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Industry 5.0: prioritizing human comfort and productivity through collaborative robots and dynamic task allocation

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Abstract

Moving from Industry 4.0 to Industry 5.0 marks a substantial shift in the way technology is incorporated into workplace design. In Industry 4.0, the emphasis was on automating the production process to maximize efficiency and output. However, with Industry 5.0, the focus has shifted towards placing people at the heart of the production process. This involves creating workspaces that prioritize human comfort and productivity and integrating technology that enhances human abilities. Collaborative robots, or cobots, are a critical technology in this transition as they work alongside humans to improve efficiency while enabling greater human involvement. However, to make the most of cobots, it is necessary to design workspaces that optimize human comfort and productivity, by considering the needs and preferences of both human and robotic resources. A promising strategy for achieving this goal is the implementation of a dynamic multi-objective task allocation system. The method proposed in this work uses physiological and performance data to assess the well-being of human operators and reallocates tasks dynamically to avoid overworking or fatiguing them. This represents a significant step towards creating production environments that prioritize the well-being and productivity of human workers.

Keywords: Industry 5.0; Cobots; Human Factors; Productivity; Wellness; Human-Centered Design; Human-Robot Collaboration.

1. Introduction

The integration of cobots and human operators can affect performance and highlights the importance of taking human factors into account. The human-centered design in the workspace, known as one of the key principles of Industry 5.0, prioritizes the wellness of operators. To achieve this, various human factors such as ergonomics, mental workload, skills, and capabilities need to be considered in the design of the work cell.

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The multi-objective task allocation strategy is an approach that considers the different characteristics of resources and optimizes for multiple objectives. Assigning tasks to resources effectively and efficiently is essential to maximize productivity and minimize idle time in collaborative systems. A well-designed task allocation strategy can create a harmonious work environment where human and robotic resources can work together seamlessly, increasing overall system performance.

To optimize productivity, flexibility, and human factors, a dynamic multi-objective task allocation system is necessary. This system combines traditional static allocation with the digitalization of the human operator, allowing for real-time consideration of human variability. It is essential to have a dynamic task allocation system that can adjust in real-time to achieve this level of collaboration. Flexibility is especially important regarding the focus on the operators' needs in Industry 5.0 since these are not static and can change throughout the day or with different operators.

An example of task allocation problem for collaborative cells is offered by [1], who introduced a novel algorithm for Disassembly Sequence Planning (DSP). The algorithm aimed to minimize the overall time required for completing tasks while ensuring safety requirements were met, resulting in multi-objective optimization. The study accounted for a flexible sequence and the potential for both human operators and cobots to collaborate on one or more tasks.

Another solution was presented by [2], which included unpredictable events in the optimization model and considered cobot re-planning capability to minimize different cost functions. Unpredictability was also analyzed by [3], who proposed a planning method capable of capturing the behaviors of autonomous agents.

[4] proposed a flexible collaborative manufacturing system with re-planning capability through a two-level breakdown for each job, while [5] introduced a centralized algorithm to address complex temporal and spatial constraints for real-world problems. This solution was able to reach optimal solutions for larger problems than those previously reported in the state of the art.

Despite these works, none of them introduced the ability to dynamically reprogram tasks assigned to resources online in real-time. This is a crucial aspect for effective and efficient task allocation in collaborative systems.

One of the first attempts to address this problem was done by [6], who developed a genetic algorithm capable of real-time subtask allocation to meet cost-effectiveness requirements. Another similar solution was proposed by [7], which included a dynamic scheduler layer that allocated tasks based on resource requests but lacked real-time monitoring of objective function values.

To meet the demands of both Industry 4.0 and Industry 5.0, researchers have explored ways to incorporate operator well-being in collaborative cells. One approach, as demonstrated by [8], involved using a complex system with a Deep Neural Network (DNN) to predict operator fatigue and assign tasks accordingly. However, this approach was limited to a small number of tasks due to the need for offline DNN training.

Another solution proposed by [9] involved developing an ergonomic assessment index that considered the physical and cognitive workload of the operator, which was used to evaluate the impact of various task allocations on operator well-being. Even though the use of wearable technology was a novel solution to address the issue of ergonomics in human-robot cooperation, it was limited to only monitoring and maintaining ergonomic standards at work.

