Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 253 (2025) 415–424

Procedia Computer Science

www.elsevier.com/locate/procedia

6th International Conference on Industry 4.0 and Smart Manufacturing

A neural network approach for collaborative cells: an innovative online rescheduling strategy for maximizing productivity

Irene Granata[a,*], Matthias Bues[b], Martina Calzavara[a], Maurizio Faccio[a], Benjamin Wingert[b]

[a]*Department of Management and Engineering, University of Padua, Stradella San Nicola 3, Vicenza, 36100, Italy*
[b]*Fraunhofer Institut für Arbeitswirtschaft und Organisation, Nobelstr. 12, Stuttgart, 70569, Germany*

Abstract

Transitioning from Industry 4.0 to Industry 5.0 signifies a significant change in how technology integrates with workplace dynamics. While Industry 4.0 focused on streamlining production through automation, Industry 5.0 centers on human-centric approaches. This entails designing work environments that prioritize human comfort and efficiency by incorporating technology that complements human capabilities. Collaborative robots, known as cobots, play a pivotal role in this shift, aiding humans in tasks while fostering increased human involvement. However, maximizing the benefits of cobots necessitates workspace designs that optimize both human and robotic resources' needs and preferences. A promising strategy involves implementing a dynamic task allocation system. This approach employs a neural network to adaptively reallocate tasks to prevent any loss in performance. Such advancements represent a significant stride towards establishing production settings that prioritize the effectiveness of human workers.

Keywords: Industry 5.0; Cobots; Neural Network; Productivity; Well-being; Human-Centered Design; Human-Robot Collaboration.

1. Introduction

Collaborative robots, commonly referred to as cobots, have garnered significant attention in recent years due to their unique blend of productivity and adaptability, particularly in assembly setups [1]. One of their key advantages lies in their ability to work alongside human operators seamlessly, contributing to enhanced efficiency while maintaining safety standards [2]. In today's evolving landscape of workspace design, which places a strong emphasis on human well-being and ergonomics, integrating cobots requires careful consideration of various factors to ensure optimal performance and harmony between human and robotic elements [3, 4].

* Corresponding author: Irene Granata
E-mail address: irene.granata@phd.unipd.it

1877-0509
10.1016/j.procs.2025.01.103

A critical aspect of maximizing the potential of collaborative assembly systems is the implementation of a strategic task allocation system. Such a system serves to optimize productivity, effectively utilizing available resources, and aligning operations with the overarching objectives of Industry 5.0. However, achieving efficient task allocation in dynamic environments where human and robotic resources coexist poses unique challenges that necessitate innovative solutions.

Efforts to address these challenges have included introducing real-time ergonomic evaluation tools to provide continuous feedback on human comfort and safety within collaborative work environments [5]. These tools enable ongoing adjustments to task allocations and workspace configurations, further enhancing the overall efficiency and effectiveness of collaborative production systems.

Despite the significant strides made in collaborative systems integrating humans and cobots, there persists a pressing need for cost-effective and real-time methodologies for task allocation. While prior studies have proposed diverse approaches, the hurdles of real-time implementation and cost-efficiency continue to present challenges.

This paper endeavors to tackle these obstacles by presenting a groundbreaking system that harnesses motion capture technology alongside neural networks. The objective of this system is twofold: first, to prognosticate potential productivity downturns, and second, to dynamically reconfigure task schedules among resources to counteract these declines. By seamlessly melding motion capture data with sophisticated neural network architectures, our system emerges as a promising avenue for amplifying productivity and streamlining operations within collaborative assembly environments.

The contribution of this paper extends beyond the confines of the manufacturing sector, marking a notable advancement in the realm of human-robot collaboration. Its potential ramifications transcend industry boundaries, offering insights and solutions applicable to a wide array of domains where humans and robots collaborate synergistically. Through empirical validation and theoretical underpinnings, this paper sets a precedent for future research endeavors in optimizing collaborative systems for enhanced efficiency and productivity.

