Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 59-10 (2025) 1832–1837

A resilient optimization methodology for integrated workforce scheduling and system configuration in manufacturing

Tullio Tolio * Maria Chiara Magnanini * Gaia Gatti *
Antonio Grieco ** Pierpaolo Caricato **

* *Politecnico di Milano (Italy)*
** *Università del Salento, Lecce (Italy)*

Abstract: Scheduling and configuration problems in manufacturing systems are frequently viewed as separate entities, despite their interconnectedness. This research delves into intricate scheduling management, proposing a model that augments performance through optimization. Effective optimization necessitates evaluating system performance, but intricate scheduling impedes this process. Conventional methods often fail to provide insightful analysis of the system. This study introduces a model capable of generating response curves, thereby unveiling system behaviors influenced by configuration and scheduling. The methodology is validated through the application of a specific scheduler and demonstrated in a footwear case study, highlighting its practical relevance and potential for long-term decision-making.

Keywords: scheduling, configuration, response curve, optimization

1. INTRODUCTION

Manufacturing Systems optimization improves performance, reduces costs, and achieves objectives like quality and sustainability. While system performance is typically evaluated by performance evaluators, jobs scheduling and resource assignments is often overshadowed by configuration. Historically, these have been separate areas of research, but global competitiveness and technological advancements highlight their interdependence. Shifts in one impact the other, demanding integrated strategies. In labor-intensive sectors, reconfiguring floors by relocating workers or lightweight machinery fosters adaptability. Fixed configurations, especially for luxury goods and high-precision manufacturing, limit outcomes. Complex scheduling frequently requires specialized algorithms, not just simplistic rules. Traditional evaluators lack the capacity for such complexity, and simulations, though more sophisticated, face challenges with meta-heuristic approaches. A unified scheduling-configuration model is proposed, recognizing companies tend to fix configuration early while scheduling remains dynamic, increasingly driven by digital tools like cloud computing. Overly simple scheduling rules yield flawed performance evaluations, as advanced scheduling affects overall results. Current evaluators do not robustly capture such complexities, thus requiring external schedulers and risking irregular performance response curves. The proposed model generates a regular curve, optimizing scheduling and configuration simultaneously by examining sufficient data points via the scheduler. This curve goes beyond fixed production volumes, incorporating value-at-risk to handle varying demands. The approach integrates seamlessly with digital architectures, aligning decision-support systems at different control levels, thereby promoting digitally enhanced manufacturing. By capturing system behavior comprehensively, the method enhances operational decisions and fosters sustainable competitiveness. Ultimately, it unites design and execution. Section 2 delves into the review of literature pertaining to the scheduling and configuration evaluation of manufacturing systems. Section 3 presents a case study involving a manufacturing system of a luxury sector company, that provides the inspiration for the developed approach. Section 4 outlines the methodology proposed for solving the problem. It encompasses the algorithm for constructing the approximated response hyper-surface and the optimization algorithm employed. In this case, the presented algorithm is compared to another existing algorithm. Section 5 validates the proposed methodology on an explanatory case. Finally, Section 6 presents a discussion on the next developments already being conducted to test the approach on a wider range of production environments.

* This work was funded by European Union – NextGenerationEU, M4C2 I1.1, Progetto PRIN 2022 "MAGELLANO", Prot. 2022NRMS4X, CUP D53D23005440001, and partially supported by Ministero delle Imprese e del Made in Italy, Accordo Innovazione DM 31/12/2021 (Primo Bando), under the project MS Packaging for Water – (MSP4Water) — CUP: B89J23001430005.

2. RESEARCH GAP AND OBJECTIVES

Traditionally, configuration and scheduling of manufacturing systems are two distinct research areas. In fact, the types of decisions as well as the time horizon in which the decisions have impact are usually different. However, configuration aspects have a strong effect on scheduling policies and performance, particularly in complex systems. Complexity may be caused by high variety in the product mix, short production runs, flexible machines and workforce management. Any configuration decision, e.g. number of stations with specific capacity and capability, layout of resources, hired workforce, may be seen

