Human-Centered Scheduling with a Heterogeneous Workforce in the Context of Industry 5.0: A Proof of Concept from a Learning Factory

Hajer Hamdaoui [1], Safa Bhar Layeb [1,2*], Amel Jaoua[1] and Elisa Negri [3]

[1] LR-OASIS, National Engineering School of Tunis, University of Tunis El Manar, Tunis, Tunisia
[*] safa.layeb@enit.utm.tn
[2] Centre Génie Industriel, Université Toulouse, IMT Mines Albi, Albi, France
[3] Management, Economics and Industrial Engineering, Politecnico di Milano, Milano, Italy

Abstract. This research focuses on task allocation in a diverse workforce to address the challenges modern companies face in the competitive business environment within the context of Industry 5.0. It examines the potential of Simulation-Based Optimization (SBO) in resolving these issues. Initially, a mathematical model is developed to validate the simulation model's solution to the optimization problem involving task allocation under deterministic conditions. It then extends its analysis to consider the complexities of stochastic situations while accounting for differences in task execution time. This project aims to identify the mathematical model's limitations in addressing these challenges and demonstrate the potential of Simulation-Based Optimization as a valuable alternative in considering human behavior.

Keywords: Industry 5.0, Modular Production Systems, Mixed Integer Linear Programming, Simulation-based Optimization, Gantt Chart.

1 Introduction

Motivated by the ideas of sustainability, the transition from Industry 4.0 to Industry 5.0 represents a tremendous change [1]. Industry 5.0 represents not just a development but also a dedication to a human-centered and resilient sustainable industrial paradigm. This shift places an emphasis on inclusivity and employee well-being by introducing flexible and customized work settings [2].

In the context of Industry 5.0, workers are the central element of factories, where they showcase a wide range of skills and competencies, reflecting a heterogeneous workforce. Various factors contribute to this diversity, including mental and physical health, as well as years of experience [3]. Indeed, effective scheduling has become a critical component of productivity, necessitating consideration of the heterogeneity of workers during task assignments.

S. Krichen et al. (eds.), *Proceedings of International Conference on Decision Aid and Artificial Intelligence (ICODAI 2024)*, Atlantis Highlights in Intelligent Systems 12,
https://doi.org/10.2991/978-94-6463-654-3_13

The goal of this work is to tackle a scheduling challenge in the context of Industry 5.0 while accounting for a heterogeneity workforce. Our project started with the development of a mathematical model for deterministic task allocation, emphasizing its efficiency in smaller-scale scenarios but impracticality in larger and more complex tasks. Aware of the limitations of mathematical modeling in handling large instances and stochastic conditions, we introduced Simulation-Based Optimization (SBO) as an efficient alternative. Furthermore, we investigated the impact of variability in stochastic models on completion time.

This paper is organized as follows. The relevant literature is reviewed in Section II, and the study's background and the topic under investigation are described in Section III. The mathematical model is provided in Section IV, the simulation-optimization model is presented in Section V, and the results are reported in Section VI. Section VII concludes with recommendations for future research.

2 Related Work

2.1 Human factor in production systems

In the literature, various standards for worker modeling have been highlighted. Selecting a worker based on their skills is one of those strategies [4]. In this characterization, a worker may possess different skills, which can lead to variations in their efficiency depending on the task or machine they work with. These skill variations can cause changes in task processing time, influencing task scheduling. However, a problem arises when tasks are assigned to the most efficient worker because it can result in negative effects such as muscle fatigue and cognitive confusion. [5] developed an optimization model to address this issue by minimizing both maximum worker fatigue and makespan. In fact, fatigue has been identified as one of the most common issues that workers may encounter during production. [6] pointed out how human variables have a considerable impact on production performance, highlighting the importance of taking these elements into account when planning production and managing operations.

In a recent study conducted by Hashemi-Petroodi et al. [7], an exhaustive survey was conducted to investigate the use of collaborative systems involving human and machine interaction within the context of industrial manufacturing. The authors took into account the heterogeneity of operators in terms of skills and efficiency, which could affect the final objective function. Many other studies have also explored the importance of considering worker heterogeneity to minimize makespan in the industry. A review of these works reveals a strong emphasis on utilizing frameworks such as Discrete Event Simulation to schedule task assignments while accounting for worker variability [7].

