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Human-Centered Task Allocation: A Simulation-Based Case Study

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Abstract: This study investigates human-centered task allocation, focusing on factors such as cognitive load, physical demand, and ergonomics. A discrete event simulator was developed to validate the task allocation results of the Q-learning optimization. The simulation evaluates the process and resulting task allocation plan based on predefined human-centered objectives. Through a case study on remanufacturing, we demonstrate how to optimize the coordination of a robotic arm and two human operators to reduce overall workforce requirements. The simulation allows for the analysis of operators' cognitive and physical workloads over time, enabling exploration of not only typical time balances but also cognitive and physical burdens.

Keywords: Task allocation, human-centered, cognitive load, physical demand, ergonomics, DES, simulation, optimisation

1. INTRODUCTION

In industrial settings, task allocation methodologies typically prioritize optimizing time and performance metrics. However, this narrow focus often overlooks crucial human-centered considerations that are essential for creating efficient and sustainable work environments. The current paradigm fails to consider the varied cognitive, physical, and ergonomic demands placed on human operators, leading to suboptimal task distributions that could compromise both productivity and worker well-being (Petzoldt et al., 2023). Therefore, there is an urgent need for an advanced approach that prioritizes human-centric factors, in task allocation strategies. As the number of agents in a system exceeds the dyadic setup, considerations for human well-being become more complex and urgent. Heightened agent count amplifies system complexity, leading to increased uncertainties. Addressing these complexities is crucial for effectively integrating multiple agents while prioritizing human welfare alongside technological advancements.

In a manufacturing environment, workers can perceive psychological stress (Lazarus, 2020) because of the physical environment (Vischer, 2007), the work setting known as the work context (WHO, 2020), and the work content, which is the demand of their assigned tasks (Hacker, 1993). Stress manifests itself as a state of worry and mental or physical tension when workers are faced with physical or psychological demands that exceed their capabilities (WHO, 2020). Although several studies focused only on physical (Kuijer et al., 1999) or mental workload (Rusnock and Borghetti, 2018), in the general case industrial workers have to perform a complex combination of these two (Permatasari and Anis, 2021).

Several studies have addressed task allocation, especially in dyadic systems, focusing on key performance metrics such as waiting time, production time, mean flow time, and cost in human-robot collaboration (HRC) (Petzoldt et al., 2023; Kousi et al., 2022; Schmidbauer et al., 2023). Recently, there has been growing interest in task allocation within multi-human robot teams, prompting several research endeavors in this domain(Skaltsis et al., 2021). Despite these advances, research on task scheduling in multi-human robotic systems is still lacking, especially with regard to prioritizing human welfare. Addressing this gap is critical to optimizing human-centered task allocation in such systems, and calls for further research and development in this area.

(Granata et al., 2024) emphasizes the importance of considering human elements in Industry 5.0 manufacturing, prioritizing operator well-being through cobot integration. It proposes a dynamic multi-objective task allocation system, evaluating human welfare via physiological and performance data to prevent excessive workloads and fatigue in real-time, balancing productivity and operator well-being. (Cunha et al., 2021) proposes achieving balanced harmony among safety, ergonomics, and effectiveness in collaborative frameworks. They demonstrate task distribution between humans and robots to improve working conditions and resource cooperation. In multi-objective task assignment optimization, cognitive workload of the workforce is prioritized alongside traditional objectives (Calzavara et al., 2023).

This study aims to explore the complexities of human-centered task assignment in industrial contexts. Recogniz-

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ing the limitations of conventional approaches that overlook crucial human factors, our research aims to bridge this gap by proposing a novel framework that emphasizes the holistic well-being of human operators. At the core of our approach is the discrete event simulator developed to validate the Q-learning (Jang et al., 2019) optimization-based human-centered task assignment. The defined human-centered factors allow us to allocate tasks based not only on traditional metrics, but also on human-centered objectives such as cognitive load, physical demand, and ergonomic considerations.