Despite the advancements in collaborative systems involving humans and cobots, there is still a considerable requirement for low-cost and real-time techniques for task allocation with multiple objectives, such as productivity and worker well-being. Previous research has proposed various methods, but the lack of real-time implementation and cost-effectiveness remains a challenge. Moreover, incorporating multiple objectives into the task allocation process adds complexity, making it challenging to find the best solutions. This discrepancy highlights the need for further research and development in this field, with a focus on cost-effectiveness and real-time implementation. The aim of this paper is to present a novel solution for dynamic task allocation that considers multiple objectives. Specifically, the proposed approach takes into account two critical metrics - makespan for productivity and operator's energy expenditure for wellness - to ensure efficient and safe collaboration between human operators and robots. The key highlight of this approach is the ability to allocate tasks dynamically in real-time, thus ensuring optimal performance and well-being of the human operator. The proposed solution provides a more comprehensive method for task allocation, which can improve productivity while minimizing the negative impact on the operator's health. This paper presents a significant contribution to the field of human-robot collaboration, and its potential benefits extend beyond the manufacturing industry to other areas where humans and robots collaborate.

The paper is organized as follows: Section 2 presents the dynamic rescheduling with the task allocation model and the control system; in Section 3 an extensive case study is analyzed, while Section 4 concludes the work.

2. Dynamic task allocation

The proposed dynamic task allocation process is shown in Figure 1, which presents the whole system.

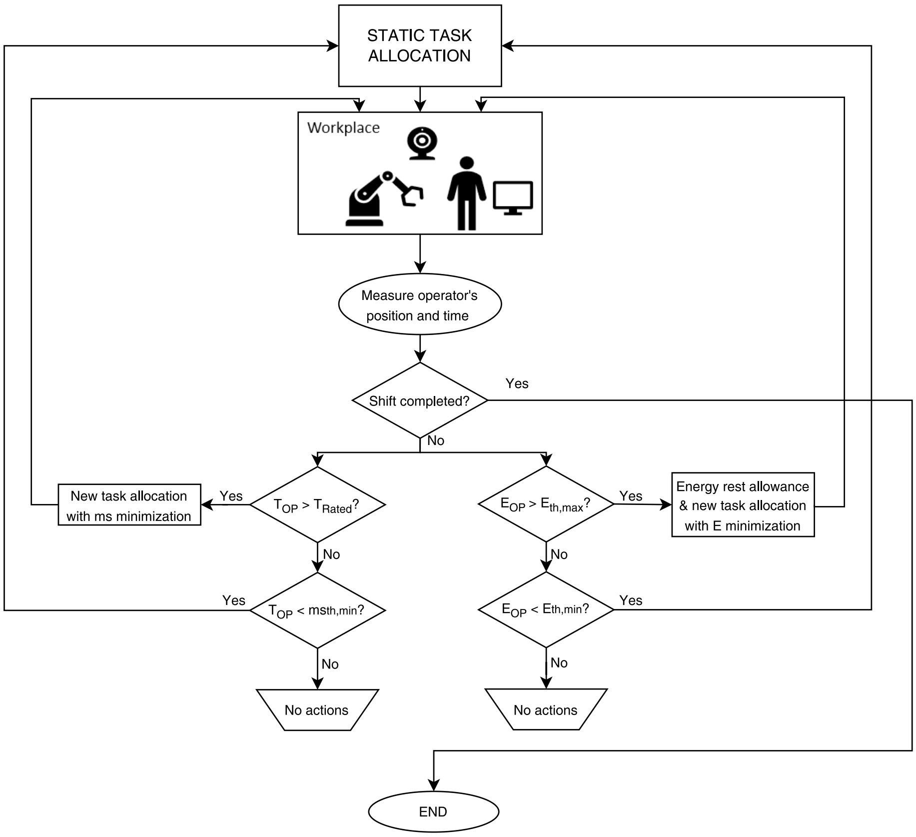


Fig. 1: Workflow of the proposed dynamic task allocation

In particular, it consists of $K = 2$ resources, i.e., a human operator and a collaborative robot, that have to work in a shared workspace. In such a case, precise tracking of their positions is a vital aspect to enable the dynamic allocation of tasks based on their locations, since each task is associated with a precise position in the workspace. In this way, the change of position of a resource indicates the end of the task it is performing and the beginning of the next. To achieve this, a markerless motion capture system has been implemented in the architecture. This system provides a non-invasive way of tracking the positions of the human operator and the cobot without requiring any special markers or sensors. This makes it a more convenient and user-friendly option than other motion capture systems available.

