Human-Centered Design in Industry 5.0: Leveraging Technology for Maximum Efficiency

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Abstract: The shift from Industry 4.0 to Industry 5.0 represents a significant change in how technologies are approached in workplace design. Industry 4.0 was characterized by the automation of the production process, with a focus on maximizing output and efficiency. However, as Industry 5.0 becomes more relevant, the focus is moving toward the importance of putting people at the center of the production process. This means designing workspaces that prioritize human comfort and productivity and finding ways to integrate technology that supports and enhances human abilities. One of the key technologies that is helping to facilitate this transition is collaborative robots or cobots. By working alongside humans, cobots can help improve production efficiency while allowing for greater human involvement in the production process. However, to fully leverage the potential of cobots, it is essential to design workspaces that are optimized for human comfort and productivity. This requires taking into account the needs and preferences of both human and robotic resources and finding ways to allocate tasks in a way that maximizes efficiency while also taking into account human well-being. One promising approach to achieving this goal is the implementation of a dynamic multi-objective task allocation system, as presented in this work. This method uses physiological and performance data to evaluate the well-being of human operators and dynamically re-allocate tasks to ensure that operators are not overworked or fatigued. This is a significant step towards creating truly human-centered production environments that prioritize the well-being and productivity of human workers.

Keywords: Cobot, Human Factors, Modern Production Systems, Productivity, Industry 5.0.

I. INTRODUCTION

In the last decade, collaborative robots, or cobots, have experienced significant growth in adoption due to their unique advantages [1]. Cobots offer a combination of productivity and flexibility, making them ideal for assembly systems [2]. Unlike traditional robots that are specialized for a specific product variant, cobots can easily adjust to new designs or production volume changes [3]. They can also work directly with human operators without the need for safety fences, improving production while avoiding the need for additional safety measures.

The shift towards a human-centered design in the workspace, known as Industry 5.0, prioritizes the wellness of operators [4]. 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 [5,6]. The integration of cobots and human operators can affect performance and highlights the importance of taking human factors into account [7].

To link productivity, flexibility, and human factors, a multi-objective task allocation strategy for collaborative assembly systems can be developed. This approach 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 [8].

This task allocation can include as objectives to optimize the makespan for productivity and the operator's energy expenditure for human factors. The task allocation is typically developed offline and given to resources as input, allowing for the optimal global solution, but may be time-consuming, and this can be seen as against the Industry 5.0 idea of flexibility [9]. 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. Therefore, flexibility is critical when designing a collaborative workspace to ensure effective collaboration [10]. A dynamic task allocation system that can adjust in real-time is necessary to achieve this level of collaboration. This system combines traditional static allocation with the digitalization of the human operator, allowing for real-time consideration of human variability [11,12].

For this purpose, in this paper, a solution for a dynamic multi-objective task allocation is presented, considering the makespan for productivity, and the operator's energy expenditure as a wellness metric.

The paper is organized as follows: Section II presents an accurate analysis of the state of the art, followed by Section III in which the multi-objective model is explained. Section IV proposed the real-time control, and Section V draws the conclusions.

II. LITERATURE REVIEW

The scheduling problem has become increasingly important in collaborative systems that involve both cobots and human operators, leading to a greater focus on task allocation. Dynamic task allocation is particularly critical in collaborative systems, where resources are assigned tasks based on their current capabilities, resources, and objectives. The primary goals of dynamic task allocation are to optimize system performance, minimize delays, and ensure that all tasks are completed successfully, while also considering the operator's needs.

Various approaches have been suggested, including a recent study [13] that introduced a novel algorithm for Disassembly Sequence Planning (DSP) within collaborative cells. 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 similar solution was presented by [14], which included unpredictable events in the optimization model and considered cobot re-planning capability to minimize different cost functions. Unpredictability was also analyzed by [15], who proposed a planning method capable of capturing the behaviors of autonomous agents.

[16] proposed a flexible collaborative manufacturing system with re-planning capability through a two-level breakdown for each job, while [17] 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.

A task planner proposed by [18] considered ergonomic, quality, and productivity criteria for resource assignment and cell layout in the planning stage. 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 [19], who developed a genetic algorithm capable of real-time subtask allocation to meet cost-effectiveness requirements. Another similar solution was proposed by [20], which included a dynamic scheduler layer that allocated tasks based on resource requests but lacked real-time monitoring of objective function values.

In order to meet the demands of Industry 5.0, researchers have explored ways to incorporate operator well-being in collaborative cells. One approach, as demonstrated by [21], 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 [22] involved developing an ergonomic assessment index and using IMUs to monitor and intervene in real-time if ergonomic limits were exceeded. While this approach provided a unique solution to the problem of ergonomics in human-robot collaboration, it was still limited to the use of wearable technology for monitoring and maintaining ergonomic standards in the workplace.