10.1016/j.ifacol.2025.09.308

as constraint in a scheduling problem. This is especially relevant in labor-intensive manufacturing systems. In this work, the focus is on the integration of configuration and scheduling decisions, by embedding an analytical response curve representing the system performance in an optimization problem. The integration of these two problem fields is still often unexplored. Configuration models assume quite simple scheduling rules, as First-In-First-Out (FIFO). Recently, a renewed push towards Reconfigurable Manufacturing Systems (RMS), as well as novel concepts of line-less and matrix manufacturing, brought the interest to the integrated configuration-scheduling problem. For instance, some studies show the concurrent optimization of the configuration and scheduling in Reconfigurable Manufacturing Systems or Reconfigurable Flow Lines using Heuristic or Meta-Heuristic Methods. These are usually multi-objective optimizations that assess the problems simultaneously trying to reach conflicting objectives. In particular, in Dou et al. (2020), an analytical model is proposed to solve the concurrent configuration design and scheduling of a multi-part flow-line RMS by first defining a mixed integer nonlinear programming model and from it deriving a mixed integer linear programming one. A comparison of the results obtained with the ones found through the NSGA-II is carried out. Even if the analytical method was able to identify the Pareto front correctly, its efficiency to solve large-sized problems remains problematic. Other studies integrate multiple aspects belonging to system configuration, production planning and scheduling. Gao et al. (2021) tackles simultaneously process planning, scheduling and layout optimization. Once again, this was realized by defining a NSGA-II algorithm with various objectives including environmental considerations. Similarly, Martínez et al. (2019) address configuration, lot-sizing and scheduling. The branch-and-check with logic-based Bender cuts and an MIP heuristic for large instances are proposed, and the problem is solved exactly. In relation to workforce management, Hashemi-Petroodi et al. (2021) provide an up to date survey of the state of the art in workforce reconfiguration strategies in manufacturing systems and propose a classification of the works in this research area. They focus on two main aspects that characterize such topic, namely: the type of production system and the workforce reconfiguration strategy. The production system can be one among: dedicated manufacturing system, flexible manufacturing system, reconfigurable manufacturing system, cellular manufacturing system and assembly line; while the main workforce reconfiguration strategies reviewed in the survey include: utility workers, temporary workers, walking workers, bucket brigades and cross-trained workers. A thorough analysis of each type of production system and workforce reconfiguration strategies is conducted in the cited work. This work focuses on manually operated, continuously moving assembly lines with a combination of the walking worker and the cross-trained workers strategies. Reconfigurable machine tools enhance manufacturing flexibility but require workforce considerations. In Rohaninejad M. and T. (2024), a MILP model and a decomposition heuristic are proposed to optimize lot-sizing and scheduling under workforce constraints. Cloud manufacturing enhances reconfigurable manufacturing system performance by minimizing job processing, overtime, and cloud resource costs. Vahedi-Nouri et al. (2022) explore workforce planning and production scheduling using a reconfigurable manufacturing system, considering workers' health risks and preferences for flexible hours, and authors provide a mathematical model integrating workforce allocation, production scheduling, and cloud resources utilization. Following modern technological advancements and the arise of Industry 4.0, researches are also starting to investigate the possibility to solve the integrated configuration-scheduling problem through neural networks and deep reinforcement learning, most of all for what concerns the real-time optimization as in Yang et al. (2023). This work addresses the optimization of the integrated problem of configuration and scheduling in manufacturing systems. Building upon the previously generated approximate response curve, it seeks to enhance the efficiency of optimization processes. The complexity of intricate production systems that rely on scheduling algorithms, rather than analytical evaluations or simulations to generate performance response curves, often renders conventional dispatching rules insufficient, necessitating the utilization of heuristic or meta-heuristic methods. While these approaches can generate solutions, they typically yield irregular, non-monotonic response curves. The irregularities in these curves stem from various factors. Heuristics provide satisfactory solutions rather than optimal ones, incorporate stochastic elements that introduce variability, and the discrete nature of job sequences can lead to non-continuous choices. Despite these challenges, the productivity response curve of a manufacturing system is generally concave and monotonic. Indeed, enhancements in system features (such as buffer capacity or machine speed) result in increased output, albeit at diminishing returns. The production function proposed by Magnanini et al. (2022) encapsulates this relationship, illustrating that while output increases with input, the rate of increase diminishes. We propose the development of an algorithm that approximates the response curve of manufacturing systems, ensuring it maintains concavity and monotonicity while integrating configuration and sequencing information. The approximated response curve serves as a refined representation of the original curve derived from scheduling methods.