The paper is organized as follows: Section 2 introduces the concept of dynamic task allocation for collaborative systems, with the developed system; Section 3 presents the experimental campaign for the system validation with the analysis and discussion of the results, while Section 4 concludes the work.

2. Dynamic task allocation

Dynamic task allocation in collaborative systems is a pivotal process that orchestrates the allocation of tasks among human operators and robotic resources in real-time, responding to the dynamic nature of production environments [6]. It encompasses the adaptive assignment of tasks based on various factors such as resource availability, skill levels, and current operational conditions. This methodology aims to optimize resource utilization, enhance productivity, and ensure the smooth operation of collaborative assembly systems. Through dynamic adjustment of cobot behavior based on operator needs, the system fosters a conducive work environment that prioritizes worker satisfaction. Moreover, the centralized control offered by the developed user interface enables seamless integration of diverse inputs, allowing for flexible adaptation to evolving production requirements and operational scenarios. Despite its advanced functionalities, the system remains cost-effective, offering a pragmatic solution for enhancing productivity within collaborative assembly settings. Additionally, the modular design of the system facilitates scalability, making it suitable for deployment across diverse manufacturing environments with varying complexities and resource constraints.

With the integration of advanced technologies such as motion capture and neural networks, this study proposes a novel system designed to predict and mitigate productivity losses by dynamically adjusting task schedules in response to changing operational conditions. By leveraging real-time data insights and predictive analytics, the proposed system offers a holistic approach to task allocation optimization, empowering manufacturers to achieve higher levels of efficiency, flexibility, and worker satisfaction in collaborative work environments.

2.1. Static Task Allocation

The present study involves the collaboration of two resources, namely a human operator and a collaborative robot, within a shared workspace.

As soon as the resources start to work, they receive as first input a static task allocation, based on the minimization of the makespan. 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 [7]. By enhancing productivity, this approach can contribute to increased profitability and competitiveness in the market.

The model here used is the same as in [8], and here briefly recalled. The objective function is the minimization of the makespan ms as in Eq. 1, in performing J tasks by the $K = 2$ resources.

$$\begin{aligned} & min\ ms \\ & ms \geq \sum_{j=1}^{J} x_{j,k} \cdot T_{j,k}\ \forall k \end{aligned} \tag{1}$$

where T_{jk} is its execution time when it is performed by the resource k.

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

$$x_{jk} = \begin{cases} 1 \text{ if the task } j \text{ is performed by the resource } k \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

The following constraints are introduced:

$$\sum_{k=1}^{K} x_{jk} = 1 \quad \forall j \tag{3}$$

$$x_{jk} \in \{0, 1\} \quad \forall j, k \tag{4}$$

$$\sum_{j=1}^{J} x_{jk} \geqslant 1 \quad \forall k \tag{5}$$

$$x_{jk} = 0 \quad \forall j \in U_k \tag{6}$$

Eq. 3 and Eq. 4 are the *occurance* and *integrality* constraints, that assure that each task is performed by only one resource. Eq. 5 it is necessary to guarantee that both resources have at least one task assigned to them and Eq. 6 is the technological constraint for the tasks that can not be performed by one or the other resource.

2.2. Dynamic Rescheduling

In order to correctly perform the dynamic rescheduling each task corresponds to a specific position in the workspace, and the transition of a resource's position signifies the completion of one task and the initiation of the next. To facilitate this, a marker-based motion capture system, specifically the Vive Trackers by Lighthouse, is employed due to its precise location tracking capabilities, particularly suited for confined workspaces requiring accurate position monitoring. In this study, two Vive Trackers are utilized, one for each hand of the human operator, to afford maximum freedom and dexterity.