2.2 Factors Impacting Worker Efficiency

Worker heterogeneity, with variations in efficiency, stems from factors like physical and mental health, social networks, and work experience. This sub-section explores these factors.

Physical and mental health One of the most critical factors that have a significant impact on worker efficiency and productivity is the condition of their physical and mental health [6]. It is important to note that every worker can be susceptible to various physical health issues. Different types of workers are affected by specific occupational health problems. These can include physical problems such as high blood pressure, headaches, high cholesterol, and stomach ulcers.

Workers can also be affected by mental health issues that have a direct impact on their productivity, such as low self-esteem, job dissatisfaction, job-related tension, anxiety, and depression. These physical and mental illnesses reduce workers' efficiency and productivity, affecting their performance directly. As a result, these factors not only affect the workers, but also have a negative impact on the industry's productivity, resulting in a decrease in output levels [7].

Social network A social network refers to the relationships and interactions among workers, and it has the potential to significantly influence worker efficiency in diverse ways. When workers allocate most of their time to work and lack sufficient time to go out and spend time with friends and family, it can result in isolation from their usual social network [5]. This isolation can lead to feelings of loneliness and a lack of social support. Furthermore, workers who are required to work far from their families and live-in isolation can experience increased levels of stress.

Years of work experience The number of years a worker has spent in the workforce can have a dual effect on their efficiency. On one hand, workers with extensive work experience often possess valuable knowledge and skills that enable them to perform their tasks effectively. Their accumulated experience enables them to navigate challenges more effectively and respond rapidly to unexpected problems [6]. Experience plays a pivotal role in enhancing worker efficiency by improving their expertise and decision-making capabilities. On the other hand, long periods of continuous work can cause physical fatigue and weariness. The physical capacities of an older worker may be impacted over time by the combined effects of devoted work and potential health issues, particularly as they age. As a result, older workers may perform less effectively when given challenging jobs that generally call for the energy associated with youth. So, it's crucial to find a balance between an older worker's experience and physical health in order to evaluate their productivity appropriately.

3 Project Context

This work was carried out by a team of researchers from the National Engineering School of Tunis (ENIT) and Politecnico di Milano, specifically within the Lab4.0 of ENIT. The Lab4.0 contains several 3D printers, a Modular Production system Festo:MPS 403-1®, and an Autonomous Mobile Robot Festo: Robotino®,as depicted in Fig.1. A Learning Factory has been established within this laboratory to emulate a miniature production system capable of fulfilling the customization requirements of

Industry 4.0/5.0 [8]. It functions as an educational platform for investigating and developing innovative optimization techniques to meet the customization and responsiveness demands of Industry 5.0. In this lab, some studies have been done on scheduling [10], augmented reality for online 3D-BPP [9], and creating a framework for integrating an intelligent digital twin into a production system [11].

Fig. 1. The MPS of the ENIT's Lab 4.0

Within this Lab, the objective of this work is to solve a scheduling problem while taking into account heterogeneous workers in the context of Industry 5.0. The Modular Production System (MPS) presents an advanced industrial production system that feats to the make-to order approach in the e-commerce context. The general scheme of the production layout is presented in Fig.2.

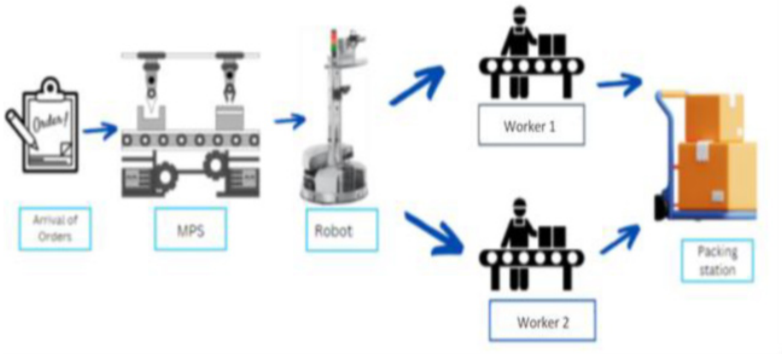

Fig. 2. Overview of the general layout

In this context, let's provide three different types of bespoke orders, designated 2p, 4p, and 6p, respectively, which correspond to batches of two, four, or six work-pieces.