Despite progress in developing collaborative systems that involve human operators and cobots, there is still a significant need for affordable and real-time strategies for allocating tasks with multiple objectives, such as productivity and operator well-being.

While previous studies have proposed various approaches, the lack of real-time implementation and cost-effectiveness remains a challenge. Additionally, incorporating multiple objectives into the task allocation process adds complexity, making it difficult to find optimal solutions. This gap highlights the need for further research and development in this area, with a focus on cost-effectiveness and real-time implementation.

III. MODEL

A. Architecture setup

A collaborative work cell has been developed for dynamic task allocation, where a human operator and a cobot work together in the same space. It is essential to monitor their positions to dynamically assign tasks based on their locations, which is achieved using a markerless motion capture system. This system does not require the use of special markers or sensors, making it more convenient than other motion capture systems. An *Intel RealSense D435* camera is used to measure distance, providing accurate depth data for identifying the position and movement of objects and people in 3D space. The *OpenPose* [23] library is utilized for real-time recognition of body joint positions, enabling fast and precise motion tracking.

In order to achieve real-time performance, the system utilizes a DELL-ALIENWARE R11 equipped with an Intel Core i7-10700KF CPU 3.80GHz and 32 GB of RAM. To achieve a frequency rate of 30fps, the middleware Robotic Operating Systems (ROS) is employed. The system can operate in a distributed computing environment using ROS middleware, which is crucial for real-time performance. ROS provides a modular and scalable framework for developing and deploying software, making integrating different motion capture system components easier. The high-performance computing hardware ensures that the system can process data quickly and accurately, even when tracking multiple people and objects in real-time.

B. Bi-objective optimization model

The two objectives of the optimization model are here described:

Makespan:

The makespan in a production system is the total time required to complete all necessary tasks [24]. This factor plays a crucial role in determining the system's productivity, as a lower makespan indicates a higher quantity of products produced or assembled within a specific timeframe. Makespan is fundamental to all scheduling problems [25], and minimizing it can significantly improve a company's competitiveness by reducing product delivery time. To optimize system throughput, this study integrates makespan as an objective function via the variable ms. The proposed task allocation method aims to efficiently allocate tasks by minimizing the ms value, which results in a lower overall makespan and a higher quantity of products produced or assembled in a given timeframe. This approach enhances productivity and contributes to increased profitability and competitiveness in the market.

Operator's energy expenditure:

As Industry 5.0 continues to develop, there is an increasing emphasis on prioritizing the well-being of operators in the workplace. In alignment with this trend, the proposed task allocation method includes energy consumption as the second objective function. The assessment of energy expenditure was initially introduced by [26], who presented an approach to assess the metabolic rate for manual

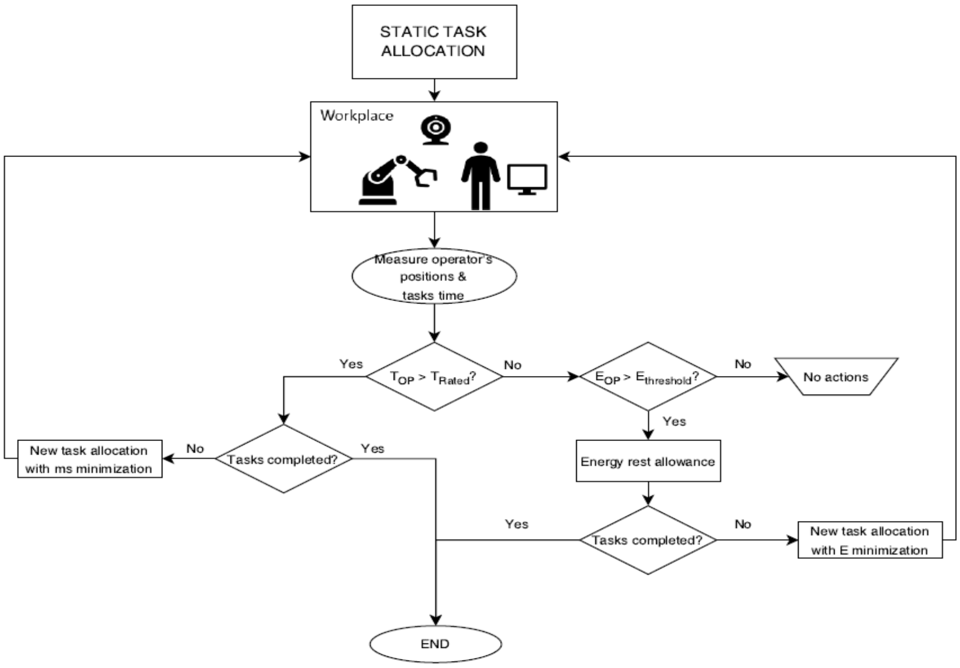

Fig. 1. Operating dynamic task allocation workflow

labour and walking movements, which encompassed various human aspects, such as age, body weight, gender, height, load weight, and more. Evaluating energy expenditure is critical for assessing ergonomic risks [27,28] since it includes metrics such as the duration, level, and repetitiveness of physical tasks that indicate the stress caused by physical jobs [29].