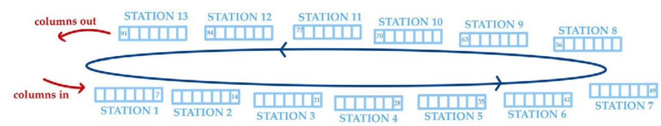

Fig. 1. Graphical representation of the system

3. INDUSTRIAL MOTIVATION

The proposed approach is currently undergoing testing in an Italian plant that manufactures luxury footwear. The focus is on the assembly department, which comprises two identical assembly lines. Each assembly line features a circular conveyor system that transports carts containing shoes at a constant speed. Each cart can accommodate a predetermined number of shoes in pairs. As the cart traverses the system, it passes through distinct stations where various operations are performed, with a substantial portion of them performed by skilled operators. The assembly line comprises 13 stations, each with seven positions for carts, enabling the simultaneous presence of 91 carts in the system. The conveyor operates at a speed of 11 carts per hour, which implies that each cart is available for processing at each station for approximately five minutes. A graphical representation of such a system is presented in Figure 1. Both a minimum and a maximum number of workers are defined for each station, and the total number of workers on the line is also provided. The plant manager is responsible for allocating the exact number of workers for each station within a specific programming horizon. The scheduling process in such a situation is significantly influenced by the production capacity of each station, which is determined by the number of workers allocated to each station. Workforce reconfiguration strategies, such as utility workers and cross-trained workers, enhance the resilience and flexibility of the manufacturing system and contribute to improving the resilience and flexibility of manufacturing systems. As also emerges from Hashemi-Petroodi et al. (2021), insufficient attention has been paid to the simultaneous resolution of the challenges of configuration and production planning up to now. Production orders are scheduled weekly and can vary significantly in volume and mix due to seasonality and demand fluctuations. Luxury brands typically produce small batches of diverse products, making the order of shoe processing crucial for performance. Each operator has a fixed time to process a full column of shoes, but different shoe types require varying processing times. To address this, a scheduler using a Tabu Search algorithm was developed to optimize job sequencing, aiming to minimize total production time and station saturation while considering production capacity and operator availability. The algorithm allows for over-saturation (beyond 100%) at stations, reflecting the practical operation of fully loaded columns, but aims to minimize it as its objective function. The production system under investigation heavily relies on human operators, making their management a complex task. Factors such as absenteeism, fluctuating demand, and the need for temporary additional assistance further complicate the allocation of operators across various stations. Each operator corresponds to one Full-Time Equivalent (FTE), which equates to eight working hours, enabling flexible assignment of working hours. For instance, allocating 1.33 FTE to a station means one operator works full-time while another contributes part-time. The allocation of operators directly influences the optimal scheduling sequence, necessitating the simultaneous assessment of both tasks. If operator configuration is determined independently from scheduling, using simple rules like First-In-First-Out (FIFO), the resulting optimal solution may differ when scheduling is factored in. This scenario aligns well with the paper's focus, as it applies a complex meta-heuristic scheduler to a more intricate case involving multiple stations, thereby enhancing the overall efficiency of the production process.

4. METHODOLOGY DESCRIPTION

Our focus is on concurrently evaluating and optimizing the short-term planning and configuration of intricate manufacturing systems, employing heuristic-based schedulers. We propose an algorithm to generate an approximate response curve based on the scheduler, at the same time guaranteeing properties such as concavity and monotonicity. Then, the response curve is used in configuration optimization problems as meta-model. A pivotal aspect of this methodology is treating the throughput at specific points on the curve as a Value at Risk (VaR). This approach aims to generate an overall response curve rather than one constrained to specific production volumes or mixes. The throughput for a configuration is defined as the percentile of cases that the analyst desires to be satisfied, indicating that the throughput is met for that percentage of potential production scenarios. This is accomplished by repeatedly evaluating the configuration with varying production volumes and mixes, derived from historical data or demand forecasts, to compute the desired percentile values. Hence, in this way the traditional intertwinning between configuration and scheduling is reversed. In fact, scheduling is used as kernel for the performance evaluation of complex manufacturing systems, while the configuration problem is solved within the optimization problem based on mixed-integer linear programming.