To demonstrate the practical applicability of our framework, we present a compelling case study in the field of remanufacturing. Through a simulation-based analysis, we show how the coordination of machines and human operators can be optimized to reduce overall workforce workloads while also reducing cognitive and physical burdens. By integrating human-centric considerations with operational efficiency, our case study exemplifies the transformative potential of our proposed approach in real-world industrial settings.

2. HUMAN FACTORS IN TASK ALLOCATION

Consideration of various human factors, including ergonomic level, mental workload, skills, and abilities, is crucial in designing a work cell (Colim et al., 2020), with an assessment of their impact, alongside collaborative robots, on system productivity. Extending the influence of human factors engineering throughout the system design and task assignment phases is critical (Cheng et al., 2019). By integrating productivity, flexibility, and human factors, an optimal task allocation strategy can be formulated to simultaneously achieve improved productivity and create a human-centered workplace that minimizes both operator energy expenditure and mental workload (Calzavara et al., 2023). An approach is presented to improve the performance of manufacturing systems by quantifying occupational health impacts and incorporating other operational aspects into optimization processes (Sobhani et al., 2015). The importance of human factors in manufacturing, particularly fatigue, is explored to investigate an agent modeling architecture (Fruggiero et al., 2016). While numerous studies have addressed individual human factors or environmental issues, there remains a need for an integrated approach to comprehensively analyze both social benefits and financial gains (Cheng et al., 2019).

The physical task load is characterized by three components: posture, force and time (Berlin and Adams, 2017). This type of load can be measured by separate measures such as the REEDCO Posture Score Sheet (Manske and Magee, 2020) for posture, force in Newtons and time in seconds, or by collective measures such as cardiovascular load (Dias et al., 2023). Mental task load is analyzed as visual, auditory, cognitive and psychomotor according to the four components of the VACP model (Aldrich et al., 1989). This type of load can be measured by subjective methods such as self-reported questionnaires, i.e. the Borg Workload Scale and the National Aeronautics and Space Administration Task Load Index (NASA-TLX) (Webster and Weller, 2018). The Cognitive Load Assessment for Manufacturing (CLAM) is an analytical method and tool designed to assess cognitive load in manufacturing processes, particularly assembly tasks (Thorvald et al., 2017). The primary goal of CLAM is to reduce the cognitive load of assembly workers on the shop floor, with a strong emphasis on practical applicability and usability. The method emphasizes simplicity, ensuring that it can be easily implemented by practitioners without requiring expert knowledge. In addition, CLAM includes supporting documentation, such as a handbook, to guide users in applying the method and interpreting the results. Efficient task allocation in multi-human, multi-robot interaction systems requires consideration of operator-specific workload thresholds and cognitive constraints to optimize system performance (Malvankar-Mehta and Mehta, 2015).

Considering human factors in simulations is vital, given that human operators are regarded as adaptable elements in manufacturing enterprises. These simulations offer valuable insights into system design, assessment, and improvements, accounting for factors such as skills, fatigue, health, and environmental conditions (Zhang et al., 2008). We have incorporated three key human factors - physical demand, ergonomics, and cognitive load - to evaluate task assignment. Each factor is rated on a three-point scale: low, medium, and high. Ergonomics (ER) is categorized into standard risk levels - safe, risk, and danger zones labeled 1, 2, and 3, respectively. Cognitive Load (CL) is assessed using the low, moderate, and high intervals of the CLAM method, with very low cognitive load ratings deemed inappropriate for the assembly line processes under study. In addition, physical demand is categorized into low, moderate, and high levels based on task ratings such as the weight of semi-finished products, tools, or the assembly activity itself.

3. THE DEVELOPED HUMAN-CENTERED TASK ALLOCATION

In our study, we developed a cost function based on three essential human factors - cognitive load, ergonomics, and physical demand - in addition to productivity metrics. Using a Q-learning algorithm, we optimized task allocation within an assembly production process to minimize the impact of human factors while maximizing efficiency. Q-learning algorithms are off-policy reinforcement learning techniques aimed at determining the most advantageous action based on the current state (Jang et al., 2019). To validate and evaluate the effectiveness of our approach, we built a discrete event simulation model. This model allowed us to assess the impact of human factors on productivity and provided valuable insights into the effectiveness of our task allocation strategy.