To gauge the energy expenditure needed to perform a task, this study employs the approach introduced by [26], which calculates the energy e_{jk} required by a resource k to complete task j, with the variable E serving as the objective function. By considering energy consumption as an objective function, the proposed task allocation method seeks to optimize task allocation in a manner that minimizes the energy expenditure required by the operator, promoting their well-being and reducing the risk of physical stress.

Indeed, the objective functions to minimize are:

$$\min \boldsymbol{ms} = \min\left(\boldsymbol{max}\left(\sum_{k=1}^{K}\sum_{j=1}^{J}(\boldsymbol{S_{jk}} + \boldsymbol{P_{jk}})\,\boldsymbol{x_{jk}}\right)\right) \quad (1)$$

where S_{jk} denotes the start time of task j carried out by resource k, while P_{jk} indicates the duration needed to finish the task j by the same resource k;

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

where the operator's energy expenditure is determined by adding up e_{jk}, which represents the energy needed to complete each assigned task j.

The assignment results in a binary variable defining what tasks are given to each resource:

$$\boldsymbol{x_{jk}} = \begin{cases} \boldsymbol{1}\ \boldsymbol{if\ the\ task\ j\ is\ performed\ by\ the\ resource\ k} \\ \boldsymbol{0}\ \boldsymbol{otherwise} \end{cases} \qquad (3)$$

The model is subjected to the following constraints:

$$\sum_{t=0}^{T}\sum_{k=1}^{K} \boldsymbol{x_{jk}} = \boldsymbol{1} \quad \forall \boldsymbol{j} \qquad (4)$$

$$\boldsymbol{x_{jk}} \in \{\boldsymbol{0}, \boldsymbol{1}\} \quad \forall \boldsymbol{j}, \boldsymbol{k} \qquad (5)$$

$$\sum_{j=1}^{J} \geq \boldsymbol{1} \quad \forall \boldsymbol{k} \qquad (6)$$

$$\boldsymbol{x_{jk}} = \boldsymbol{0} \quad \forall \boldsymbol{j} \in \boldsymbol{U_k} \qquad (7)$$

Where Eq. 4 and Eq. 5 represent the occurrence and integrality constraints, while Eq. 6 ensures that every resource is assigned to at least one task. Lastly, Eq. 7 establishes the technological constraints, which dictate that each resource k is only capable of performing tasks not included in the set of unfeasible tasks U_k.

The model resolution produces a set of optimal solutions represented by the Pareto Frontier. To select a single solution from this set, the one that minimizes the distance from the Utopia Point, where all objectives have a minimum value (as stated in Eq. 9) [30] , is chosen.

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

IV. DYNAMIC RESCHEDULING

The goal of this dynamic task allocation is to achieve a balance between workload and wellness while minimizing energy expenditure and maximizing throughput. By allocating tasks dynamically, it is possible to respond quickly to changes in the environment or workload, adapt to new requirements, and achieve better overall performance compared to static task allocation approaches.

Indeed, it is required to real-time track the operator's position and task time since it influences directly the makespan and indirectly, the energy expenditure, as shown in Fig.1.

Here, the assumptions made were that the operator follows the imposed scheduling, derived as input from the static task allocation described in Section III, and each task is assigned to a specific position in the workspace. These allow measuring exactly the start time and the end time of each task, by monitoring the operator position change.

The system operates by taking a static task allocation as input, which refers to the initial assignment of tasks to the available resources. As soon as the operator begins his/her task, the system starts measuring the time he/she is taking to complete it. Once the task is finished, the system compares the execution time with the rated one to evaluate the efficiency and compliance with the established standard times.

At this point, two scenarios may occur. The first scenario is when the actual time taken to complete the task exceeds the rated time. In this case, if there are still remaining tasks to be performed, a new task allocation is required to minimize the makespan while disregarding energy consumption. This optimization is done in real-time, utilizing a single-objective approach that focuses on minimizing makespan with the remaining tasks.

