \mathrm{Min} f_2(x) \tag{17}$$

Therefore, the final model is as follows.

$$
\begin{aligned}
&\mathrm{Max}\, f_1(x) \\
&\mathrm{Min} f_2(x) \\
&\mathrm{S.T.}\ 0 \le x_i \le 1, i = 1, 2, \ldots, 7
\end{aligned}
\tag{18}
$$

A weighted Lp-metric-based model was used to solve the Eq. (18) model using compromise programming (Zeleny 1973). Defining $f_i^*(x)$ and $f_{i*}(x)$ as the ideal and non-ideal solutions of $f_i(x), i = 1, 2$ respectively, the Lp-metric objective function is formulated as follows.

$$
\begin{aligned}
&\mathrm{Min}\left[\sum_{i=1}^{2} w_i \left(\frac{f_i^*(x) - f_i(x)}{f_i^*(x) - f_{i*}(x)}\right)^p\right]^{1/p} \\
&\mathrm{S.T.}\ 0 \le x_i \le 1, i = 1, 2, \ldots, 7
\end{aligned}
\tag{19}
$$

Where $W = \left(w_1, w_2\right)$ is the weight vector of objectives in a way that $w_i \ge \varepsilon$ and $w_1 + w_2 = 1$. The above problem is usually solved for $p = 1, 2$ and ∞. Since the approximated objective functions are expected to be second-order polynomial; thus, the above model is a nonlinear programming model.

5 Case study

The FMSs of an elevator control panel and electric boards produced by an Iranian manufacturing organization were considered as a case study to illustrate the application of the proposed framework in this paper. The FMS used to produce the elevator control panel and electric boards were launched in 2007. In 2007, the factory was established on a $500m^2$ site. After four years, they moved to a larger, brand-new site with all the developed facilities. Continuous improvement, the lowest delivery time, and quality control were the main strategies for the organization to satisfy its customers. The main activities were internal and external logistics, electrical operations, control panel operations, production quality control, sales, after-sales services, and marketing. The information about the production line and the required equipment was gathered from interviews with company experts at the end of November 2020. An initial list of company experts was compiled based on their experience (at least three years), electronic equipment knowledge (at least a bachelors degree in engineering), and their knowledge regarding the current production system (at least managerial level). As a result, eight experts were nominated for the initial list. The board of directors introduced this list by considering the abovementioned criteria. According to this list, the board of directors compiled a final list of experts using the Borda method and expert selection criteria (Du and Gao 2021). Thus, the weight of each expert was measured accordingly. Table 3 illustrates the results of the Borda method analysis. Consequently, experts No. 5 to 8, i.e., CEO, Planning Manager, Financial Manager, and Quality Manager, were selected for data gathering. The data gathering was carried out through interviews and a questionnaire.

The interviews included a briefing on the research and a structured interview using the questionnaire/protocol represented in Appendix A. Regarding the surveys and BWM questionnaire; the authors thoroughly explained the methodology steps. The questions were sent to the interviewees five days before the interview session. As a result, 75 min were spent on average for each interview. Furthermore, the BWM questionnaire (Appendix B) was presented by the research team and given to the experts. These were then collected three weeks later, in December 2020. The manufacturing system studied included two main production lines (i) Cabin and (ii) Control panel and board production lines.

Moreover, there was an automated storage and retrieval system for warehousing. The automated elevator control panel consisted of various types of equipment such as AGVs, AS/RS warehousing systems, automated machines, robots, CNC machines, cabins production lines, jigs and fixtures, conveyors, and an automated packing system. Thus, the

Table 3 The results of the Borda method for experts weighting and selection

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Rank 8	Sum of Scores	Weights	Rank
Expert 1	10	5	5	10	5	15	0	15	210	9.95%	7
Expert 2	5	10	5	10	15	20	5	20	250	11.85%	5
Expert 3	5	5	10	20	0	5	15	0	220	10.43%	6
Expert 4	0	10	0	5	20	0	15	5	155	7.35%	8
Expert 5	20	0	20	0	15	10	15	15	320	15.17%	3
Expert 6	15	5	15	5	10	5	0	5	270	12.80%	4
Expert 7	15	10	5	20	5	20	15	10	340	16.11%	2
Expert 8	10	20	15	10	5	10	5	15	345	16.35%	1
Score	7	6	5	4	3	2	1	0	2110		

production line of the control panel was based on a mechanical process and included wiring, board and drive installation and assembly, final quality control, and packing. An overview of the studied production line is illustrated in Fig. 4.

The organization (known as CAP Co.) can employ the proposed framework and relevant results when developing manufacturing systems, automated tools, and related CAD/CAM solutions to optimize productivity and increase production capacity. The company employed some of these automated systems on a small scale. Consequently, more than 20% improvement in production rate, an 8% reduction in WIP and an increase in the capacity of workstations were achieved.