The resources receive the inputs through a MATLAB (MathWorks) user interface, developed to have a centralized control, able also to manage the data from the motion capture system and the cobot.

2.1. Static Task Allocation

As soon as the resources start to work, they receive as first input a static task allocation, based on the minimization of two objective functions: the makespan and the operator's energy expenditure, with the aim of realizing a human-centered scheduling, while preserving the productivity standards. In fact, the total time required to complete all necessary tasks in a production system, commonly known as the makespan, is a crucial factor in determining the system's productivity. A lower makespan indicates a higher quantity of products produced or assembled within a specific timeframe, making it fundamental to all scheduling problems. Minimizing the makespan has been shown to significantly improve a company's competitiveness by reducing product delivery time [10]. By enhancing productivity, this approach can contribute to increased profitability and competitiveness in the market.

On the other hand, with Industry 5.0 making strides in the development of more human-centric workplaces, there is a growing recognition of the need to prioritize the well-being of operators in the workplace. To align with this trend, this study includes energy consumption as a second objective function. The evaluation of energy expenditure has been introduced in previous studies since it is critical for assessing ergonomic risks and identifying metrics such as the duration, level, and repetitiveness of physical tasks that can indicate the stress caused by physical jobs [11, 12].

To measure the energy expenditure needed to perform a task, this study employs the approach introduced by [13], which calculates the energy required by a resource to complete a task. The proposed task allocation method, indeed, considers energy consumption as an objective function. The objective is to optimize the task allocation in a way that minimizes the energy expenditure required by the operator, promoting their well-being, and reducing the risk of physical stress.

The model here used is the same as in [14], and here briefly recalled. The objective functions are the minimization of both the makespan ms as in Eq. 1 and the operator's energy expenditure E as in Eq. 2, in performing J tasks by the $K = 2$ resources.

$$min\ ms = min\left(max \sum_{j=1}^{J} (S_{jk} + P_{jk})\right) \tag{1}$$

where S_{jk} is the starting time of the task j and P_{jk} is its execution time when it is performed by the resource k.

$$min\ E = min\left(\sum_{j=1}^{J} e_{jk} \cdot x_{jk}\right) \quad k = 1\ (OP) \tag{2}$$

where e_{jk} is the energy requirement to complete the task j performed by the resource k.

Consequently, the output is the binary variable x_jk that assigns each task to one resource.

$$x_{jk} = \begin{cases} 1 \text{ if the task } j \text{ is performed by the resource } k \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

The following constraints are introduced:

$$\sum_{k=1}^{K} x_{jk} = 1 \quad \forall j \tag{4}$$

$$x_{jk} \in \{0, 1\} \quad \forall j, k \tag{5}$$

$$\sum_{j=1}^{J} x_{jk} \geqslant 1 \quad \forall k \tag{6}$$

$$x_{jk} = 0 \quad \forall j \in U_k \tag{7}$$

Eq. 4 and Eq. 5 are the *occurance* and *integrality* constraints, that assure that each task is performed by only one resource. Eq. 6 it is necessary to guarantee that both resources have at least one task assigned to them and Eq. 7 is the technological constraint for the tasks that can not be performed by one or the other resource.

A multi-objective optimization can be solved through the search of the Pareto Frontier, which offers a set of non-dominated points [15]. Among these optimal solutions, it is possible to choose, as input for the resources, the one that minimizes the distance from the Utopia Point (Eq. 8).

$$d_{ut} = \sqrt{\left(\frac{ms - ms^*}{ms_{max} - ms^*}\right)^2 + \left(\frac{E - E^*}{E_{max} - E^*}\right)^2} \tag{8}$$

where ms^* and E^* are the anchor points, while ms_{max} and E_{max} are the maximum achievable values.