These bespoke orders are made in the MPS once they are received. After that, they are moved to two manual assembly workstations by a mobile, autonomous robot.

An employee processes an incoming order at these manual assembly stations in two steps. Assembling the proper kind of package comes first, followed by packing the incoming customer order into the package. A setup time is needed if the employee needs to switch up the order type by utilizing a different set of packaging materials. These workers are diverse in terms of age and skill level. Heterogeneity in this context refers to the fact that certain workers exhibit higher efficiency factors than others, allowing them to do jobs more quickly. Higher values of the efficiency factor, which ranges from 0 to 1, indicate higher efficiency. Assuming that a worker with an efficiency factor of one exists, we will suppose that there is a standard processing time that represents ideal conditions. To determine the assembly time for each task performed by each worker, the standard processing time will be divided by their efficiency factor. The objective is to schedule the tasks in a way that minimizes the Makespan which clocks in the packing of the final client job by hand worker, or the time from the start of the first customer job to the end of all jobs.

4 Mathematical Model

Three different order types are taken into consideration in this scheduling problem. These orders are represented as jobs designated by i (where $i = 1,...,N$), which correspond to a batch of two workpieces (2p), four workpieces (4p), and six workpieces (6p). Let K denote the types number, in our case $K=3$. One of the manual laborers, designated by m, (where $m = 1,...,M$), is required to pack each task. It is crucial to remember that every worker m has a distinct efficiency factor e_m. We express the varying skill levels among workers using the efficiency factors. Higher values of the efficiency factor, which ranges from 0 to 1, indicate higher efficiency. Because of their greater expertise, older individuals are typically seen to be more efficient in manual processes. Their years of experience have culminated in an advanced skill set. The number of efficiency factors and the number of workers are equivalent. Cutting down on the total completion time is the aim. Every task is given to a single employee. As a result, every task i has a certain expected time of arrival A_i The time needed for a worker m to finish the task i of assembling and packing the customer order of type k is known as the assembly time, and it is denoted by P_{ikm}. The robot's transportation time of task i with type k to the manual assembly station of worker m is denoted by Q_{ikm}. The nature of the task and the particular designated worker to whom the robot will deliver it both affect the traveling time. The objective is to minimize the total completion time.

The amount of time required to complete each item on the list is expressed by the total completion time, denoted by $C_{\max}$. Let's denote by S_{im} and T_{im} the continuous decision variable that represent the starting time and the completion time of task i, $i = 1,...,N$, by worker m, $m = 1,...,M$, respectively. Furthermore, let X_{im} be the binary decision variable that takes 1 if task i, $i = 1,...,N$, is assigned to worker m, $m = 1,...,M$, and 0, otherwise.

Following these annotations, the proposed Mixed Integer Linear Programming (MILP) model can be stated as

$$\text{Minimize } C_{\max} \quad (1)$$

The optimization objective (1) aims to minimize Cmax, which represents the completion time of all the work. Expression (1) should be minimized subject to the following constraints:

$$\sum_{m=1}^{M} X_{im} = 1, \qquad \forall\, i = 1,..,\mathrm{N} \quad (2)$$

Only one worker may be allocated to each task, given Constraint (2).

$$T_{im} = S_{im} + \left(\frac{P_{ikm}}{e_m} + Q_{ikm}\right) X_{im}, \quad (3)$$

$$\forall\, i = 1,..,\mathrm{N}, \mathrm{m} = 1,\ldots,\mathrm{M}, k = 1,\ldots K$$

The completion time constraint is enforced by Constraint (3), which determines the completion time for each worker by taking into account the time required for assembly and transportation.