The other scenario happens when the standard times are respected: in this case, it is possible that the operator's energy expenditure rate $\dot{E}$ (i.e., the ratio between the energy expenditure required for the task and the task time) may exceed the fixed threshold $\dot{E}_{th} = 4.2927 \frac{kcal}{min}$ [31]. The energy expenditure rate of each task takes into account also the residual energy effects of the previous tasks [32], according to the following equation:

$$R_j(\tau_j) = \int_0^{\tau_j} E_j \cdot e^{-\mu\tau_j} \tag{9}$$

where R_j is the residual fatigue, function of the recovery parameter μ, after the task j if the recovery time τ_j has passed. This recovery time can be both a reaction time or an idle time or even a specific amount of time purposefully included to give the operator the required rest allowance as better describer later. Consequently, the accumulated energy for the task $j+1$ has the form in Eq. 10:

$$E_{j+1} = e_{j+1,1} + R_j \tag{10}$$

where $e_{j+1.1}$ is the energy required to complete the task if performed by the operator, as described in Section III.B. Finally, the energy expenditure rate is evaluated as:

$$\dot{E}_{j+1} = \frac{E_{j+1}}{t_{j+1,1}} \tag{11}$$

where $t_{j+1,1}$ is the measured time the operator required to complete the task. This value is then compared with $\dot{E}_{th}$.

If the threshold is not met, it is necessary to evaluate the rest allowance time τ, as before mentioned, to let the operator's energy rate to return to its resting value $\dot{E}_R = 1.86 \frac{kcal}{min}$:

$$\tau = \frac{\ln(\dot{E}) - \ln(\dot{E}_R)}{\mu} \tag{12}$$

An example of a typical pattern of energy accumulation and recovery process is shown in Fig. 2.

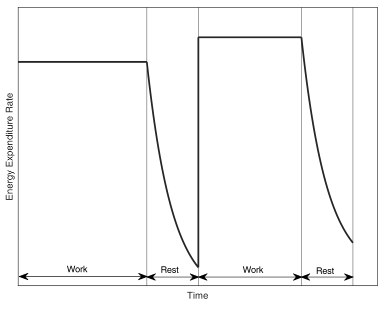

Fig. 2. Energy accumulation and recovery

Once the operator's rest period is over, the available resources are then provided with a new task scheduling that is obtained through a comprehensive optimization process aimed at minimizing the operator's energy expenditure while considering the remaining tasks that need to be performed.

The dynamic multi-objective task allocation system follows a continuous process that is designed to ensure the optimal allocation of tasks while also prioritizing the well-being of human operators. This process is repeated every time one of the two conditions occurs, namely when a task is completed or when an operator takes a rest period until all remaining tasks are completed.

By evaluating the real values of the objective functions in real-time, the system can accurately assess whether the expected values are being respected or not. Based on this evaluation, the system can then make adjustments to the task allocation process to optimize either productivity or the operator's wellness, depending on the scenario. This ensures that the system can respond promptly to any changes that occur during the production process, allowing for maximum efficiency and operator well-being. In summary, the dynamic multi-objective task allocation system is a powerful tool that helps create a truly human-centered production environment. By continuously evaluating and adjusting task allocation in real-time, this system optimizes both productivity and operator well-being, ultimately leading to a more efficient and sustainable production process.

V. CONCLUSIONS

In recent years, the shift from Industry 4.0 to Industry 5.0 has brought significant changes in the approach to workplace design, particularly in terms of technology integration and human involvement. Industry 4.0 was characterized by the automation of the production process, with a focus on maximizing output and efficiency, often at the expense of human involvement. However, as Industry 5.0 becomes more relevant, the focus is moving toward putting people at the center of the production process.

One of the key technologies that is helping to facilitate this transition is collaborative robots or cobots. These robots can work alongside humans, thereby improving production efficiency while allowing for greater human involvement in the production process.

However, to fully leverage the potential of cobots, it is essential to design workspaces that are optimized for human comfort and productivity. This requires taking into account the needs and preferences of both human and robotic resources and finding ways to allocate tasks in a way that maximizes efficiency while also taking into account human well-being.

One promising approach to achieving this goal is the implementation of a dynamic multi-objective task allocation system, as presented in this work. This method evaluated the well-being of human operators and the system productivity, in order to dynamically re-allocate tasks to ensure that the operator is not fatigued but at the same that the productivity is guaranteed.

This solution represents a significant step towards creating truly human-centered production environments that prioritize the well-being and productivity of human workers. The dynamic multi-objective task allocation system presented in this work is a novel approach that cannot be found in the literature. It demonstrates that optimizing task allocation based on both human and robotic resources' needs and preferences can lead to improved productivity and human well-being.

As limitations, the system complexity can be high since it is necessary to gather and analyze a significant amount of data; in addition, it is essential to validate its effectiveness in real-world industrial settings. That's why, in future development, this approach will be applied to real case studies, with the analysis of the parameters described, not only in the laboratory but also in the industrial field, with the aim of testing the benefits that can be introduced in the manufacturing scenario.

In summary, the shift towards Industry 5.0 highlights the importance of creating human-centered production environments that prioritize both efficiency and well-being. The dynamic multi-objective task allocation system presented in this work is a promising solution that can help achieve this goal. By considering both human and robotic resources' needs and preferences, this solution can improve productivity while ensuring the well-being of human workers.

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