The effectiveness of our proposed system is facilitated by a MATLAB (MathWorks) user interface meticulously developed to offer centralized control and seamless integration of inputs from various sources, including the motion capture system and the cobot. This interface serves as a pivotal tool for managing data, ensuring cohesive and synchronized operations. Moreover, in the development of the system, a neural network is utilized to predict the timing of future tasks within the cycle by continuously monitoring the ongoing ones. The neural network used for this application is a Nonlinear Autoregressive Neural Network (NAR), which is a type of neural network primarily used for time series prediction. Unlike traditional neural networks that process data sequentially, NAR networks can model the nonlinear relationships between past and future observations without the need for a hidden state [9]. Leveraging its ability to learn from past experiences and adapt in real-time, the neural network optimizes task scheduling and minimizes productivity losses due to inaccuracies. The utilization of a neural network within the system offers several advantages. Its prowess in pattern recognition enables accurate predictions of future task times based on historical data, enhancing operational efficiency. Additionally, the network's adaptive nature ensures responsiveness to changing worker behaviors and production dynamics, thereby optimizing overall productivity. The real-time predictive capabilities of the neural network enable proactive adjustments to task schedules, mitigating the impact of unforeseen disruptions.

Throughout the process, the system continuously monitors the position of the robot and the operator, as well as the time, in real-time for each task. As tasks are completed, the system dynamically reschedules for the subsequent cycles, ensuring task sequence integrity while optimizing resource utilization. In cases where the operator requires more time for a task, a new task allocation is generated to alleviate the burden by reallocating more time-consuming tasks to the cobot, ensuring compatibility with technological constraints. This iterative process ensures efficient task allocation while maintaining productivity and operator well-being until the predefined lower threshold for makespan is reached.

3. Experimental Campaign

To validate the system's efficacy, an experimental campaign was undertaken. This campaign involved assembling and disassembling a box composed of four distinct pieces, as depicted in Figure 1. For each task a different amount of

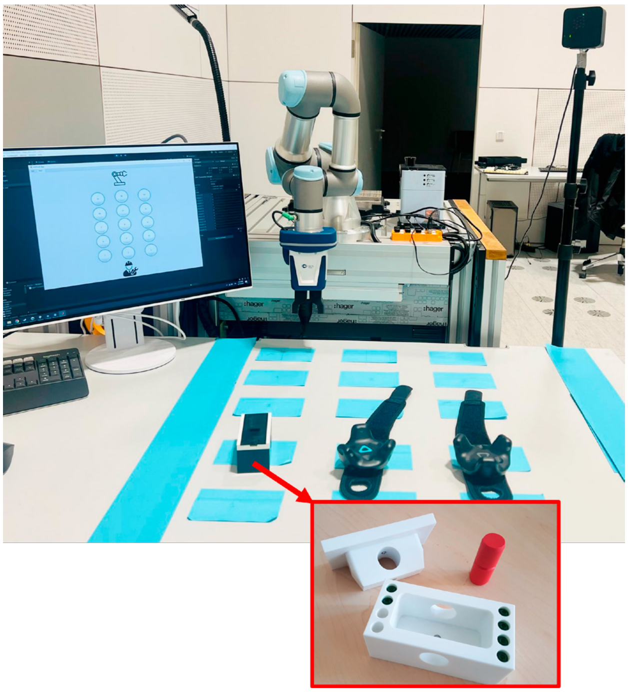


Fig. 1: Setup and box object used for the experimental campaign

times performing this process was defined, mirroring the intricacies of real-world assembly processes where items are assembled and disassembled repeatedly. Table 1 presents task times for an assembly process encompassing $J = 15$ tasks. Notably, some entries in the table are represented as "-" to denote infeasibility for the resources involved. The operator's task times were defined through the use of the MOST (Maynard Operation Sequence Technique) method [10] while the cobot ones were measured. In environments characterized by repetitive tasks, productivity can easily diminish due to factors such as monotony or operational constraints.

Table 1: Tasks time for the operator and the cobot

Task	T_{op} $[s]$	T_c $[s]$
1	10	-
2	40	-
3	30	-
4	40	-
5	30	-
6	20	-
7	30	31
8	20	23
9	30	-
10	40	40
11	20	13
12	20	28
13	-	60
14	-	84
15	-	63

The first static task allocation was resolved through the minimization of the makespan, as explained in Section 2.1. Table 2 reports the values of the objective function along with the corresponding task allocation, shown also in Figure 2, where "OP" are the tasks assigned to the operator, "C" the ones assigned to the cobot, and "Collab" the amount of collaboration established.