$$S_{1m} = A_1 X_{1m}, \qquad \forall\, \mathrm{m} = 1,\ldots,\mathrm{M} \quad (4)$$

$$T_{1m} = A_1 X_{1m} + \left(\frac{P_{1km}}{e_m} + Q_{1km}\right) X_{1m}, \qquad \forall\, \mathrm{m} = 1,\ldots,\mathrm{M}, k = 1,\ldots K \quad (5)$$

The start and end times of each worker's first task are specified in Constraints (4) and (5). They make sure the initial task is scheduled according to when it will arrive, and that the completion time is determined using the same formula as the preceding constraint.

$$S_{im} \geq A_i X_{im}, \qquad \forall m = 1,\ldots,M, \forall\, i = 2,\ldots,N, \quad (6)$$

$$S_{im} \geq T_{i-1m}, \qquad \forall m = 1,\ldots,\mathrm{M}, \forall\, i = 2,\ldots,N, \quad (7)$$

In order to guarantee that no task begins before its arrival time or before the previous task on the same worker is completed, Constraints (6) and (7) uphold the sequence and order in which tasks are executed.

$$C_{\max} \geq \quad T_{im}, \qquad \forall\, i = 1,..,N,, m = 1,\ldots,M \qquad (8)$$

Under Constraint (8), all job completion times must be met or exceeded by C_{max}.

$$T_{im} \;\geq\; 0, \qquad \forall\, i = 1,..,N,, m = 1,\ldots,M \qquad (9)$$

$$S_{im} \;\geq 0, \qquad \forall\, i = 1,..,N,, m = 1,\ldots,M \qquad (10)$$

$$X_{im} \in \;\{0,1\}, \qquad \forall\, i = 1,..,N,, m = 1,\ldots,M \qquad (11)$$

$$C_{\max} \geq 0 \qquad (12)$$

Constraints (9)-(12) express the nature of the decision variables.

5 Simulation-based Optimization Model

Model (1)-(12) cannot handle unpredictable variations in assembly time caused by human factors in real-world scenarios. To deal with stochasticity under real world conditions, we have begun by developing a Discrete Event Simulation (DES) model using Simio simulator. Fig.3 represents the environment for our assignment problem using Simio objects. This visualization provides a 3D representation of the essential elements of the simulation model.

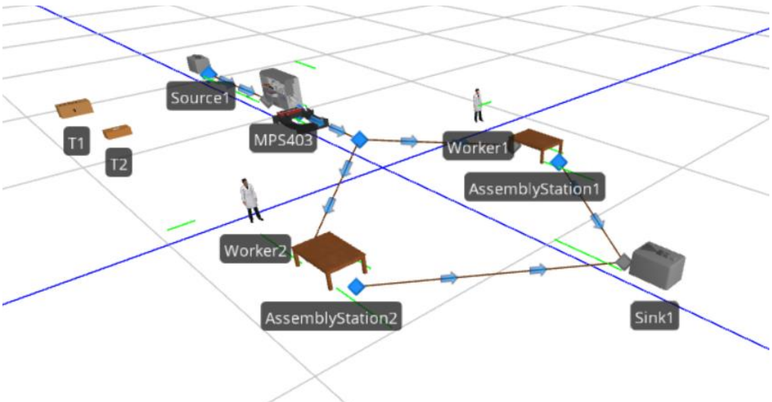

Fig. 3. 3D representation of the simulation model

Given the significance of integrating simulation and optimization for solving Combinatorial NP-hard problems under uncertainty (e.g. [12]-[13]), we have developed a Simulation Based Optimization (SBO) method that combines these two approaches to address this problem. Precisely, OptQuest, which is implemented in Simio, serves as a robust optimizer designed to tackle complex problems. Indeed, OptQuest employs a combination of metaheuristics, including tabu search, neural networks, and scatter search, and was used as the optimizer in our assignment problem. A UML sequence diagram, shown in Fig.4, is proposed to elucidate the conditional behavior and temporal sequence inherent in the SBO process that we implemented.