2.2. Dynamic Rescheduling

Once the process begins and resources start performing their assigned tasks, the system starts monitoring the position of the robot and the operator, as well as the time. The system continuously monitors these variables in real-time for each task and dynamically reschedules if necessary at the end of the current cycle to generate a new task allocation for the next one. This process is especially useful in assembly or production processes that need to be repeated several times during a shift.

The new task allocation is generated for the following cycles, as soon as the previous one is completed, while ensuring that the sequence of tasks is not altered while the resources are still performing them. In some scenarios, the operator may require more time to complete a task than the standard time allocated for it (with a tolerance). In such cases, a new task allocation is generated, with the aim of reducing the burden on the operator by assigning the more time-consuming tasks to the cobot, provided that it is compatible with the technological constraint. The new task allocation is then provided as input to the resources and maintained until the makespan lower threshold $ms_{th,min}$ is reached.

Additionally, the operator's energy expenditure rate $\dot{E}_j$ for each task is evaluated. This rate is the ratio between the energy required for a task and its completion time. If the calculated energy expenditure rate exceeds the threshold set at $\dot{E}_{th,max} = 4.2927\ kcal/min$, the system needs to generate a new scheduling aiming at reducing the energy requirements for the operator. In doing so, it is necessary also to consider the residual energy effects of previous tasks, which requires including the recovery function, described by Eq. 9 in the energy expenditure rate evaluation [16].

$$R_{j-1}(\tau_{j-1}) = \int_0^{\tau_{j-1}} \dot{E}_{j-1} \cdot e^{-\mu\tau} d\tau \tag{9}$$

where $R_{j-1}(\tau_{j-1})$ is the residual fatigue, function of $\dot{E}$ and of the parameter μ. That is the energy decrease rate, after the task $j-1$ if the recovery time τ_{j-1} has passed. This time can be both a reaction time or a Rest Allowance (RA) time, described by Eq. 10.

$$\tau = \frac{ln(\dot{E}) - ln(\dot{E}_R)}{\mu} \tag{10}$$

where $\dot{E}_R = 1.86\ kcal/min$ is the energy rest rate [17].

The energy expenditure rate becomes:

$$\dot{E}_j = \frac{e_{j,1} + R_{j-1}}{t_{j,1}} \tag{11}$$

where $t_{j,1}$ is the actual time, measured by the system, the operator required to complete the task j.

The two aforementioned lower thresholds serve as parameters to revert back to the original task allocation, in order to maintain the required productivity levels. The new schedule, which removes tasks from the operator's sequence, may create an imbalance, resulting in an increased makespan. This, in turn, increases the risk of failing to meet the productivity requirements, such as the number of pieces to be completed during the working shift.

The rescheduling strategy involves assigning all tasks that exceed either of the maximum thresholds to the cobot. However, this approach has a limitation: if none of these tasks meet the cobot technological constraint, i.e., they are not included in U_2, then the scheduling remains the same, and the operator does not receive any benefits from the system.