As described in Section 4.1, five types of FMS technologies were considered, namely (1) WS, CNCs and CAD/CAM/CAE, (2) PLCs, (3) AGV and AS/RS, (4) Jigs and Fixtures, and (5) GT. Moreover, five main performance factors, i.e. (1) MLT, (2) production rate, (3) capacity, (4) productivity, availability, and machine reliability, and (5) WIPs were employed. Furthermore, a half-CCD experiment with three replicates, i.e., 96 runs, was designed to investigate the effect of the factors on the FMS performance. The factor levels are represented in Fig. 4. In this research, the experiments were designed based on the five main equipment classes. For instance, if any equipment, e.g., a CNC machine, was eliminated, all the CNC machines in both product lines could not be used, and these processes were performed manually. To approximate productivity measures, different factor combinations were simulated. Each combination was simulated in MATLAB to analyze the results of the performance response measures. The simulation runs

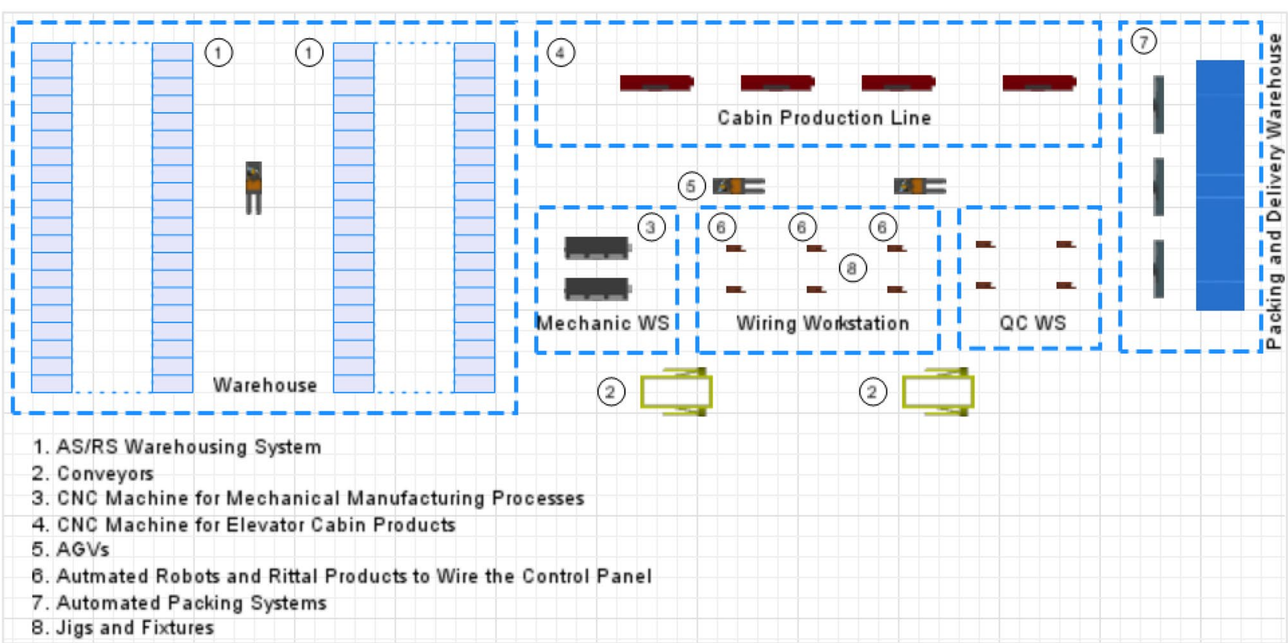


Fig. 4 The view of the automated equipment layout of the case study production line

Table 4 Simulation for six main classifications of automated equipment (sample data)

Q	N_m	T_{su}	T_{no}	S_w	Output	MTTR	MTBF
2[a]. The first classification							
11.36	0.12	0.8	0	37.5	84.25	2.512563	29.41176
2[b]. The second classification							
7.27	0.1875	1.25	0	24	53.92	1.60804	18.82353
2[c]. The third classification							
5.91	0.23	1.53	2	19.5	43.81	1.3065	15.294
2[d]. The fourth classification							
4.55	0.3	2	0	15	33.7	1.005025	11.76471
2[e]. The fifth classification							
1.82	0.75	5	1	6	13.48	0.40201	4.705882
2[f]. The sixth classification							
0.45	3	20	4	1.5	3.37	0.100503	1.176471

2[a]expected effect of this combination in different measures

2[b]one of the equipment was fully automated, and others are semi-automated

2[c]two or three types of equipment were automated, and others were partially automated

2[d]all equipment was set in level 0, which meant that 50% of the production line was automated

2[e]one of the equipment was automated, while the others were semi-automated

2[f]all of the pieces of equipment were in level -1 or all except one were in level -1

were performed for 5,000,000-time units on a PC with a Core 2 Duo CPU (2.00 GHz) and 1.99 GB of RAM, and each run took about 5 to 6 min. The equations for calculating the performance measures are presented in Section 3. The underlying logic of the simulation was to simulate the effect of designing factors on each measure. Table 4 denotes some parts of the simulation results for six main classifications of automated equipment and illustrates the impact of setting all five types of equipment as automated.

Except for MTBF, which results were obtained through each experiment, others were derived from the simulation. The approximated performance measures were evaluated by simulating 96 treatments based on the above logic. A part of the obtained results and the corresponding treatment combinations is illustrated in Table 5.

Moreover, the considered measures were weighted using the BWM by gathering the required comparisons from the panel of experts (via the questionnaire described in Appendix B). Accordingly, by implementing model (14), the importance of the FMS performance measures were 0.08, 0.17, 0.17, 0.33, 0.17 and 0.08, respectively. These weights were used for different aggregate performance measures in experimental treatments to achieve an overall performance. The BWM questionnaire was completed by a group of experts from the studied company, including four middle and high-level managers. The CR of the panel of experts was measured through Eq. (12). The results indicated that the expert panel weights were reliable (CR = 0.021).