3.1 The Q-learning optimisation model

To tackle the challenges of task assignment among agents while reducing time and human-related risks, it's crucial to employ an optimization algorithm. To address this need, we crafted a mathematical model of the objectives, considering all task attributes, and formulated a cost function to optimize the process. This method's cost function combines normalized time and human factor risks, considering cognitive, physical loads, and ergonomics. It seeks task allocation strategies to reduce time and mitigate human-related risks simultaneously.

Considering the intricate nature of our multi-objective architecture, where we aim to find optimal solutions without labeled data, we have found Q-learning to be the most suitable optimization model. In comparison to classical optimization algorithms like genetic algorithms, we opted for Q-learning due to its independence from knowledge about the underlying dynamics of the environment. This feature makes it well-suited for problems where the dynamics are complex, unknown, or difficult to model, which is common in many real-world scenarios (Kegyes et al., 2021). The Q-learning algorithm serves as the task allocator, leveraging the characteristics of each task (states) to determine the most appropriate agent for each step (action), thereby minimizing both overall time and human risks. Within this framework, we defined the reward function mirroring the cost function. In essence, when a task is assigned to a robot, only time is factored into the reward; however, if a human agent is assigned the task, both time and human risks are considered. To enhance the realism of the optimization process, we introduced variability in the time required for human tasks by sampling from a normal distribution. This approach accounts for the natural variance in human performance, where some individuals may take longer while others complete tasks more quickly. Moreover, to ensure fairness in task distribution, the algorithm endeavors to allocate tasks among two human agents in a manner that balances their overall involvement time, striving for equality or approximate parity between them.

The Q-value function is updated using the following formula. Here, the states correspond to the task steps, and the actions represent the assignment of agents to tasks.

$$Q(s,a) \leftarrow Q(s,a)+\alpha\left(R(s,a)+\gamma \max_{a'} Q(s',a')-Q(s,a)\right)$$

Where s' represents the resulting state after taking action a, a' is the next action chosen in state s', $Q(s,a)$ denotes the current estimate of the Q-value for state s and action a, α stands for the learning rate, $R(s,a)$ signifies the immediate reward received after taking action a in state s, and γ represents the discount factor.

To implement the optimization algorithm for this case study, the objectives corresponding to the reward function, such as time and human factors, were normalized to values between 0 and 1. The optimisation's objective is to reduce the reward over time, thereby discovering the optimal policy. To achieve this, Q-learning iterates through assignments, initially randomly allocating tasks but learning iteratively from previous experiences. At each iteration, expected rewards are calculated based on predefined factors, with the ultimate aim of minimizing rewards while minimizing execution time and human risks. This iterative process enables the system to adapt and improve its allocation strategies over time.

3.2 The developed simulation model

In this study, we employed Siemens Tecnomatix Plant Simulation software to integrate process simulation and human factors modeling seamlessly. This software enables simultaneous simulation of manufacturing processes and human interactions, facilitating thorough analysis and optimization. To streamline the simulation, we modeled individual sub-activities within workstations, with each workstation containing multiple tasks scheduled during task allocation. Additionally, tasks were subdivided into station elements within each workstation to enhance efficient task allocation, ensuring effective implementation of strategies.

Two types of agents were modeled in the simulation: robots and humans. Each agent's behavior and characteristics were meticulously defined to accurately depict their roles in the manufacturing process. For human agents, three key human-centered conditions—cognitive load, physical load, and ergonomics—were crucial for evaluating and enhancing human performance in the simulated environment. Tasks were assigned predefined cognitive, physical, and ergonomic demands for the workers involved, and these demands were documented. This method enabled us to evaluate and optimize the effects of task assignments on human operators.