Table 2: Objective function value and input task allocation

ms $[s]$	OP	C
270	[1,2,3,4,5, 6,7,8,9,12]	[10,11,13,14,15]

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 about 60 consecutive minutes, meaning a 10 cycles repetition test. The number of subjects involved in the experimental campaign is 12, half of which tested the system with the rescheduling mechanism, and the other half without.

Before commencing the test, each participant received thorough instructions on the tasks they were required to perform. Upon completion, participants filled out the NASA-TLX questionnaire, a well-established tool for assessing subjective workload and task demands. This questionnaire provides valuable insights into various aspects of task performance, including mental, physical, and temporal demands, as well as perceived levels of frustration and effort expended [11].

3.1. Results and discussion

After the competition of all the tests, the first analysis carried out was the evaluation of the makespan between the two different samples depicted in Figures 3 and 4. Both samples initially increase makespan in the first cycles with respect to the rated value ms^* due to experiment learning. However, in the case of utilizing the rescheduling mechanism, this increase is mitigated by the system's intervention, thereby generating a lower mean makespan compared

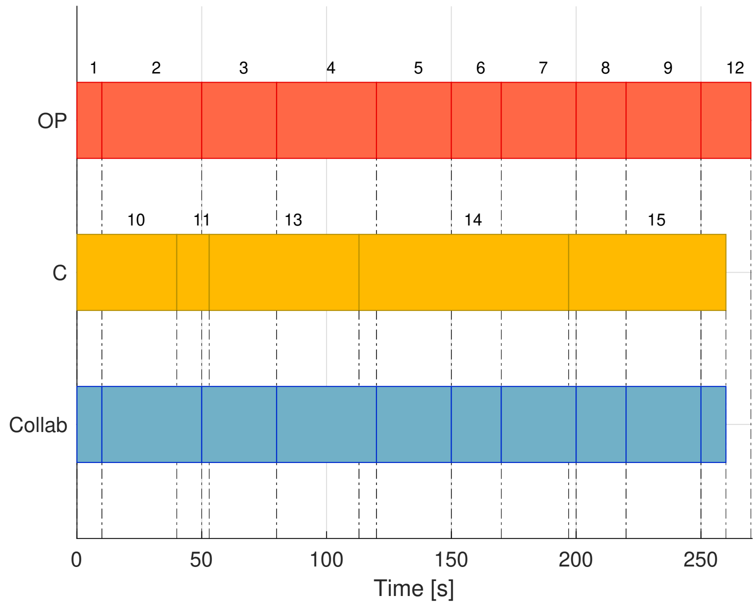


Fig. 2: Input static task allocation

to the scenario without rescheduling. Subsequently, the makespan decreases to nearly the expected value ms^*, with peaks of up to 20% less in the case of rescheduling. This phenomenon arises because when participants performed faster than expected, the system assigned them a larger quantity of tasks, thus allowing for a significant performance increase, a scenario not observed in the sample without rescheduling. In the final cycles, when fatigue sets in, there is, on average, a second increase in overall time, once again mitigated by the robot's intervention in the former sample but not the latter. Consequently, considering the average of cycles and participants, $\bar{ms}$, there is a 5% improvement in the case of rescheduling, as evident from the values of makespan in the figures. This trend is further supported by Figure 5, which demonstrates that considering the average participant times across different cycles, the makespan is almost always lower when the robot's behavior is adaptive. In addition, it is possible to notice from Figure 6 that the workload between the two resources, where "OP" is the operator and "C" is the cobot, is more balanced through the cycles when the adapting mechanism is turned on (Figure 6a) in comparison to the case without rescheduling (Figure 6b). This balanced workload distribution enhances operational efficiency and contributes to a more equitable and sustainable work environment.