After running all the required experiments, approximating performance measures and aggregating them using the weights mentioned above, the next step was to measure the functional form of the FMS performance based on the design variables. These functions were approximated through regression analysis. The complete model included five main effect terms (i.e., x_i), ten interaction terms (i.e., $x_i x_j$) and five pure quadratic terms (i.e., x_i^2). However, only the statistically significant terms were used in the models using analysis of variance (ANOVA) and the notion of the significant test. Figure 5 illustrates the obtained regression models with the corresponding statistical significance tests for each response. The box-Cox transformation was used to improve the approximated models, and all models were developed using MINITAB19. Equation (10) was approximated using the optimal Box-Cox transformation.

Table 5 Treatment combinations and the simulated performance measures (sample)

CNC and Automated PL	AGV and AS/RS	PLC	Jigs and Fixtures	GT	MLT	R_p	P_c	U	Availability	WIP
1	1	1	-1	-1	1.127	0.322	150.768	0.270	0.934	18.792
0	0	-2	0	0	4.595	0.276	39.724	0.083	0.775	20.194
0	0	2	0	0	0.616	0.272	156.868	0.332	1.298	10.693

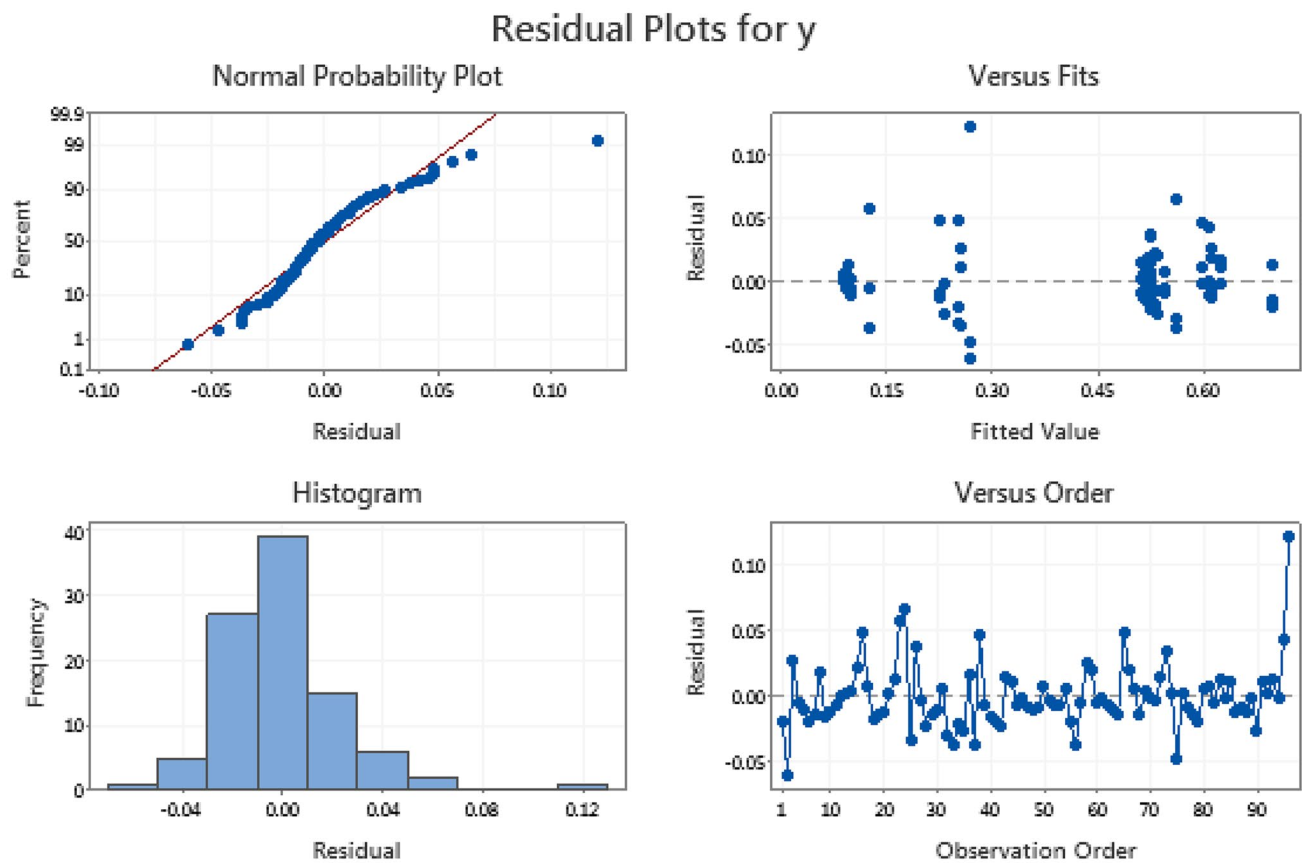


Fig. 5 Residual analysis for the approximated model

$$
\begin{aligned}
y^{1.31888} = {} & 0.52466 + 0.09154x_1 + 0.08618x_2 + 0.09204x_3 + 0.08934x_4 \\
& + 0.09639x_5 - 0.02686x_1^2 - 0.02117x_2^2 - 0.02097x_3^2 - 0.02352x_4^2 \\
& - 0.02658x_5^2 - 0.00896x_1x_2 - 0.01589x_1x_3 - 0.02022x_1x_4 \\
& - 0.01788x_1x_5 - 0.01720x_2x_3 - 0.01750x_2x_4 - 0.01995x_2x_5 \\
& - 0.00967x_3x_4 - 0.01704x_3x_5 - 0.01643x_4x_5
\end{aligned} \tag{20}
$$

In the above equation, the coefficient of determination (R^2) is 98.26%, while the adjusted R^2 is 97.80%. Furthermore, the model assumptions were tested, as shown in Fig. 5.