Furthermore, we introduced collaborative workstations where both human and robot agents were required to work together. Through process simulation, we analyze human-centric metrics and process efficiency, considering the stochastic nature of human activities with probabilistic representations of task completion times. This approach offers insights into the interplay between human factors and process performance, enhancing understanding of how uncertainty in human behavior impacts productivity and task allocation in complex manufacturing environments.

4. CASE STUDY AND RESULTS

The case study examines the optimization of a remanufacturing process by replacing an underutilized industrial robot arm with a collaborative robot (cobot) to increase productivity while improving human factors. Driven by the underutilization of a robotic arm in the maintenance testers and challenges related to human labor costs, the introduction of cobot technology creates shared workspaces on the assembly line. This strategic integration exploits the availability of cobots at two manual manufacturing workstations, especially during long test process times. A process simulation based on discrete event simulation was developed to comprehensively analyze the remanufacturing process, evaluating not only process times and efficiencies, but also human factors such as ergonomics and cognitive load. The detailed process is shown in Figure 1.

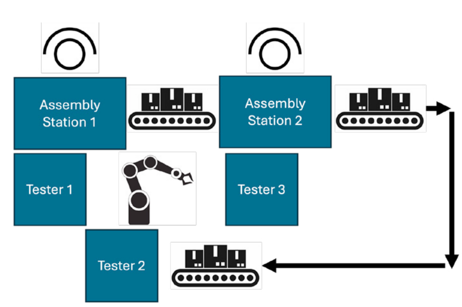

Fig. 1. The process flow of the re-manufacturing work steps

Table 1. Detailed process steps within the workstations with the required number of agents (*Req.*). The last three columns define which agent is capable to handle the task (*H.* - Human, *R.* - Robot, *A.* - Automation)

Station	Task	Task type	Req.	H.	R.	A.
Assy1	a1	Inloading	1	1	1	
Assy1	a2	Inspection	1	1		
Assy1	a3	Assign workflow	1	1		
Assy1	a4	Disassembly	2	1	1	
Assy1	a5	Component reproc.	1	1		
Assy1	a6	Component test	1			1
Assy1	a7	Assembly - complex	2	1	1	
Assy1	a8	OutLoading	1	1	1	
Assy2	a9	Inloading	1	1	1	
Assy2	a10	Assembly - simple	1	1	1	
Assy2	a11	Assembly - precise	2	1	1	
Assy2	a12	Drying	1			1
Assy2	a13	OutLoading	1	1	1	
T1	a14	Inloading	1		1	
T1	a15	Testing	1			1
T1	a16	OutLoading	1		1	
T2	a17	Inloading	1		1	
T2	a18	Testing	1			1
T2	a19	OutLoading	1		1	
T3	a20	Inloading	1		1	
T3	a21	Testing	1			1
T3	a22	OutLoading	1		1	

4.1 Data and parameters

At each workstation we have defined activities (a), each of which is associated with specific task types. These detailed activities can be assigned to different agents. Table 1 outlines the number of agents required for each activity and the agents that can be assigned to them based on their capabilities. We have assigned different human factors such as cognitive load, physical demand and ergonomics to these activity types. Each of these aspects has three levels of characterisation (see Table 2). These values are determined on the basis of the specific characteristics of the process and task, and they are depending on the traditional evaluation methods which are described in Section 2. Table 3 shows the activity times for each task type at each workstation and agent. Processing times

Table 2. Human factors definition for each type of task (*CL* - Cognitive level [1 - low, 2 - medium, 3 - high], *PD* - Physical demand [1 - low, 2 - medium, 3 - high], *ER* - Ergonomic [1 - safe, 2 - risk, 3 - danger]).

Task type	CL	PD	ER
Inloading	1	3	3
Inspection	3	1	1
Assign workflow	3	1	1
Disassembly	3	3	2
Component reproc.	2	2	1
Assembly - complex	3	3	1
OutLoading	1	3	3
Picking up	1	2	2
Placing	2	2	1
Assembly - simple	2	2	1
Assembly - precise	3	3	1
Component test	-	-	-
Testing	-	-	-

Table 3. Task type with the processing time for each agents and workstations in seconds.