Furthermore, the utilization of the neural network facilitated the prediction of the increasing trend, enabling proactive measures to counteract it effectively. By anticipating the rise in makespan and implementing rescheduling strategies accordingly, the system was able to proactively mitigate its effects, resulting in improved overall performance and keeping the workload of the two resources more balanced. This highlights the significance of leveraging advanced predictive analytics, such as neural networks, in optimizing resource allocation and operational efficiency. The successful prediction and management of the escalating trend underscore the efficacy and foresight of integrating predictive modeling techniques into task allocation systems, enhancing their adaptability and responsiveness to dynamic operational conditions.

The subsequent analysis conducted delved into the dimensions of the NASA-TLX questionnaire, aiming to comprehensively assess the impact of the rescheduling mechanism on various cognitive and affective factors. As illustrated in Figure 7, with the values reported from 0 to 100, each dimension exhibits a noticeable reduction when the rescheduling mechanism is employed. Notably, while the mental workload and performance dimensions remain relatively close between the two scenarios, they consistently register lower values with rescheduling. Conversely, significant disparities emerge in all other dimensions, highlighting the pronounced effect of rescheduling on participant experience.

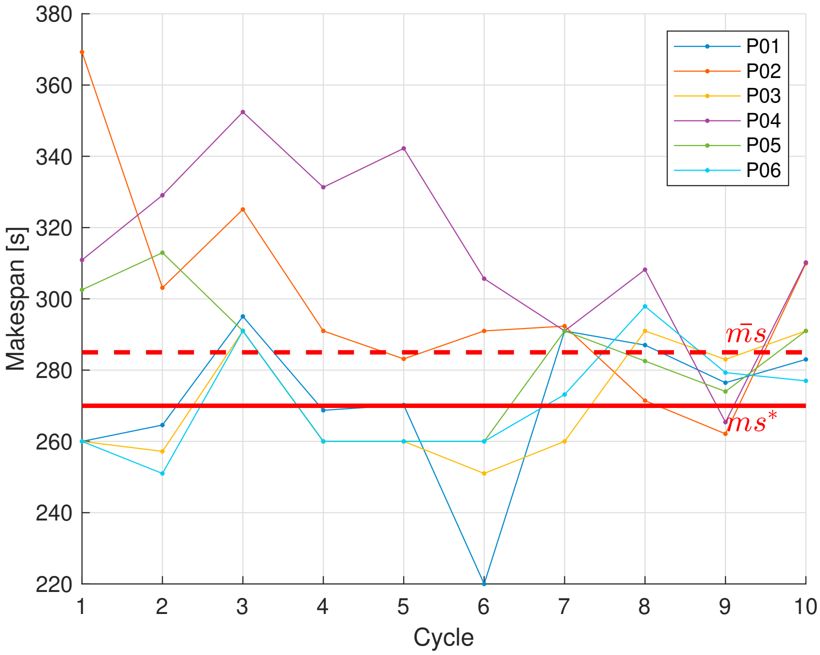


Fig. 3: Testers' makespan during the cycles with neural network

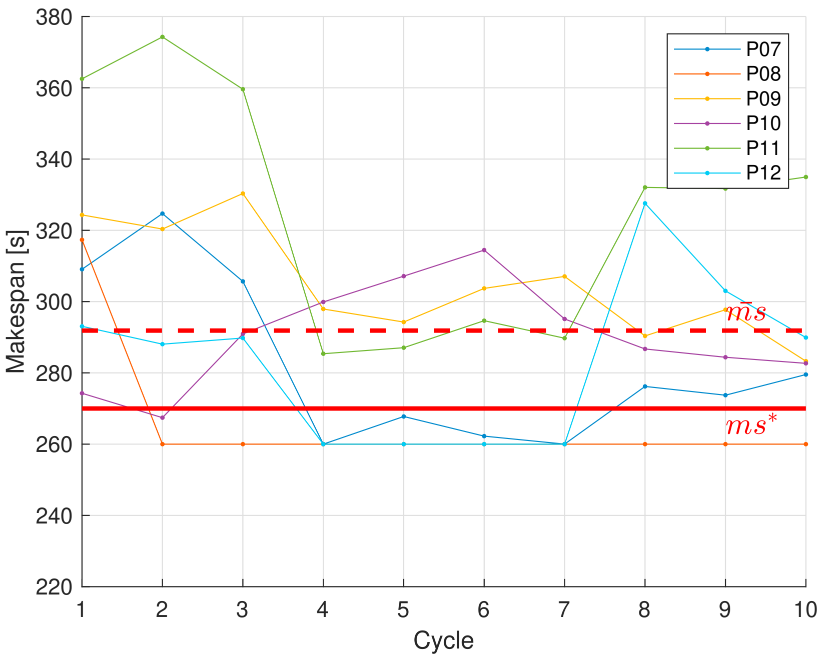


Fig. 4: Testers' makespan during the cycles without neural network

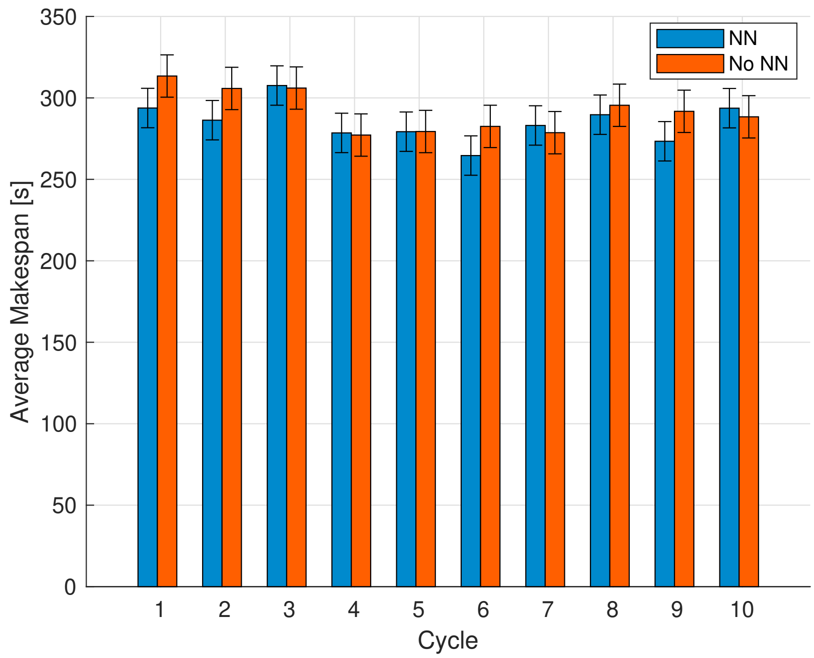
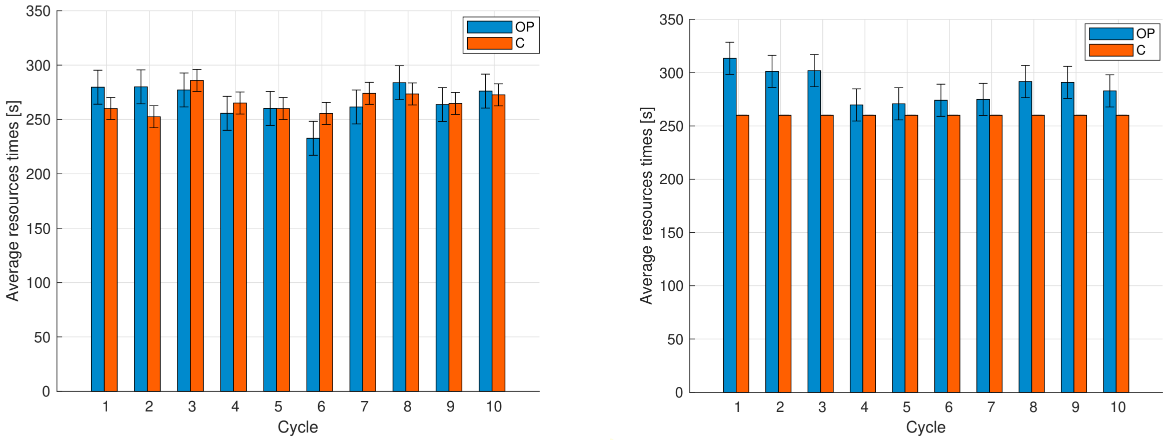