According to Fig. 5, the normal probability plot proved the normality assumption, whereas residual plots versus fit and order illustrated the homogeneity of variances and randomness. Therefore, the fitted model was acceptable. On the other hand, considering the required monetary investment for increasing the percentage of five characteristics of the FMS, the cost of different machines associated with five factors were approximated as \$39,500, \$1,000, \$115,000, \$10,000, and \$2,000, respectively. Therefore, the cost function was formulated as follows.

$$
39,500x_1 + 1,000x_2 + 115,000x_3 + 10,000x_4 + 2,000x_5 \tag{21}
$$

The studied company also considered a budget of \$100,000 to enhance its FMS performance by equipping the company with the considered machines and technologies. Therefore, the final model configuring the factors affecting the FMS performance was formulated as Eq. (22).

$$\begin{aligned}
&\text{Max } 0.52466 + 0.09154x_1 + 0.08618x_2 + 0.09204x_3 + 0.08934x_4 + 0.09639x_5 \\
&\quad - 0.02686x_1^2 - 0.02117x_2^2 - 0.02097x_3^2 - 0.02352x_4^2 - 0.02658x_5^2 - 0.00896x_1x_2 \\
&\quad - 0.01589x_1x_3 - 0.02022x_1x_4 - 0.01788x_1x_5 - 0.01720x_2x_3 - 0.01750x_2x_4 \\
&\quad - 0.01995x_2x_5 - 0.00967x_3x_4 - 0.01704x_3x_5 - 0.01643x_4x_5 \\
&\quad \text{Min } 39,500x_1 + 1,000x_2 + 115,000x_3 + 10,000x_4 + 2,000x_5 \\
&\quad \text{S.T.} \\
&\quad 39,500x_1 + 1,000x_2 + 115,000x_32 + 10,000x_4 + 2,000x_5 \le 10,0000 \\
&\quad 0 \le x_i \le 1,\ i = 1, 2, \dots, 5
\end{aligned} \tag{22}$$

The model in Eq. (22) is a multi-objective nonlinear programming model. Its Hessian matrix was constructed to investigate the concavity of the considered function, and the eigenvalues were determined. The eigenvalues of the first objectives Hessian matrix were determined as -0.1127, -0.0416, -0.0343, -0.0302 and -0.0192. Since all the eigenvalues were negative, it was concluded that the first objective was concave. Therefore, the obtained solutions were the global optimum of the problem. According to the proposed method, the next step was to find the ideal solutions. The ideal solution for the objective functions were obtained as $f_{1*} = 52.47\%$, and $f_{2*} = 100,000$. Finally, the single objective function was formulated as follows according to Eq. (19).

$$\begin{aligned}
&\text{Min}\left[w_1\left(\frac{115.35\% - f_1(x)}{62.88\%}\right)^p + w_2\left(\frac{f_2(x)}{100,000}\right)^p\right]^{1/p} \\
&\text{S.T.} \\
&39,500x_1 + 1,000x_2 + 115,000x_3 + 10,000x_4 + 2,000x_5 \le 100,000 \\
&0 \le x_i \le 1, i = 1, 2, \dots, 5
\end{aligned} \tag{23}$$

The model was solved for different values of p and w. To this aim, three distinct values of $p = 1$, $p = 2$, and $p = \infty$(inf) were considered. Moreover, the weights were respectively assigned as $w_1 = 0, 0.1, 0.2, \dots, 1$ and $w_2 = 1 - w_2$. Figure 6 illustrates the respective Pareto-optimal solutions found by solving the model.

According to Fig. 6, decision-makers can choose different solutions and select optimal FMS settings. Consider the case where $w_1 = w_2 = 0.5$. For three values of p, Table 6 represents the optimal setting of FMS factors.

For *p = 1*, the company must equip all its production lines with PLCs, all the lines must be structured as GT, and jigs and fixtures must be used. However, the other two factors were not required. Considering the costs of the above three solutions, it might seem unreasonable to increase the cost from \$13,000 to more than \$19,000 for a 3% to 5% of performance improvement. Therefore, if managers consider equal weights over cost and performance objectives, the best FMS settings were obtained using the solution for $p = 1$. On the other hand, if the company considers only the performance of the system, i.e., $w_1 = 1, w_2 = 0$, then the results are shown in Fig. 7 for different values of p.

The next concern is the sensitivity of the obtained results to the variation of parameters, especially the available budget. For different levels of objective weights, the budget is increased from \$0 to \$100,000 with a step size of 1,000. Figure 8 illustrates the results of solving 101 models with different available budgets (horizontal axis) and the optimum performance (vertical axis). According to Fig. 8, by increasing the weight of the first objective, the results become more sensitive to the available budget. The correlation of FMS performance with