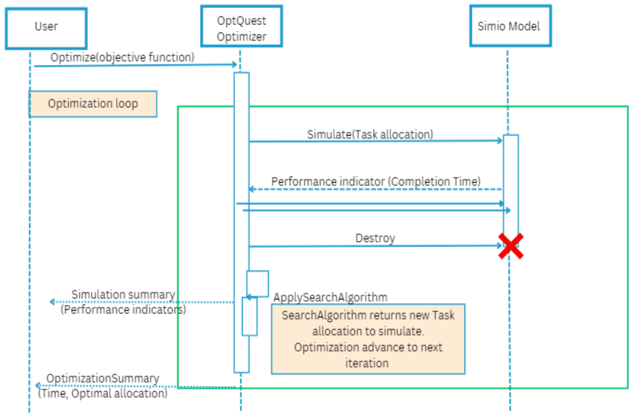

Fig. 4. UML sequence diagram for the SBO interaction

Fig. 4 shows that this interaction involves three key entities: the user, the OptQuest Optimizer, and the simulator. Initially, the user sends a request to begin the search for the best task assignment. It specifies the objective function for the optimizer. An optimization loop fragment is then created to generate and iterate through different configurations. The process of generation and simulation continues until it reaches the specified time limit (TimeUp) or an automatic stop condition defined in OptQuest. The user can set the desired duration for the process. The user can also specify how long the process should run for. Subsequently, the simulator is executed with the newly allocated tasks, and the resulting value of the objective function is fed back to the optimizer.

6 Numerical Results

We began by validating the validity of our SBO model. To accomplish this, we first looked at the deterministic Model (1) – (12) and compared its optimal solution to the outcomes of solving the SBO model under deterministic conditions. Model (1) - (15) was solved using the state-of-the-art MILP solver IBM ILOG CPLEX software package. Small-size instances were generated and tested.

The results produced from the mathematical model that calculates the optimal task allocation are consistent with those obtained using the SBO approach. Both strategies result in the same optimal job allocation and completion time. This alignment provides significant validity for our simulation model and SBO. It demonstrates the simulation model's accuracy and reliability in simulating real-world scenarios. Once the SBO model has been validated, it can be subjected to testing under stochastic real-world conditions.

In practice, the workers' assembly times fluctuate due to the unpredictable nature of human performance. Notably, the time needed by workers to complete assembly tasks can vary. To account for this variability, the assembly time follow a triangular distribution [14]. In the following models, we will examine two cases with both minor and major variability to comprehensively understand their impacts on an example of instance with 10 tasks. Case 1 corresponds to the scenario when the assembly time variability is minimal. Each part's assembly time follows a triangular distribution, ranging from a minimum of 1 minute to a maximum of 2 minutes, with a mode of 1.5 minutes (Fig.5-a). Case 2 assumes a significant variation in assembly times, which follows a triangular distribution with a minimum value of 0.5 minutes, a maximum value of 6 minutes, and a mode of 1.5 minutes (Fig.5-b). It is noteworthy that cases 1 and 2 could be indicative of the experiences of younger and older workers, respectively.

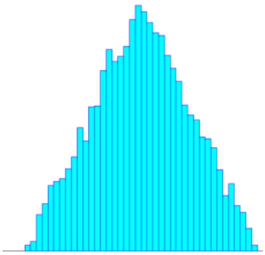

Fig. 5-a. Histogram of Triangular distribution (1,1.5,2)

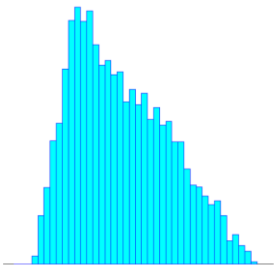

Fig. 5-b. Historgran of Triangular distribution (0.5,1.5,6)

The results of the SBO models are reported in the Gant charts displayed in Figures 6-a and 6-b. The introduction of the variability of the assembly times points out a significant shift in completion times. In Case 1, the optimal solution results in a 69-minute completion time, while in Case 2, this duration extends to 111 minutes, as shown in Figures 6-a and 6-b. Within manufacturing contexts, this 42-minute increase carries a significant effect as it introduces substantial delays in processes that are typically time-critical.