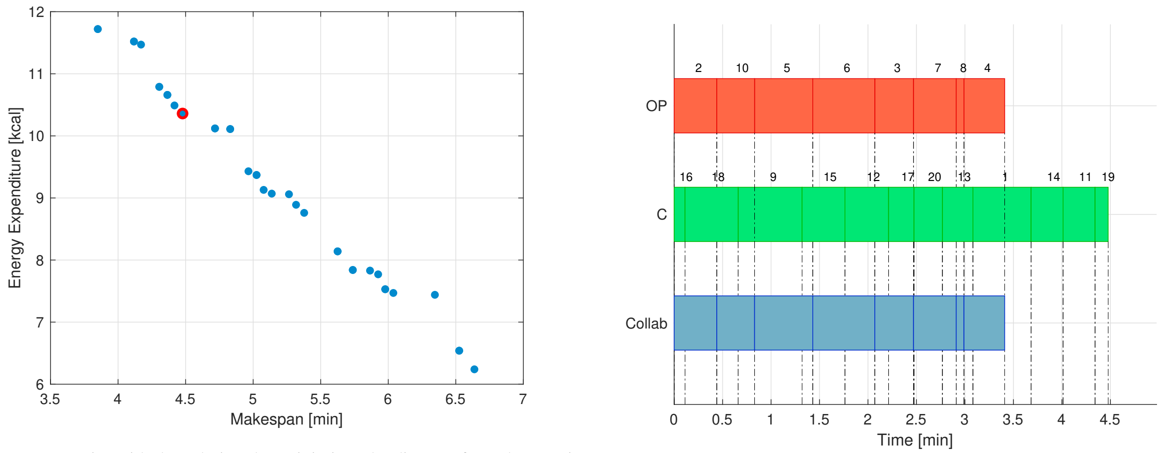
3. Case Study

To test the system, a case study is here presented. Table 1 reports the task times, and energy expenditures of an assembly process that involves $J = 20$ tasks [18]. Some values in the table are represented as "-" as they are not feasible for the resources involved. The operator's and cobot task times, along with the energy expenditure values are obtained from [14]. The genetic algorithm EMO (Evolutionary Multi-objective Optimization) [19] is used to solve the model in the MATLAB (Mathworks) environment.

Table 1: Tasks time and energy

Task	P_{op} $[min]$	P_c $[min]$	e_{op} $[kcal]$
1	0.40	0.60	1.40
2	0.44	-	1.48
3	0.40	0.60	1.23
4	0.42	-	1.44
5	0.60	0.90	1.60
6	0.64	-	1.95
7	0.44	0.66	1.29
8	0.08	-	0.18
9	0.44	0.66	1.36
10	0.39	-	1.19
11	-	0.33	-
12	0.60	0.45	1.60
13	-	0.32	-
14	0.44	0.33	1.38
15	-	0.44	-
16	0.15	0.11	0.30
17	-	0.27	-
18	0.73	0.55	1.35
19	-	0.14	-
20	0.39	0.30	1.20

From the resolution of the task allocation (Sec 2.1) the Pareto Frontier in Figure 2a, with the solution that has the minimum distance from the Utopia Point, was obtained. In addition, Table 2 reports the values of the objective functions along with the corresponding task allocation, shown also in Figure 2b, where "OP" are the tasks assigned to the operator, "C" the ones assigned to the cobot, and "Collab" the amount of collaboration established.



(a) Pareto Frontier with the solution that minimizes the distance from the Utopia Point circled in red

(b) Optimal scheduling

Fig. 2: Result of the static task allocation

Table 2: Objective functions values and task allocation of the proposed solution.

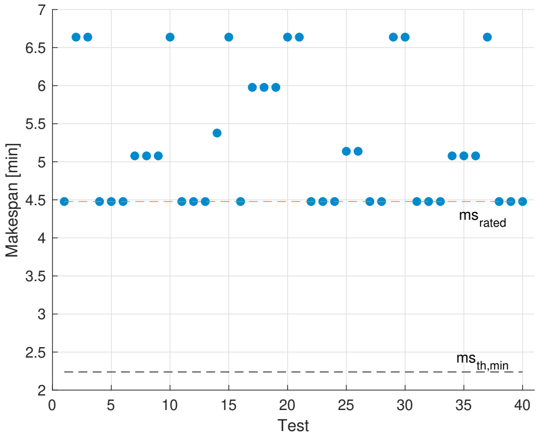
ms [min]	E [$kcal$]	OP	C
4.48	10.36	[2,10,5,6,3,7,8,4]	[16,18,9,15,12,17, 20,13,1,14,11,19]

This task allocation has been given as input to the resources as described before, and a rigorous testing protocol was employed, spanning a duration of 4 consecutive hours. The thresholds used for this case study are reported in Table 3, while the parameter $\mu = 1.5$ for the recovery function is derived from [20], since the activities have quite similar intensity and duration. The outcome of this real-time testing indicates that a total of 48 products were scheduled to be manufactured, however, only 40 units were actually produced. This shortfall can be attributed to the alterations in the scheduling process, whereby the cobot resource was identified as the key determinant of the makespan. Consequently, the reallocation of tasks to the cobot, to reduce the operator's workload, resulted in an elongation of the production time, as seen in Figure 3a.