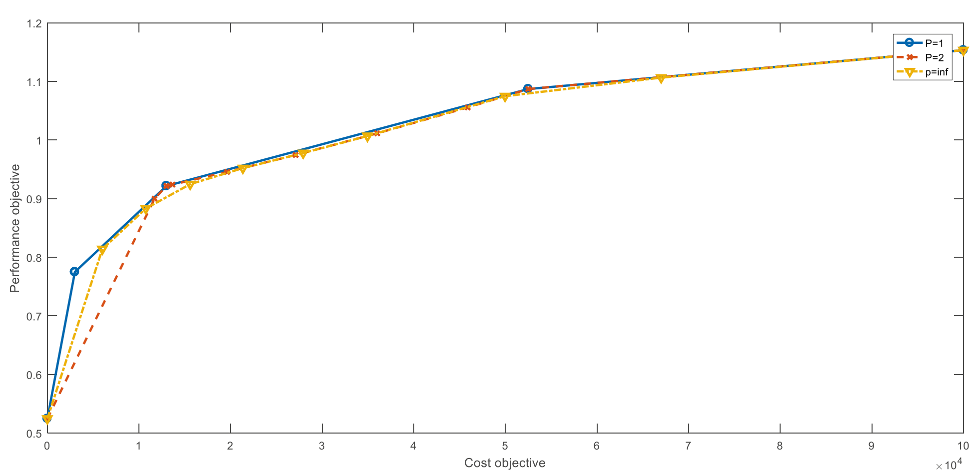


Fig. 6 The Pareto front for different values of p and w

Table 6 The optimal settings of FMS factors

	p = *1*	*p* = *2*	$p = \infty$
WS + CNCs	0%	17%	38%
PLCs	100%	100%	100%
AS/RS + AGV	0%	0%	0%
GT	100%	100%	100%
Jigs and Fixtures	100%	100%	100%
Cost	13,000	19,633	27,920
Approximated performance	92.17%	94.57%	97.79%

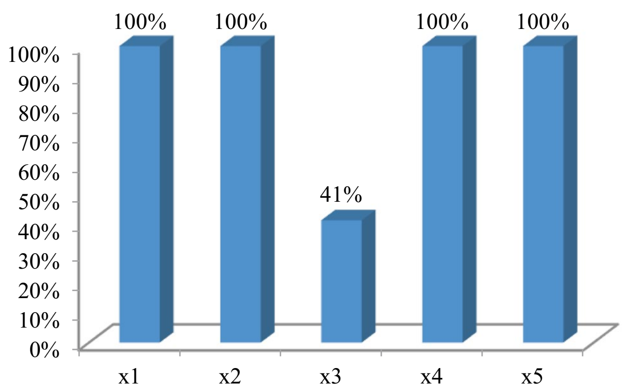


Fig. 7 The limiting case with $w_1 = 1, w_2 = 0$

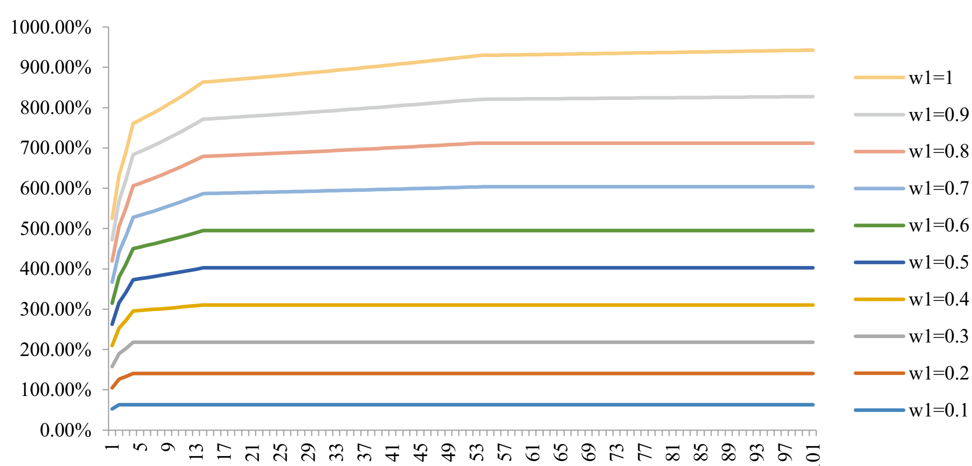
the available budget increased from 17.15% $\left(w_1 = 0.1\right)$ to 89.29%$\left(w_1 = 1\right)$. It means that the more important the FMS performance becomes, the higher budget is required.

6 Discussion

The problem of converting traditional manufacturing systems into FMSs is a challenging and cost-consuming decision. Madson et al. (2020) focused on the lack of a formal framework for designing FMSs. The problem studied in this paper is devoted to finding a suitable solution. Since FMSs are comprised of several modules with different impacts, this study determines an optimal set of these modules by simultaneously optimizing the performance of an FMS and its implementation costs. The primary response variable, i.e., x_j, was defined as the extent to which a given machine type *j* must be implemented in an FMS. However, different machines have diverse direct or indirect effects on the performance of an FMS. To find these effects, RSM was used to design experiments to study the impact of different machine implementation scenarios on the FMS performance. The performance of the FMS, known as a response, was characterized using six different and prominent measures. On the other hand, the factors affecting these performance measures were determined by the extent of implementation of different machines in the manufacturing system. A CCD was proposed to measure the direct and indirect effects, and the overall response surface was obtained. Accordingly, all considered machines had a potentially positive effect on the overall performance of the FMS. Considering the results emanated from the proposed method and illustrated in Sections 4 and 5, a one percent increase in the implementation of CNC and automated PLC had a $9.15\% \times 0.01 = 0.092\%$ positive effect on the overall performance of the FMS. Similarly, AGV and AS/RS, PLC, jigs and fixtures, and GT received 0.082%, 0.092%, 0.089%, and 0.096% positive effects, respectively. These values indicate that all the considered machines directly improve the performance of an FMS, and the GT effect is partially more than the others, while the difference is insignificant.