Fig. 5: Average makespan during the cycles



(a) With neural network

(b) Without neural network

Fig. 6: Resources average times per cycle

Particularly striking is the dimension of frustration, which exhibits a remarkable decrease of approximately 70% when rescheduling is implemented. This substantial reduction suggests that participants experienced significantly less insecurity, strain, or annoyance throughout the experiment when rescheduling was utilized. Such findings underscore the efficacy of the rescheduling mechanism not only in optimizing task allocation and performance but also in fostering a more positive and conducive experimental environment.

This observed decrease in frustration aligns with broader research indicating the detrimental impact of uncertainty and unpredictability on cognitive performance and emotional well-being. By proactively addressing potential sources of frustration through adaptive rescheduling strategies, the system effectively cultivates a more supportive and manageable experimental setting. Moreover, these findings emphasize the multifaceted benefits of integrating intelligent scheduling mechanisms into experimental protocols, transcending mere performance enhancement to encompass participant satisfaction and overall experiential quality.

In conclusion, the integration of the rescheduling mechanism has yielded multifaceted benefits, as evidenced by both the temporal analysis and the NASA-TLX questionnaire results. The observed reductions in makespan, particularly notable when employing rescheduling, underscore the system's efficacy in optimizing task allocation and mitigating the impact of fluctuating participant performance. By dynamically adapting to changing conditions, the system proactively anticipates and addresses potential inefficiencies, resulting in improved overall performance and resource utilization.

Moreover, the comprehensive assessment of participant experience through the NASA-TLX questionnaire reveals a notable decrease in frustration levels when rescheduling is employed. This signifies a more positive and conducive experimental environment, characterized by reduced strain and annoyance among participants. Such findings highlight the broader implications of intelligent scheduling mechanisms, not only in enhancing objective performance metrics but also in fostering participant satisfaction and well-being.

Overall, the synergistic integration of temporal analysis and participant feedback underscores the transformative potential of adaptive scheduling strategies in experimental settings. By harnessing predictive analytics and proactive intervention, researchers can not only optimize experimental outcomes but also cultivate a more supportive and engaging environment for participants. Moving forward, continued refinement and application of such intelligent systems promise to revolutionize experimental methodologies, driving innovation and advancement across diverse fields of study.