In addition, the variability in assembly times causes a noticeable shift in task allocation. The allocation strategy that proves effective in Case 1 cannot be simply applied to Case 2, highlighting the significant impact of time variability on task allocation. This underlines the substantial effect that time variability can have on allocation decisions. Failing to account for this variability can lead to inadequate task assignments, delaying processes and incurring unnecessary costs. In contrast, recognizing and accommodating assembly time variability can lead to more efficient task allocation, ultimately saving both time and cost. The scheduling in Case 1 cannot be applied in Case 2. Indeed, in Case 2, Task 5 and Task 9 are now assigned to Worker 1, while Task 7 and Task 10 are assigned to Worker 2. These variations in assembly time, whether minor or significant, result modifications in task assignments

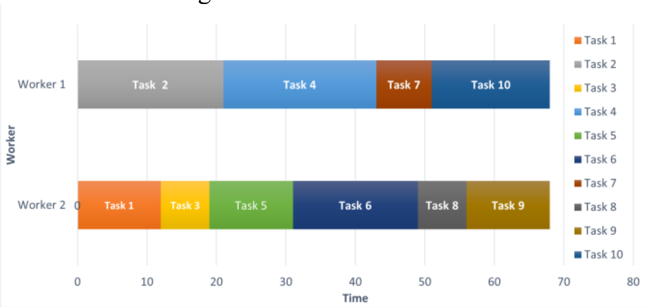

Fig. 6-a. Gantt chart of the SBO solution in Case 1

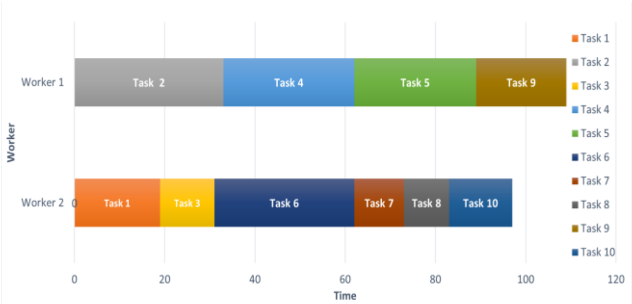

Fig. 6-b. Gantt chart of the SBO solution in Case 2

Optimizing task assignment is a pivotal component of effective scheduling, and its complexity escalates significantly when accommodating the diversity of workers. The mathematical model employed in this research emerged as a valuable tool, particularly in small-scale examples. It served a dual purpose by effectively validating the simulation model while demonstrating its efficiency in solving deterministic task assignment problems.

However, as the scale and complexity of the problem increase, the limitations of the mathematical model become apparent, rendering it incapable of solving problems with a large number of tasks SBO method emerges as a strong alternative, demonstrating its capacity to handle large instances of the problem efficiently. Furthermore, it proves to be valuable in addressing stochastic variations within the task assignment process.

The empirical results emphasize the profound impact of variability in stochastic models on task completion times. These results indicate that higher variability in stochastic models leads to significantly longer project completion times, resulting in substantial time and cost losses in factory operations. This highlights the importance of managing variability to enhance efficiency and reduce expenses in industrial settings. Further extensive computational experimentation should be conducted to assess the robustness of the proposed SBO model.

7 Conclusions and Future Work

In this work, we investigate the task assignment optimization within a heterogeneous workforce. Our primary goal is to optimize the assignment of tasks to workers by a single robot, while taking into account the workers' inherent heterogeneity. The central premise is that the robot will act as the decision-maker in this task assignment process, with the overarching goal of reducing production time. Through an exploration of mathematical modeling and simulation-based optimization, we navigated through the complexities of various scenarios to derive valuable insights.

Precisely, we started with the development of a mathematical model for deterministic task allocation, emphasizing its efficiency in smaller-scale scenarios but impracticality in larger and more complex tasks. This prompted us to investigate Simulation-Based Optimization as a potential tool for dealing with both deterministic and stochastic conditions. Indeed, Simulation Based optimization emerged as robust solution, excelling at managing complex problems and efficiently providing optimal task allocations. Our findings demonstrated the importance of managing and minimizing variability in order to improve scheduling.