For two variables x_1 and x_2, a 1% simultaneous increase impacts the performance by 0.17%. However, the curvature effects of these two variables decreased the improvement by 0.048%, and their mutual effect also had a 0.0001% negative effect on the performance of the system. On the other hand, the cost dimension can also adjust the setting of the optimal decision. For instance, according to Eq. (20), if all

Fig. 8 The sensitivity of the model to the available budget



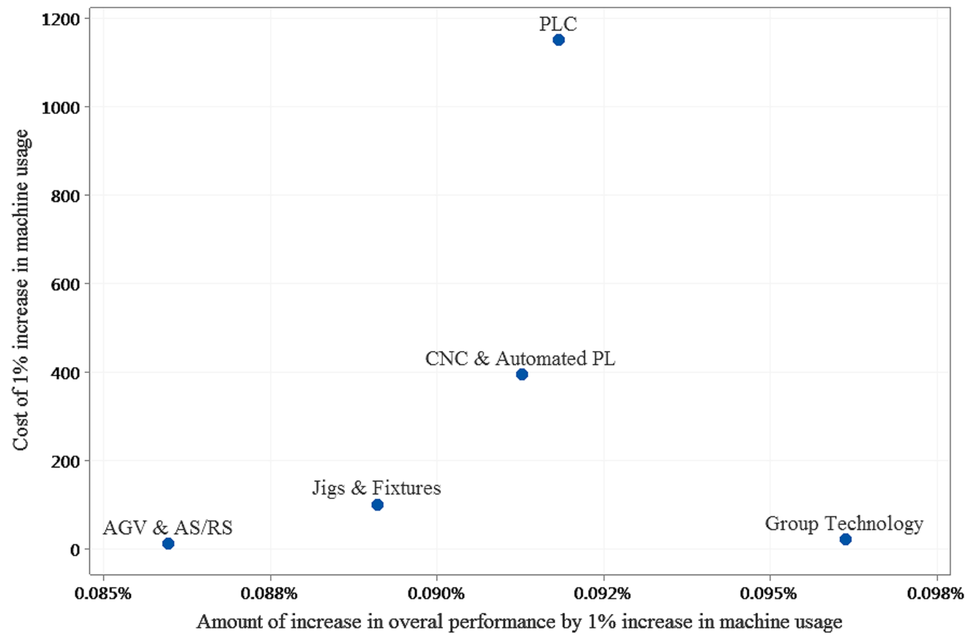


Fig. 9 Machine usage and the trade-off between cost and performance

the factors were set at 100%, an overall performance of 70% would be obtained. However, the cost of applying all the machines at the full level was $167,500. This investment is risky for a manufacturing system. Therefore, it will be required to trade off the amount of increasing the performance against its required cost. Figure 9 illustrates the effect of a 1% increase in machine usage against its imposed cost.

According to Fig. 9, increasing the usage of different machines illustrates a range of performance increase between 0.085% to less than 0.098%. Nevertheless, the cost of this 1% increase ranges between 10 to more than $11,000. This limited range of performance improvement against the wide range of costs illustrates the necessity of seeking Pareto-optimal solutions, as discussed in the previous section.

7 Conclusions

This study considers the problem of optimally using various advanced and automated manufacturing equipment. To this aim, an empirical model-building based on RSM was proposed to determine the level of deployment of different technological components of FMSs. A combination of CCD design, simulation, regression modeling, BWM, and MOO allowed the investigation of FMS performance measures and clarified design variables impact, individually and mutually. The proposed method was applied in a real-world case study. The results determined the Pareto-optimal configuration of the system for its practitioners. Theoretically, this method includes measuring manufacturing indexes based on sub-category parameters using BWM and RSM. The input factors from the simulation were WIPs, production rates, availability, and performance. Different combinations of automated manufacturing systems such as robots, CNC machines, automated warehouse systems and AGVs were the output of RSM, and the regression equation and the performance of the system in each status were the models results. Hence, this analytical method was applied to balance the production line indexes, elaborate on the details of production factors, and change different factors to reach the best solutions. This method can be easily used for other large-scale FMSs and is not limited to any specific system.

Furthermore, changing the parameters and indexes and even the combinations of automated manufacturing technologies is possible. Designing FMSs is expensive, and this technique and stages of this research enabled us to reach the best combination of automated equipment used in FMSs as accessible as possible since this method is cheaper and more flexible for different production lines. Using DoE to enter "y" for each experiment is one of the practical benefits of this research, as this hard-to-change model cannot calculate the inputs of DoEs. Simulation enables enterprises to measure them simply and with minimum time. Thus, a notable innovation of this research was measuring all the responses without reasonable expenses and experiments. Improving production line productivity, controlling WIPs, working on machines and equipment efficiency, comparing suitable technologies, elaborating production problems, and reducing the workforce were some of the consequences and results of using this system. However, although simulation is a valuable tool, the results might defer from reality and should be considered a significant constraint.

The respective Pareto-optimal values based on the cost and performance objectives make it possible to choose various solutions and required FMS combinations, including advanced machines, CNCs, PLCs, AS/RS, AGV, GT, Jigs and Fixtures. Also, decision-makers can compare these FMS settings and choose the combination that is possible to implement. Besides, as the three values of p illustrated, it is required to spend more budget to reach higher production performance.