4.1 Generation of the Response Curve Algorithm

We address the challenge of generating a response curve for complex manufacturing systems, which cannot be directly obtained through analytical methods or simulations but only via scheduling algorithms. This results in an irregular response curve that lacks the desired properties of concavity and monotonicity. The proposed solution involves a curve-building algorithm that approximates this response curve, referred to as the approximated response curve. The algorithm aims to construct a multi-dimensional response curve by selectively testing relevant points, minimizing the number of evaluations needed. This is achieved through interpolation, where the performance of a limited number of points is used to estimate the rest of the curve. The methodology focuses on adding points that maximize the difference in throughput between the linear approximation created by tangent hyperplanes and the interpolated hyper-surface. This iterative process enhances the accuracy of the approximation by identifying points of maximum deviation, thereby improving the overall shape of the interpolated curve. The main steps of the algorithm can be seen in Figure 2A significant challenge with traditional interpolation methods is their requirement for a regular grid of points, which can lead to high computational costs. To address this, we employ Radial Basis Function (RBF) interpolation, a mesh-free method that does not necessitate a regular grid. RBFs depend solely on the distance from central points, allowing for a more flexible and efficient interpolation process. Despite the advantages of RBF interpolation, it does not inherently incorporate concavity constraints. To mitigate this, we propose an optimization step that ensures the generated surface adheres to concavity requirements. This involves ensuring that each point on the curve is greater than or equal to the average of its neighboring points, which is effective when points are evenly spaced.

4.2 Optimization of Configuration/Scheduling Algorithm

The optimization approach enables performance evaluation without the need to rerun the scheduler, as all

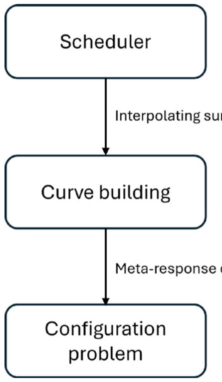

Fig. 2. Graphical representation of the proposed approach

tested points are derived from the response curve. The optimization problem can be formulated in two ways: determining the optimal capacity distribution for maximum throughput or identifying the minimum capacity required to achieve a target throughput. We generalize these formulations for broader applications in configuration optimization, encompassing operator allocation and machine selection.

5. VALIDATION STUDY

In order to validate the proposed methodology, the model was applied to a simple scheduler based on Johnson's algorithm. The validation will be applied to the case of a system composed of two machines, but it does not lose generality when defined in multiple dimensions. Johnson's algorithm is a method used to minimize the total time required to complete a set of jobs on two machines in series and it was first proposed by S.M. Johnson in 1954. The main steps of the algorithm on two machines are the following:

(1) List the Jobs: each job must be listed with its processing time both on machine 1 and machine 2.
(2) Identify the Shortest Processing Times: the job with the shortest processing time is identified, regardless which machine it belongs to.
(3) Sequencing: (i) If this processing time is on machine 1, schedule this job as soon as possible in the sequence. (ii) If this processing time is on machine 2, schedule this job as late as possible in the sequence.
(4) Remove the Job: once a job is placed in the sequence, remove it from the list.
(5) Repeat: repeat steps 2-4 until all jobs have been scheduled.

In the case investigated by this validation, the line is in charge of processing 200 jobs each week, whose mix might change depending on seasonality and demand fluctuations. Each job has a specific processing time on each stage of the line. The configuration choice refers to the fact that for each of the two stages of the line a choice among 20 possible machines is available; a different machine leads to different processing times of each of the 200 jobs. In particular, machines going from number 1 to number 20 are progressively faster. Having at disposal the VaR of the processing times of the 200 jobs on machines 1 (both for stage 1 and 2 of the line) corresponding to the 0.9 quantile based on historical data of the demand of 20 weeks, the

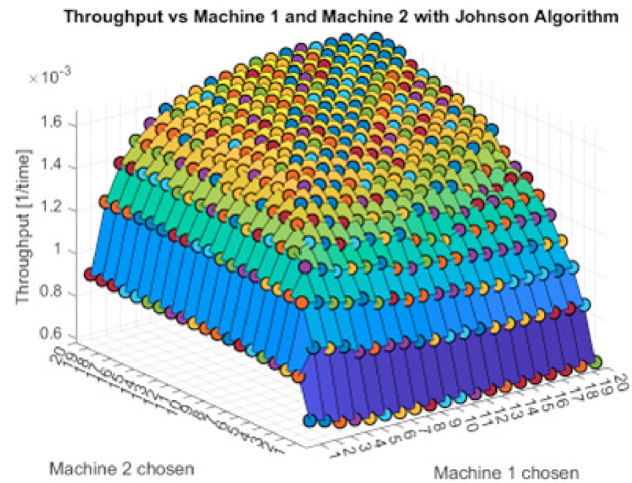

Fig. 3. Job order sequence for each combination.