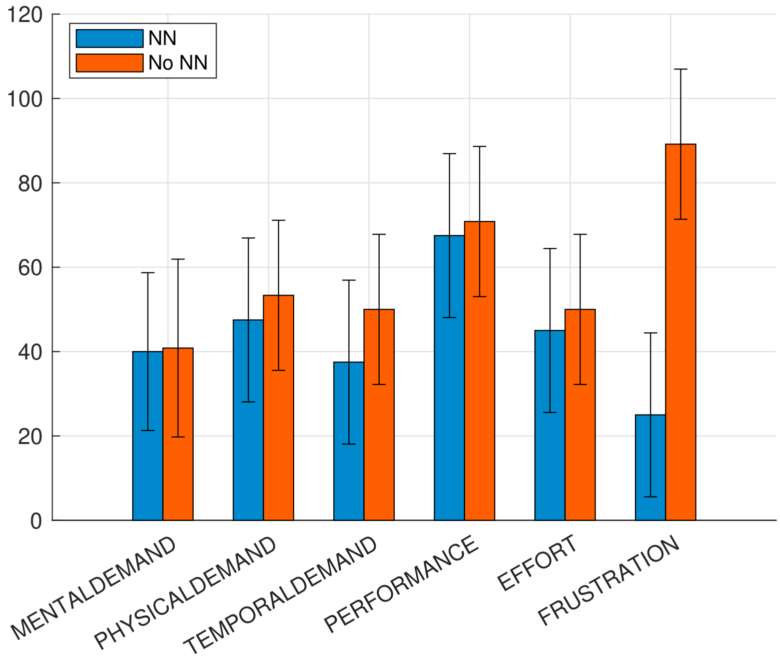


Fig. 7: Nasa-TLX results

4. Conclusion

This study presents a novel approach to task allocation optimization in collaborative assembly systems, leveraging motion capture technology and neural networks to dynamically adjust task schedules in response to changing operational conditions. Through empirical validation and theoretical underpinnings, the research has demonstrated the efficacy of the proposed system in enhancing productivity, worker satisfaction, and overall experiential quality within collaborative work environments.

The experimental campaign conducted provided valuable insights into the system's performance, with both temporal analysis and NASA-TLX questionnaire results highlighting the tangible benefits of integrating the rescheduling mechanism. The observed reductions in makespan, particularly notable when employing rescheduling, underscore the system's efficacy in optimizing task allocation and mitigating the impact of fluctuating participant performance. Furthermore, the significant decrease in frustration levels among participants when rescheduling is employed signifies a more positive and conducive experimental environment, enhancing overall experiential quality.

These findings not only contribute to the advancement of collaborative assembly systems but also offer broader implications for human-robot collaboration across various domains. By synergistically integrating temporal analysis and participant feedback, our study underscores the transformative potential of adaptive scheduling strategies in enhancing productivity and worker well-being. Moving forward, continued refinement and application of intelligent systems promise to revolutionize experimental methodologies, driving innovation and advancement across diverse fields of study.

In conclusion, our research represents a significant step towards optimizing task allocation in collaborative assembly systems, offering practical insights and solutions to enhance productivity, worker satisfaction, and overall operational efficiency. As we continue to explore the possibilities of intelligent scheduling mechanisms, we envision a future where human-robot collaboration reaches new heights, unlocking unprecedented levels of productivity and innovation in a wide range of industries and applications.

Funding

This study was carried out within the PNRR research activities of the consortium iNEST (Interconnected North-Est Innovation Ecosystem) funded by the European Union Next-GenerationEU (Piano Nazionale di Ripresa e Resilienza (PNRR) – Missione 4 Componente 2, Investimento 1.5 – D.D. 1058 23/06/2022, ECS_00000043). This manuscript reflects only the Authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

References

[1] I. Granata, M. Faccio, G. Boschetti, Industry 5.0: prioritizing human comfort and productivity through collaborative robots and dynamic task allocation, Procedia Computer Science 232 (2024) 2137–2146.

[2] S. Takata, T. Hirano, Human and robot allocation method for hybrid assembly systems, CIRP annals 60 (2011) 9–12.

[3] D. Romero, J. Stahre, Towards the resilient operator 5.0: The future of work in smart resilient manufacturing systems, Procedia CIRP 104 (2021) 1089–1094.

[4] M. Faccio, I. Granata, A. Menini, M. Milanese, C. Rossato, M. Bottin, R. Minto, P. Pluchino, L. Gamberini, G. Boschetti, G. Rosati, Human factors in cobot era: a review of modern production systems features, Journal of Intelligent Manufacturing (2022). doi:10.1007/s10845-022-01953-w.

[5] 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.

[6] 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.

[7] 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.

[8] M. Faccio, I. Granata, R. Minto, Task allocation model for human-robot collaboration with variable cobot speed, Journal of Intelligent Manufacturing 35 (2024) 793–806.

[9] R. Sarkar, S. Julai, S. Hossain, W. T. Chong, M. Rahman, et al., A comparative study of activation functions of nar and narx neural network for long-term wind speed forecasting in malaysia, Mathematical Problems in Engineering 2019 (2019).

[10] K. B. Zandin, MOST work measurement systems, CRC press, 2002.

[11] S. G. Hart, L. E. Staveland, Development of nasa-tlx (task load index): Results of empirical and theoretical research, in: Advances in psychology, volume 52, Elsevier, 1988, pp. 139–183.