In this paper, the levels of design variables were specified at fixed levels while considering the range [0, 100]. However, a random effect model can be developed in future studies. On the other hand, since non-controllable and external factors can affect the optimal combination of design variables, robust designs are also recommendable for future studies to eliminate the harmful effects of external nuisance. A combination of design and operational variables is also considerable for future researchers to hybridize the strength of the current study with previous ones. Accessing accurate data (e.g., manufacturing process details, resources, precise real-world parameters, etc.) was another limitation of this research. As a result, some required information was gathered from experts based on their subjective judgment. This data-gathering approach may negatively impact the performance indexes and simulation results. Hence, these issues have influenced the generalizability of the research. As a recommendation, future investigators could focus on gaining access to the response level of experimental design, the discrete event simulation results, and reaching precise data. This change in information could be used for more complicated models and large-scale manufacturing systems. Moreover, this study focused on the design variables of an FMS at the highest level. However, the design is extendable to more operational variables. Moreover, this research neglected environmental and social factors in designing the FMS and should be considered in future investigations.

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Data availability The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declarations

The authors declare and confirm that no financial or non-financial interests are directly or indirectly related to this work submitted for publication.

References

Ali M, Murshid M (2016) Performance evaluation of flexible manufacturing system under different material handling strategies. Glob J Flex Syst Manag 17(3):287–305

Bergquist BE, Vanhatalo E, Nordenvaad ML (2011) A Bayesian analysis of unreplicated two-level factorials using effects sparsity, hierarchy, and heredity. Qual Eng 23(2):152–166

Bi X, Yu D, Liu J, Hu Y (2020) A preference-based multi-objective algorithm for optimal service composition selection in cloud manufacturing. Int J Comput Integr Manuf 33(8):751–768

Chattinnawat W (2013) Effects of quality levels, lot size, WIP and product inventory to MFCA cost-based throughout supply chain. Proceeding of the 16th Environmental Management Accounting Network Conference on Material Flow Cost Accounting 181–187

Chen J, Gao X, Hu Y, Zeng Z, Liu Y (2019) A meta-model-based optimization approach for fast and reliable calibration of building energy models. Energy 188:116046

Choi BK, Kang D (2013) Modeling and simulation of discrete event systems. John Wiley and Sons, Hoboken, New Jersey

Demesure G, Defoort M, Bekrar A, Trentesaux D, Djemai M (2017) Decentralized motion planning and scheduling of AGVs in an FMS. IEEE Trans Indust Inform 14(4):1744–1752

de Oliveira LG, de Paiva AP, Balestrassi PP, Ferreira JR, da Costa SC, da Silva Campos PH (2019) Response surface methodology for advanced manufacturing technology optimization: theoretical fundamentals, practical guidelines, and survey literature review. Int J Adv Manuf Tech 104(5–8):1785–1837

Du L, Gao J (2021) Risk and income evaluation decision model of PPP project based on fuzzy Borda method. Math Probl Eng 2021:1–10

Edh Mirzaei N, Hilletofth P, Pal R (2021) Challenges to competitive manufacturing in high-cost environments: checklist and insights from Swedish manufacturing firms. Oper Manag Res 14(3–4):272–292

Elmaghraby SE (2011) Production capacity: Its bases, functions and measurement. In: Kempf KG, Keskinocak P (eds) Planning production and inventories in the extended enterprise: a state of the art handbook. Springer, New York, pp 119–166

Florescu A, Barabas SA (2018) Simulation tool for assessing the performance of a flexible manufacturing system. In IOP Conf Ser Mater Sci Eng 398(1):012023

Florescu A, Barabaş S, Sârbu F (2017) Operational parameters estimation for a flexible manufacturing system. A case study. MATEC Web Conf 112:05008. EDP Sciences

Ghadirpour M, Rahmani D, Moslemipour G (2020) Routing flexibility for unequal–area stochastic dynamic facility layout problem in flexible manufacturing systems. Int J Ind Eng Prod Res 31(2):269–285

Gothwal S, Raj T (2016) Performance evaluation of flexible manufacturing system using digraph and matrix/GTA approach. Int J Manuf Technol 30(3–4):253–276

Gothwal S, Raj T (2017) Analyzing the factors affecting the flexibility in FMS using weighted interpretive structural modeling (WISM) approach. Int J Syst Assur Eng Manag 8(2):408–422

Grifell-Tatjé E, Knox Lovell CA (2015) Productivity accounting the economics of business performance. Cambridge University Press, New York

Groover MP (2020) Fundamentals of modern manufacturing: materials, processes, and systems. John Wiley and Sons

He Y, Gu C, Chen Z, Han X (2017) Integrated predictive maintenance strategy for manufacturing systems by combining quality control and mission reliability analysis. Int J Prod Res 55(19):5841–5862

Ivanov A, Jaff T (2017, April) Manufacturing lead time reduction and its effect on internal supply chain. Int Conf Sustain Des Manuf 398–407. Springer, Cham

Jaff T, Ivanov A (2016) Manufacturing lead-time reduction and knowledge sharing in the manufacturing sector. InImpact: J Innov Impact 8(2):618

Jain V (2018) Application of combined MADM methods as MOORA and PSI for ranking of FMS performace factors. Benchmarking Int J 25(6):1903–1920

Jain V, Raj T (2016) Modeling and analysis of FMS performance variables by ISM, SEM and GTMA approach. Int J Prod Econ 171(1):84–96

Jain V, Soni V (2019) Modeling and analysis of FMS performance variables by fuzzy TISM. J Model Manag 14(1):2–30

Jerbi A, Ammar A, Krid M, Salah B (2019) Performance optimization of a flexible manufacturing system using simulation: The Taguchi method versus OptQuest. Simulation 95(11):1085–1096

Kabir QS, Suzuki Y (2018) Increasing manufacturing flexibility through battery management of automated guided vehicles. Comput Ind Eng 117:225–236