operating time of the other machines were estimated. The response curve of the system was obtained by running the scheduler for each possible combination of the 40 machines (20 for the first stage and 20 for the second stage). The VaR throughput was obtained by computing reciprocal of the makespan obtained through Johnson's method. For each possible configuration the specific sequence of jobs scheduled was saved. It was interesting to notice that many different job orders were chosen depending on the configuration considered. This clearly shows that the scheduling and the configuration problems are strictly correlated.

5.1 Curve-building algorithm

In order to run the curve building algorithm, some initial parameters must be defined. The identifier of the various configurations is the number of the machine chosen for each stage going from 1 to 20 (so, for example, the point defined by the choice of machine 2 for stage 1 and machine 7 for stage 2 will have coordinates 2 and 7 in the x and y directions respectively). ϵ, the required distance of the interpolating points, was set to 3. The tolerance γ for the convergence condition was set to 0.05 and it must be satisfied 3 (C) consecutive times to end the algorithm. The number of stations involved are $N = 2$. The algorithm took 29 iterations to get to convergence, meaning that the final number of interpolating points were 29+5=34. The original curve and the final curve obtained are depicted in Figure 4 and the identified interpolating points are shown as red dots. It can be noticed that the curve generated by the proposed algorithm is much more regular and seems to respect the properties of concavity and monotonicity. In particular, it is interesting to notice that the final response curve does not necessarily pass from the interpolating points. This is due to the concavity optimization phase of the model, which can change the value of the points in order to ensure concavity. In fact, being the original curve irregular, it is reasonable to assume that its points might need to be slightly moved to make it regular. We show now the step to optimize the concavity of the curve, in order to make it usable in optimization problems. The RBF interpolation does not allow to include concavity constraints. For this reason, an optimization is necessary to

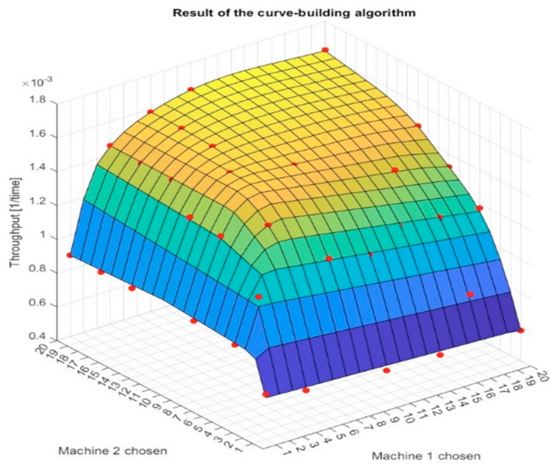

Fig. 4. Interpolation points for the curve-building.

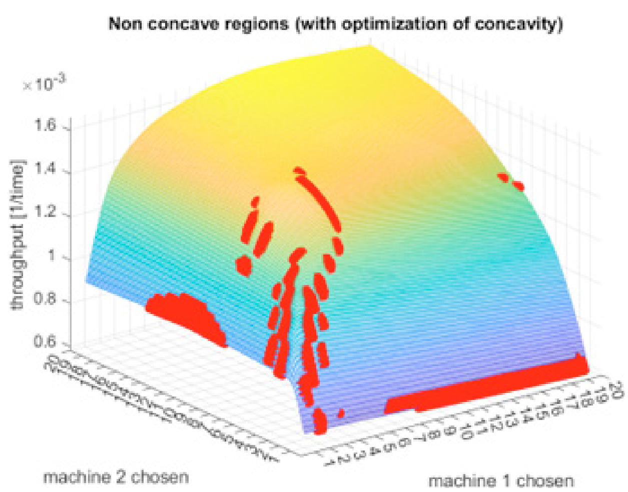

Fig. 5. Areas targeted by the concavity optimization.

fix, or at least improve, this condition. The final response curve is shown in Figure 5.