Task type	H	R	A
Inloading	10, 1, 6, 15	15	
Inspection	50, 10, 40, 30		
Assign workflow	90, 20, 60, 210		
Disassembly	120, 20, 80, 210	150	
Component reproc.			20
Assembly - complex	180, 30, 120, 240	200	
OutLoading	10, 3, 6, 20	15	
Picking up	5, 1, 3, 8	10	
Placing	10, 3, 6, 20	15	
Assembly - simple	120, 20, 90, 180	30	
Assembly - precise	180, 30, 120, 240	200	
Component test			120
Testing			300
Drying			120

for human agents are represented by a truncated normal distribution with parameters $[\mu, \sigma, LB, UB]$, where μ is the mean, σ is the standard deviation, and LB and UB are the lower and upper bounds respectively.

The simulation model, depicted in Figure 2, showcases the primary structure created with Siemens Tecnomatix Plant Simulation software. Workstation activities are depicted by station units, each designated to a particular workplace. The cobot is simulated as a basic pick-and-place unit, with activity times based on its transportation capabilities. Task allocation is guided by selectors within the model, referencing the task scheduling table from the optimization process. For activities involving both human and robot participation, we employ DismantleStation and AssemblyStation units for precise process modeling.

4.2 Task allocation results and simulation-based validation

Task allocation was conducted across three scenarios, each assigning different weights to objectives within the reward function. In Scenario 1, tasks were allocated traditionally, with one operator per workstation. In Scenario 2, productivity was emphasized, given double the weight of human factors. Conversely, Scenario 3 prioritized human factors, with double the weight of execution time. These scenarios enabled exploration of different prioritization strategies, offering insights into how task allocation decisions are influenced by varying emphasis on productivity and human welfare.

The quantitative results of different scenarios in terms of productivity metrics are presented in Table 4. For three different scenarios, the table illustrates the percentage of agent utilisation and the number of products produced within a single shift (8 hours). Notably, each scenario shows an imbalance due to the complexity of the assembly process, including dual agent requirements and the stochastic nature of human behaviour. In addition, the analysis shows minimal differences in productivity, all less than 5%. In particular, the robot is given more tasks in the scenarios focused on human assistance.

Figure 3 shows a sample period illustrating the cognitive load of operator 1 under traditional task allocation. This analysis provides valuable insights into the factors that influence human workers during shifts, providing a deeper understanding of their cognitive workload.

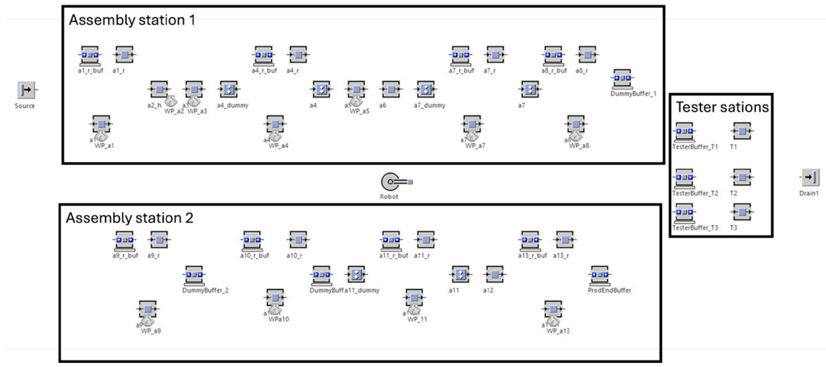

Fig. 2. The structure of the developed simulation model

Table 4. Quantitative results of the different scenarios related to the productivity metrics.