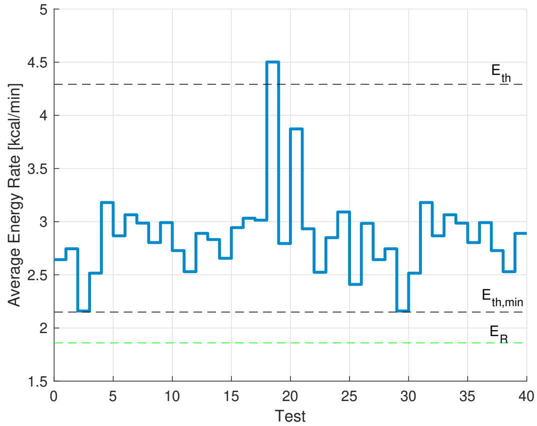
Table 3: Thresholds for the rescheduling

$ms_{th,min}$	$\dot{E}_{th,min}$	$\dot{E}_{th,max}$
$0.5 \cdot ms$	$0.5 \cdot \dot{E}_{th,max}$	4.2927 [kcal]

The average trend of the energy expenditure rate, instead, is shown in Figure 3b, in which are also displayed the maximum and minimum thresholds, along with the energy rest rate. The plot illustrates that the average energy expenditure rate remains within the safe range throughout the duration of the study, with occasional deviations observed during the execution of the assigned tasks. However, it is noteworthy that the operator can exceed the limit during the completion of certain tasks, as shown in Figure 4. This indicates that the current task allocation strategy may not be optimal for the operator's well-being and productivity. As such, a new task allocation is generated to prevent the occurrence of fatigue-related issues.



(a) Makespan variation during the tests



(b) Average energy expenditure rate during the tests

Fig. 3: Makespan and average energy expenditure

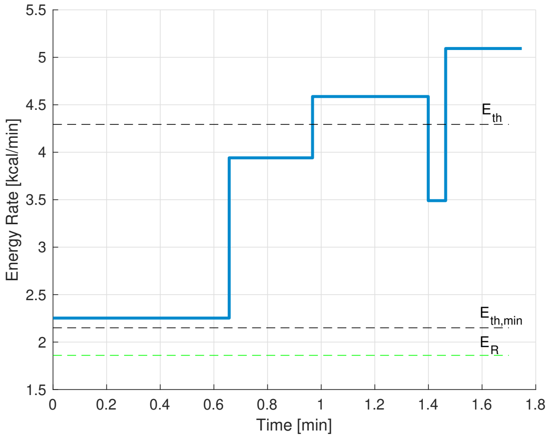


Fig. 4: Energy expenditure rate during a single cycle

The elongation of production time resulting from the reallocation of tasks to the cobot is a concern for the overall efficiency of the manufacturing process. Any delays or inefficiencies in the production process can lead to a loss of time, which can ultimately have economic consequences for the company. It is important to note that this can happen only if the cobot is the resource that determines the makespan. If the operator is the leading resource, by assigning the cobot the tasks that take longer to complete, a better balance can be achieved. This new balance assures the optimization of resource utilization and the minimization of the risk of production delays or deficiencies. Such a scenario may arise when the technological constraint is less strict, meaning that both resources have the capacity to perform a higher number of tasks, for example, 18 out of 20 tasks. In such cases, the allocation of tasks becomes more flexible, and a better balance can be achieved by assigning the cobot tasks that take longer to complete, thus allowing the operator to focus on tasks that require greater human dexterity.

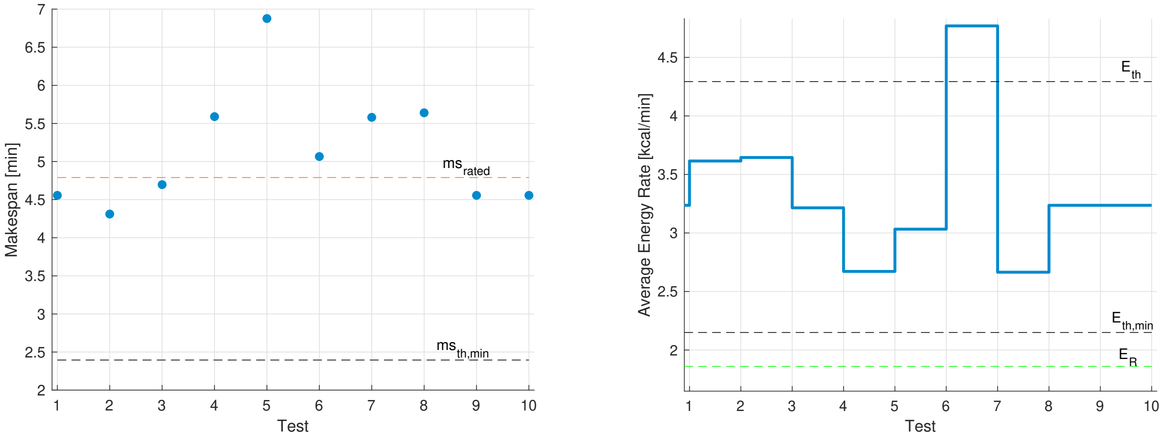
By considering this scenario, the task allocation given as input to the resources is reported in Table 4.