Even if there are still some convex points characterizing this curve, it is important to notice that the optimization of concavity allows to significantly improve the quality of the response surface generated by the algorithm. The biggest areas are placed closed to the bottom edges of the curve, which is coherent with the fact that the concavity optimization focuses on the internal areas; these zones are not particularly concerning as it is not likely that the analyst will look for solutions in these areas. In conclusion, even if concavity is not entirely solved by the optimization, it can be asserted that the results obtained are satisfactory and should not cause significant issues during the Hyperplane-based Algorithm. We now investigate the error committed by the approximated response curve built with respect to the original one. The error is computed as the difference in corresponding points between the performance evaluated by the response curve generated by the proposed methodology and the one obtained through the scheduler, found by running this last for all possible configurations. Different indicators were evaluated: the mean squared error (MSE), the mean absolute error (MAE), R-squared (R2), the root mean square error (RMSE) and the mean, the maximum and the distribution of the absolute

	With optimization concavity
MSE [1/time^2]	$5.3905 \cdot 10^{-4}$
MAE [1/time]	0.0183
$\mathbf{R^2}$	0.9936
RMSE [1/time]	0.0232
MAPE [%]	1.537
MAXPE [%]	8.422

Table 1. Optimally concave curve indicators.

percentage error (MAPE and MAXPE). Focusing on the indicators obtained by also including the optimization for concavity, the results obtained are encouraging, as in Table 1. MSE, MAE and RMSE are all quite low, which is a good result. R2, which measures the proportion of the variance of the observed data with respect to the model, is very high (0.99356); this indicates that the obtained surface is able to capture 99.356% of the variance of the original data, which is an excellent result and suggests a very good prediction ability.

5.2 Optimization results

The optimization to be carried out consists in choosing the configuration of the system that, considering simultaneously its scheduling, either minimizes the investment costs to reach a desired throughput or maximizes the throughput given a maximum available budget. The optimization problem is framed according to the algorithm proposed and extensively validated in Magnanini et al. (2022), for configuration problems. We solve the problem consisting in finding the configuration of the system that allows to reach a target throughput th^* by minimizing the required investment cost. The performance evaluation consists in extrapolating the throughput of a given configuration from the response curve previously built, while the optimization model was defined as follows:

Decision Variables:

$n_k \in \{n \in N | 1 \leq n \leq 20\}$ machine chosen for stage k

$th_{app} \in R$ approximation of the throughput

Objective Function

$$min(\sum_{k=1}^{K} n_k \cdot (n_k + 4)) \qquad (1)$$

Constraints:

$$thapp \geq th^* \qquad (2)$$

$$thapp \leq th_{max} \qquad (3)$$

$$n_k \leq maxval_k \qquad (4)$$

$$thapp \leq th_w + \sum_{k=1}^{K} \frac{\delta th}{\delta n_k} \cdot (n_k - n_k^w) \qquad \forall w \qquad (5)$$

(6)

where:

- k is the stage $k = 1, 2$;
- w is the tested scheduling sequence at each iteration
- $maxval_k = 20$ is the maximum number of stations per stage;
- th_{max} is the maximum throughput of the system
- $thapp$ is the linear approximation of the throughput
- th_w is the throughput of the tested scheduling sequence w.

The problem has been solved for a variety of cases, according to the target throughput. In all cases the exact optimal solution as in the original Jackson problem was found, with a limited number of iterations. In Table 2 we report one detailed solution, for the optimization problem having a target throughput $th^* = 1,400 parts/timeunit$.

Iteration	M1	M2	Th [1/t.u.]	ObjF
1	1	1	0.647	10
2	4	1	0.874	37
3	4	3	1.228	53
4	7	3	1.297	98
5	6	4	1.365	92
6	5	6	1.334	105
7	6	5	1.410	105

Table 2. Details of the optimization problem

The optimization algorithm identifies iteratively an optimal solution based on the set of constraints that is updated until the final solution is reached. In particular, the solution obtained by embedding the linear approximation of the performance indicator, i.e. the throughput, is verified in the response curve. If the response curve value is different, an additional linear constraint is added to the MILP problem and solved again. This is re-iterated until the response curve value is valid and satisfies the target throughput, as in 2, last line.