Karimi B, Akhavan Niaki ST, Haleh H, Naderi B (2019) Reliability optimization of tools with increasing failure rates in a flexible manufacturing system. Arab J Sci Eng 44(3):2579–2596

Khan M, Hussain M, Cárdenas-Barrón LE (2017) Learning and screening errors in an EPQ inventory model for supply chains with stochastic lead time demands. Int J Prod Res 55(16):4816–4832

Lalwani V, Sharma P, Pruncu CI, Unune DR (2020) Response surface methodology and artificial neural network-based models for predicting performance of wire electrical discharge machining of inconel 718 alloy. J Manuf Mater Process 4(2):44

Lee S, Issabakhsh M, Jeon HW et al (2020a) Idle time and capacity control for a single machine scheduling problem with dynamic electricity pricing. Oper Manag Res 13:197–217

Lee DK, Shin JH, Lee DH (2020b) Operations scheduling for an advanced flexible manufacturing system with multi-fixturing pallets. Comput Ind Eng 144:106496

Madson KM, Franz B, Molenaar KR, Kremer GO (2020) Strategic development of flexible manufacturing facilities. Eng Constr Archit Manag 27(6):1299–1314

Mahdiraji HA, Zavadskas EK, Skare M, Kafshgar FZR, Arab A (2020) Evaluating strategies for implementing industry 4.0: A hybrid expert oriented approach of B.W.M. and interval valued intuitionistic fuzzy T.O.D.I.M. Econ Res-Ekon Istra 33(1):1600–1620

Mahmood K, Karaulova T, Otto T, Shevtshenko E (2017) Performance analysis of a flexible manufacturing system (FMS). Procedia CIRP 63:424–429

Mishra R (2020) Empirical analysis of enablers and performance outcome of manufacturing flexibility in an emerging economy. J Manuf Technol Manag 31(6):1301–1322

Moretti E, Tappia E, Limère V et al (2021) Exploring the application of machine learning to the assembly line feeding problem. Oper Manag Res 1–17

Myers RH, Montgomery DG, Anderson-Cook CM (2011) Response surface methodology: process and product optimization using designed experiments, 3rd edn. John Wiley and Sons, New Jersey

Nabi HZ, Aized T (2020) Performance evaluation of a carousel configured multiple products flexible manufacturing system using Petri net. Oper Manag Res 13(1–2):109–129

Pellegrinelli S, Cenati C, Cevasco L, Giannini F, Lupinetti K, Monti M, Parazzoli D, Tosatti LM (2018) Configuration and inspection of multi-fixturing pallets in flexible manufacturing systems Evolution of the Network Part Program approach. Robot Comput Integr Manuf 52:65–75

Priore P, Ponte B, Puente J, Gómez A (2018) Learning-based scheduling of flexible manufacturing systems using ensemble methods. Comput Ind Eng 126:282–291

Rao MS, Naikan VN (2016) Review of simulation approaches in reliability and availability modeling. Int J Performability Eng 12(4):369–388

Rezaei J (2015) Best-worst multi-criteria decision-making method. Omega 53:49–57

Rifai AP, Nguyen HT, Aoyama H, Dawal SZM, Masruroh NA (2018) Non-dominated sorting biogeography-based optimization for bi-objective reentrant flexible manufacturing system scheduling. Appl Soft Comput 62:187–202

Shin JH, Yu JM, Doh HH, Kim HW, Lee DH (2020) Batching and scheduling for a single-machine flexible machining cell with multi-fixturing pallets and controllable processing times. Int J Prod Res 58(3):863–877

Silva AL, Ribeiro R, Teixeira M (2017) Modeling and control of flexible context-dependent manufacturing system. Inf Sci 421:1–14

Souier M, Dahane M, Maliki F (2019) An NSGA-II-based multi-objective approach for real-time routing selection in a flexible manufacturing system under uncertainty and reliability constraints. Int J Adv Manuf Technol 100(9–12):2813–2829

Sprodowski T, Sagawa JK, Maluf AS, Freitag M, Pannek J (2020) A multi-product job shop scenario utilising Model Predictive Control. Expert Syst Appl 162:113734

Wang YC, Chen T, Chian H, Pan HC (2016) A simulation analysis of part launching and order collection decisions for a flexible manufacturing system. Simul Model Pract Theor 69:80–91

Wang XN, Xing KY, Li XL, Luo JC (2018) An estimation of distribution algorithm for scheduling problem of FMS using petri nets. Appl Math Model 55:776–788

Yadav A, Jayswal SC (2018) Modelling of flexible manufacturing system: a review. Int J Prod Res 56(7):2464–2487

Yadav A, Jayswal SC (2019) Evaluation of batching and layout on the performance of flexible manufacturing system. Int J Adv Manuf Technol 101(5–8):1435–1449

Zeleny M (1973) Compromise programming. In: Cochrane JL, Zeleny M (eds) Multiple Criteria Decision Making. University of South Carolina Press, Columbia, pp 262–301

Zhang HY, Xi SH, Chen QX, Smith JM, Mao N, Li X (2021) Performance analysis of a flexible flow shop with random and state-dependent batch transport. Int J Prod Res 59(4):982–1002

Zhang K, Zhang Z, Wang S, Yang C, Yu Y, Li H (2020) Design and experiment of electronic seeding system based on response surface method. Int J Comput Integr Manuf 33(10–11):982–990

Zhengmin Z, Zailin G, Lei Y, Chuangjian W, Hao W (2019, June) A production planning and scheduling method based on heuristic rules for forming-sintering production system. IOP Conf Ser Mater Sci Eng 565(1):012001. IOP Publishing