As before, the makespan and average energy expenditure rate are shown, respectively, in Figures 5a and 5b.

It is noteworthy that, in this specific case, the makespan is determined by the operator's times. By analyzing the results of the test number 5, it is evident that the execution times of the operator exceed the maximum threshold, indicating a potential bottleneck in the manufacturing process. To address this issue, a new task allocation is generated

Table 4: Objective functions values and task allocation with a less restrictive technological constraint

ms [*min*]	*E* [*kcal*]	OP	C
4.79	14.6	[1,5,9,20,2, 8,6,4,3,10,15]	[13,14,7,18, 12,17,11,16,19]



(a) Makespan variation during the tests

(b) Average energy expenditure rate during the tests

Fig. 5: Makespan and average energy expenditure with a less restrictive technological constraint

and given as input for the next cycle to the resources. The revised task allocation strategy resulted in a significant reduction in the makespan, thus improving the overall efficiency. It is worth noting that the success of the revised task allocation strategy is a testament to the importance of optimizing the allocation of tasks based on the strengths and limitations of each resource, whether it be a human operator or a cobot.

4. Conclusions

The importance of considering human factors in manufacturing processes becomes even more evident with the integration of cobots and human operators. Industry 5.0, a human-centered design approach, prioritizes the wellness of operators by taking into account various factors such as ergonomics, mental workload, skills, and capabilities in the design of work cells. A multi-objective task allocation strategy is a key approach for optimizing the allocation of tasks to different resources in collaborative systems. Such a strategy considers the unique characteristics of each resource and aims to optimize for multiple objectives. By doing so, this strategy can effectively and efficiently assign tasks to resources, maximizing productivity and minimizing fatigue. It can also create a harmonious work environment where human and robotic resources can work together seamlessly, increasing overall system performance. To optimize productivity, flexibility, and human factors, a dynamic multi-objective task allocation system is necessary. This system can adapt to changing conditions in the work environment and allocate tasks accordingly. By adopting such an approach, manufacturing companies can create a more efficient and effective manufacturing process that prioritizes both the productivity and well-being of their operators. The allocation of tasks in manufacturing processes is critical for achieving optimal productivity and efficiency. In situations where a cobot is a resource that defines the makespan, changes in the allocation of tasks to lighten the operator's workload can lead to a lengthening of production time and potential inefficiencies, but there can be a benefit for the operator's fatigue. However, if the operator is the leading resource, allocating to the cobot the tasks that surpass the rated time can generate a better balance and optimize resource utilization while minimizing the risk of production delays or deficiencies. Key performance indicators such as makespan and energy expenditure rate are crucial in evaluating the efficiency of manufacturing processes.

Regular monitoring and analysis of these metrics can help identify potential bottlenecks in the process and inform the allocation of tasks. Overall, this type of system should prioritize the optimization of the allocation of tasks based on the strengths and limitations of each resource, whether it be a human operator or a cobot. By doing so, companies can improve their productivity and economic outcomes while minimizing the risk of production delays or deficiencies.