6. CONCLUSIONS AND FUTURE PROSPECTS

This study aims to improve production systems by refining short-term planning strategies. The primary challenge lies in the fact that performance evaluation is limited to scheduling, as complex algorithms are impractical in performance evaluators. While existing literature explores concurrent optimization of scheduling and configuration using multi-objective meta-heuristic methods, these approaches often yield solutions without providing insights into system behavior, necessitating a fresh analysis for each optimization problem. In contrast, the proposed model generates a multi-dimensional response curve that incorporates data from various production volumes and mixes. Each point on this curve represents the throughput risk associated with a configuration, enabling evaluations of overall system behavior and long-term decision-making. The curve-building algorithm accomplishes two key objectives: it generates the response curve by evaluating a limited number of points through the scheduler, thereby conserving computational resources; and it enhances the curve's features, addressing irregularities and non-concave regions. More in general, it aims to change the integration perspective of configuration analysis and optimal scheduling, as it uses the scheduler as performance evaluation meta-model. The optimization step is based on the hyperplanes method, enabling repeated optimization without the need to recompute the scheduler for each point and ensuring optimality. In modern manufacturing, strictly optimal solutions often focus solely on maximizing efficiency or minimizing cost. However, these methods can be highly sensitive to disruptions, failing to accommodate unexpected variations in production, demand, or supply chain disturbances. In contrast, robust or resilient strategies deliberately sacrifice a small fraction of optimization gains in favor of enhanced stability and adaptability. The proposed approach focuses on optimal solutions, but in order to effectively react to changes; hence, it provides a tool to address both aspects at once. Integrating the proposed model with ERP and MES systems can enhance real-time decision-making and production efficiency: real-time data feeds from inventory management and from production equipment, sensors, and operator inputs, can enable both dynamic scheduling adjustments and workers' movements in the system to effectively respond to changes. This type of integration requires essential data, including historical demand records for forecasting production volumes, as well as precise job processing times obtained from MES logs or machine monitoring systems. Additionally, workforce data, such as operator skills, shift schedules, and productivity metrics, are needed to allow the model to integrate human resource allocation into the optimization process. Due to the need for evaluating numerous scheduling configurations, scalable computing resources are vital. Cloud-based platforms enable the parallel processing of scheduler evaluations using distributed computing frameworks. This approach significantly reduces computation time and facilitates handling large-scale problems.

REFERENCES

Dou, J., Su, C., and Zhao, X. (2020). Mixed integer programming models for concurrent configuration design and scheduling in a reconfigurable manufacturing system. *Concurrent Engineering*, 28(1), 32–46.

Gao, S., Daaboul, J., and Le Duigou, J. (2021). Process planning, scheduling, and layout optimization for multi-unit mass-customized products in sustainable reconfigurable manufacturing system. *Sustainability*, 13(23), 13323.

Hashemi-Petroodi, S.E., Dolgui, A., Kovalev, S., Kovalyov, M.Y., and Thevenin, S. (2021). Workforce reconfiguration strategies in manufacturing systems: a state of the art. *International Journal of Production Research*, 59(22), 6721–6744.

Magnanini, M.C., Terkaj, W., and Tolio, T.A. (2022). A novel algorithm for optimal buffer allocation in automated asynchronous unreliable lines. *The International Journal of Advanced Manufacturing Technology*, 122(11), 4405–4419.

Martínez, K.P., Adulyasak, Y., Jans, R., Morabito, R., and Toso, E.A.V. (2019). An exact optimization approach for an integrated process configuration, lot-sizing, and scheduling problem. *Computers & Operations Research*, 103, 310–323.

Rohaninejad M., Vahedi-Nouri B., H.Z. and T., T.M. (2024). An integrated lot-sizing and scheduling problem in a reconfigurable manufacturing system under workforce constraints. *International Journal of Production Research*, 62(11), 3994–4013.

Vahedi-Nouri, B., Tavakkoli-Moghaddam, R., Hanzálek, Z., and Dolgui, A. (2022). Workforce planning and production scheduling in a reconfigurable manufacturing system facing the covid-19 pandemic. *Journal of Manufacturing Systems*, 63, 563–574.

Yang, S., Wang, J., Xin, L., and Xu, Z. (2023). Real-time and concurrent optimization of scheduling and reconfiguration for dynamic reconfigurable flow shop using deep reinforcement learning. *CIRP Journal of Manufacturing Science and Technology*, 40, 243–252.