Using SBO, we have taken a significant step toward improving the decision-making process for task assignments involving diverse workers; however, this work is still in progress, as it serves as a foundation for future projects: (i) Real-time allocation through the utilization of a Digital Twin: Given the fluctuations in demand, we lack precise task arrival times. To address this, we can integrate a digital twin to facilitate dynamic allocation. (ii) Integration of re-manufacturing: In a world increasingly focused on Eco-friendliness, incorporating a worker responsible for disassembling and reusing boxes to minimize their environmental impact is paramount. By introducing the disassembly step, we can explore its impact on the system's performance.

Acknowledgment. This project has received funding from the European Union's "Erasmus+ Capacity Building in the field of Higher Education" program under grant agreement No 2019-1949 / 001-001 (correspondent to the project shortly entitled "NePRev", "NExt Production REVolution").

References

1. Golovianko, M., Terziyan, V., Branytskyi, V., & Malyk, D. (2023). Industry 4.0 vs. Industry 5.0: Co-existence, transition, or a hybrid. Procedia Computer Science, 217, 102-113.
2. Sarkar, B. D., Shardeo, V., Dwivedi, A., & Pamucar, D. (2024). Digital transition from Industry 4.0 to Industry 5.0 in smart manufacturing: A framework for sustainable future. Technology in Society, 102649.
3. Mahiri, F., Najoua, A., Souda, S. B., & Amini, N. (2023). From Industry 4.0 to Industry 5.0: The transition to human centricity and collaborative hybrid intelligence. Journal of Hunan University Natural Sciences, 50(4).
4. Destouet, C., Tlahig, H., Bettayeb, B., & Mazari, B. (2023). Flexible job shop scheduling problem under Industry 5.0: A survey on human reintegration, environmental consideration and resilience improvement. Journal of Manufacturing Systems, 67, 155-173.
5. Tan, W., Yuan, X., Wang, J., & Zhang, X. (2021). A fatigue-conscious dual resource constrained flexible job shop scheduling problem by enhanced NSGA-II: An application from casting workshop. Computers & Industrial Engineering, 160, 107557.
6. Neumann, W. P., & Village, J. (2012). Ergonomics action research II: a framework for integrating HF into work system design. Ergonomics, 55(10), 1140-1156.
7. Hashemi-Petroodi, S. E., Thevenin, S., Kovalev, S., & Dolgui, A. (2020). Operations management issues in design and control of hybrid human-robot collaborative manufacturing systems: a survey. Annual Reviews in Control, 49, 264-276.
8. Layeb, S. B., Jaoua, A., & Noomen, M. (2023, May). New Horizons in Engineering Education: From Additive Manufacturing to Immersive Learning. In Advances In Additive Manufacturing Conference (pp. 87-91). Cham: Springer Nature Switzerland.
9. Jaoua, A., Negri, E., Layeb, S. B., & Ayed, Z. (2023, April). Framework for smart online 3D bin packing using augmented reality. In 2023 IEEE International Conference on Advanced Systems and Emergent Technologies (IC_ASET) (pp. 01-06). IEEE.
10. Jaoua, A., Negri, E., Hamdaoui, H. & Layeb, S. B. (2024, May), "A Simulation-based Optimization Approach Towards Human-Centric Scheduling in Presence of Heterogeneous Workforce", The 2024 Annual Modeling and Simulation Conference (ANNSIM 2024), Washington D.C., USA.
11. Jaoua, A., Masmoudi, S., & Negri, E. (2024). Digital twin-based reinforcement learning framework: application to autonomous mobile robot dispatching. International Journal of Computer Integrated Manufacturing, 1-24.
12. Layeb, S. B., Jaoua, A., Jbira, A., & Makhlouf, Y. (2018). A simulation-optimization approach for scheduling in stochastic freight transportation. Computers & Industrial Engineering, 126, 99-110.
13. Antit, A., Jaoua, A., Layeb, S. B., & Triki, C. (2023). Pre-auction optimization for the selection of shared customers in the last-mile delivery. Annals of Operations Research, 1-38.
14. Dar-El, E. M. (2013). Human learning: From learning curves to learning organizations (Vol. 29). Springer Science & Business Media.