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References

[1] M.-L. Lee, S. Behdad, X. Liang, M. Zheng, Task allocation and planning for product disassembly with human–robot collaboration, Robotics and Computer-Integrated Manufacturing 76 (2022) 102306.
[2] L. Johannsmeier, S. Haddadin, A hierarchical human-robot interaction-planning framework for task allocation in collaborative industrial assembly processes, IEEE Robotics and Automation Letters 2 (2016) 41–48.
[3] A. Casalino, A. M. Zanchettin, L. Piroddi, P. Rocco, Optimal scheduling of human–robot collaborative assembly operations with time petri nets, IEEE Transactions on Automation Science and Engineering 18 (2019) 70–84.
[4] N. Nikolakis, N. Kousi, G. Michalos, S. Makris, Dynamic scheduling of shared human-robot manufacturing operations, Procedia CIRP 72 (2018) 9–14.
[5] M. C. Gombolay, R. J. Wilcox, J. A. Shah, Fast scheduling of robot teams performing tasks with temporospatial constraints, IEEE Transactions on Robotics 34 (2018) 220–239.
[6] F. Chen, K. Sekiyama, F. Cannella, T. Fukuda, Optimal subtask allocation for human and robot collaboration within hybrid assembly system, IEEE Transactions on Automation Science and Engineering 11 (2013) 1065–1075.
[7] A. Pupa, W. Van Dijk, C. Secchi, A human-centered dynamic scheduling architecture for collaborative application, IEEE Robotics and Automation Letters 6 (2021) 4736–4743.
[8] C. Messeri, A. Bicchi, A. M. Zanchettin, P. Rocco, A dynamic task allocation strategy to mitigate the human physical fatigue in collaborative robotics, IEEE Robotics and Automation Letters 7 (2022) 2178–2185.
[9] E. Merlo, E. Lamon, F. Fusaro, M. Lorenzini, A. Carfì, F. Mastrogiovanni, A. Ajoudani, An ergonomic role allocation framework for dynamic human–robot collaborative tasks, Journal of Manufacturing Systems 67 (2023) 111–121.
[10] M. Pinedo, K. Hadavi, Scheduling: Theory, algorithms and systems development, in: W. Gaul, A. Bachem, W. Habenicht, W. Runge, W. W. Stahl (Eds.), Operations Research Proceedings 1991, Springer Berlin Heidelberg, Berlin, Heidelberg, 1992, pp. 35–42.
[11] K. E. Stecke, M. Mokhtarzadeh, Balancing collaborative human–robot assembly lines to optimise cycle time and ergonomic risk, International Journal of Production Research 60 (2022) 25–47.
[12] I. Granata, M. Faccio, M. Calzavara, Energy expenditure and makespan multi-objective optimization for cobots systems design, Procedia Computer Science 217 (2023) 126–135. URL: https://www.sciencedirect.com/science/article/pii/S1877050922022864. doi:https://doi.org/10.1016/j.procs.2022.12.208, 4th International Conference on Industry 4.0 and Smart Manufacturing.
[13] A. Garg, D. B. Chaffin, G. D. Herrin, Prediction of metabolic rates for manual materials handling jobs, American Industrial Hygiene Association Journal 39 (1978) 661–674.
[14] G. Boschetti, M. Faccio, I. Granata, Human-centered design for productivity and safety in collaborative robots cells: A new methodological approach, Electronics 12 (2022) 167.
[15] A. Messac, A. Ismail-Yahaya, C. A. Mattson, The normalized normal constraint method for generating the pareto frontier, Structural and multidisciplinary optimization 25 (2003) 86–98.
[16] M. Y. Jaber, Z. Givi, W. P. Neumann, Incorporating human fatigue and recovery into the learning–forgetting process, Applied Mathematical Modelling 37 (2013) 7287–7299.
[17] A. Price, Calculating relaxation allowances for construction operatives—part 1: Metabolic cost, Applied ergonomics 21 (1990) 311–317.
[18] M. Calzavara, M. Faccio, I. Granata, Multi-objective task allocation for collaborative robot systems with an industry 5.0 human-centered perspective, The International Journal of Advanced Manufacturing Technology (2023) 1–18.
[19] K. Deb, Multi-objective Optimisation Using Evolutionary Algorithms: An Introduction, Springer London, London, 2011, pp. 3–34. URL: https://doi.org/10.1007/978-0-85729-652-8_1. doi:10.1007/978-0-85729-652-8_1.
[20] V. Valentina, S. Fabio, C. Martina, P. Alessandro, Fatigue accumulation in the assignment of manual material handling activities to operators, IFAC-PapersOnLine 51 (2018) 826–831.