Scenario	Prod.	H1 work	H2 work	R work
Traditional	60	38.81%	76.18%	82.7%
Productivity	58	65.31%	46.62%	80.31%
Human	57	34.93%	66.69%	86.28%

Figure 4 shows the results of the three factors across different scenarios. We observe fluctuations in the values for each human agent across the three scenarios. The distribution of cognitive load proves to be the most challenging aspect, while ergonomics shows minimal significance in all cases, crucially avoiding the dangerous level 3 category. The highest physical demand consistently decreases to zero in all scenarios, reaching its lowest value in the human-centred scenario, which is a favourable result. In addition, the distribution of cognitive load between the two human agents is evident, with operator H1 experiencing the highest load, which decreases significantly for H2, indicating an overall improvement.

4.3 Discussion

One of the key achievements of this study is the adoption of human factors based task assignment strategies, a concept that has been successfully validated using the simulation model we developed. The capability to individually evaluate human factors represents a notable advancement, enabling researchers to conduct experiments and analyze real-world data with increased precision and depth. Human factors directly impact the performance, efficiency, acceptance, and various other components of Human-Robot Collaboration (HRC) systems (Hopko et al., 2022). By applying the evaluation techniques discovered, such as online optimization and deeper integration of simulation and optimization processes, we are able to improve task assignment methods. This includes the use of real-time data from the shop floor, laying the foundation for an evolution toward digital twin-based task allocation approaches. Through these advances, we can ensure that our simulations and optimizations are more accurate and reflect real-world scenarios, ultimately leading to more efficient and effective manufacturing processes.

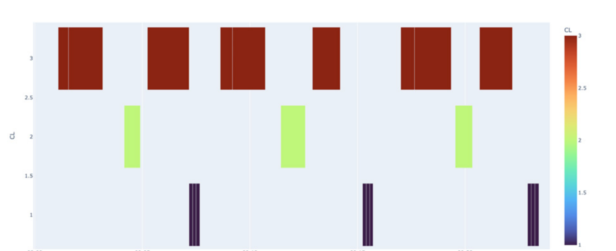

Fig. 3. Example period of a cognitive load on operator 1 during the traditional task allocation.

5. CONCLUSION AND LIMITATIONS

In this study, we address human-centred task allocation, prioritising factors such as cognitive load, physical demand and ergonomics. Our approach involves the development of a discrete event simulator that is seamlessly integrated with Q-learning optimisation techniques to efficiently allocate tasks while meeting pre-defined human-centred objectives. Through a case study focusing on remanufacturing, we show how optimal coordination between a robotic arm and two human operators can significantly reduce the overall manpower requirements. Using our simulation, we analyse the cognitive and physical workloads of the operators over time, allowing a comprehensive examination of time balances and strains. Our results highlight the applicability and effectiveness of our proposed concept in the context of remanufacturing processes. Future work entails integrating real-time human factors and feedback of physiological data to dynamically (re)allocate tasks, addressing human-centered issues effectively.

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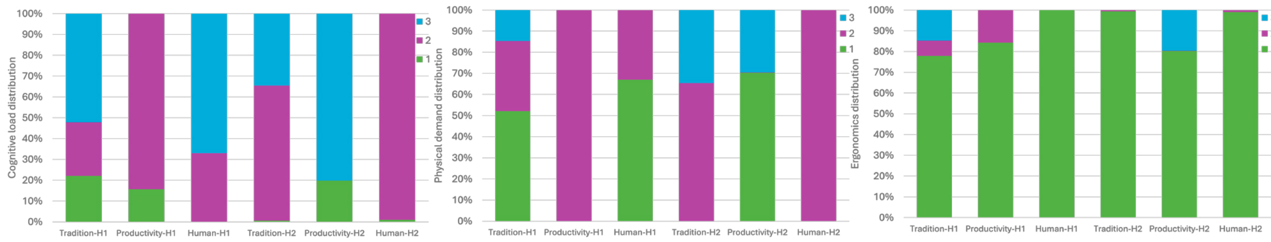

(a) Cognitive load (b) Physical demand (c) Ergonomics

Fig. 4. Results of the human factors during the three scenarios

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