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Task Scheduling Optimization for Multi-Human Multi-Robot Collaborative Remanufacturing

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Abstract— **The increasing proliferation and evolution of robotics and its capabilities is having a significant impact on smart manufacturing and remanufacturing. Within the popular frameworks of Industry 4.0 and Industry 5.0, Human-robot collaboration (HRC) has emerged to integrate the best capabilities of humans like their problem solving with those of robots like their precision. These systems are continuing to scale rapidly and are beginning to introduce multi-human multi-robot collaboration (MHMRC) environments, offering a greater degree of productivity and flexibility. Both HRC and MHMRC are still faced with underexplored challenges, such as task allocation and scheduling. In this study, we propose a nature-inspired, objective function-constrained task scheduling optimization solution for multi-human multi-robot collaborative remanufacturing. Different objective functions for the Dingo Optimization Algorithm are developed to investigate how human participants perceive task assignments and interpret the disassembly process under varying objectives in MHMRC. We conduct a real-world multi-human multi-robot collaborative remanufacturing user study in which participants disassemble an end-of-life desktop computer in a shared workspace with two robots to test and validate the proposed approach. Participants are surveyed using the NASA-TLX, along with additional questions. Experimental results demonstrate the effectiveness of the developed approach, and directions for future work are also discussed.**

I. Introduction

The increasing capabilities and applications of robotics are shaping innovation, industry, and research in many ways. Human-robot collaboration (HRC) has emerged as a critical focus within this growing area [1-3]. This trend is expected to continue as robotics plays a central role in the implementation of both Industry 4.0 and the emerging Industry 5.0. Industry 4.0 is primarily characterized by the concept of smart factories and the use of advanced digital technologies, whereas Industry 5.0 emphasizes the integration of these technologies with a focus on resilience, sustainability, and human-centric design [4]. Studies have explored and identified HRC and robotics more generally as important to a human-centric vision of Industry 5.0 and its future implementations [5-8]. Advances in sensing, computing, and theory have pushed robots from isolated automated tasks toward active collaboration with humans within shared working environments [9, 10]. In recent years, the integration of robots into human environments and industrial workflows has created not only the opportunity for individual HRC scenarios but also multi-human multi-robot collaboration (MHMRC) contexts.

These MHMRC environments involve multiple human and robot agents working together on potentially various tasks [11]. MHMRC systems seek to take advantage of the various capabilities of different agents to complete tasks to potentially a greater degree and scale than normal HRC can achieve. While MHMRC have advantages, it also introduces new challenges for researchers and industries to consider. These challenges include the proper distribution of labor or task allocation, redundancy or fault tolerance, the potential for large-scale concurrent task execution, human factors like trust [12, 13], and much more. These challenges are also present in normal HRC but are further burdened by increased scale and complexity. Future industry implementations of HRC or MHMRC will depend heavily on whether researchers and industry sectors can address these issues. The authors of [14] suggested that the human workers in Industry 5.0 will have fewer physical tasks and a lot more decision-making and problem-solving tasks. In [15, 16], the authors identified several problems in disassembly applications, such as worries about flexibility and high variability of end-of-use or end-of-life products. These unaddressed, interconnected challenges in disassembly demonstrate the vital importance of pursuing remanufacturing research in HRC and MHMRC contexts to realize the visions of Industry 4.0 and 5.0.

Applying HRC and MHMRC in research and industry requires the use of various technologies and a thorough consideration of the entire specific problem scenario. The scenarios in which HRC and MHMRC are expected to thrive usually involve many uncertainties, and the application of HRC or MHMRC needs to have pathways to resolve these issues. A survey in [17] outlined several different common architectures, communication methods, and application domains found in research. This work shows that there are diverse roles that different agents can assume in MHMRC research and how the interaction between agents is mediated and utilized across different research goals. Some ideas, like the integration of machine learning and optimization algorithms into HRC and MHMRC research, have yielded preliminary results as well. The authors of [18] utilized machine learning to classify trust via a preference-based optimization algorithm in a chemical industry scenario. Others, like the work [19], employed reinforcement learning to help a robot properly assist a human collaborator in lifting a table. The authors of [20] looked into the uses of vision systems for scene understanding across several other research studies and how these studies utilize this information for decision-making, collaboration, and general scene understanding. Other studies focus primarily on the safety aspects associated with HRC and MHMRC in general as well. In HRC and MHMRC, task optimization and allocation or sequence planning are extremely important considerations, especially in disassembly or assembly scenarios. The authors of [21] used Ant Colony Optimization to solve their role-oriented task allocation problem. In [22], the authors utilized a mixed-integer linear programming approach for solving their human multi-robot task allocation problem while also considering varying skills, roles, and human parameters.

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However, in multi-human multi-robot collaboration contexts, task allocation and scheduling present many underexplored challenges due to the presence of more agents and greater uncertainties. A critical factor in such settings is deciding precisely when and where an agent should, or should not, perform an action, as this directly impacts trustworthiness and user satisfaction. This is especially crucial in remanufacturing tasks [23], which can be defined as the restoration of used and non-functional parts to "like-new" condition. In these scenarios, disassembling and rebuilding components of various products is a complex and multi-step process. Motivated by these issues, we propose an objective function-constrained task scheduling optimization solution for multi-human multi-robot collaborative remanufacturing in this study. The objective functions take in a set of task variables and produce target outputs that are referred to as costs, while also subject to certain constraints. The developed optimization algorithm employs the objective function as a guide to navigate the solution space, evaluate alternatives, and generate an optimized solution. The main contributions of this study can be summarized as:

(1) A nature-inspired, objective function-constrained task scheduling optimization solution is proposed for multi-human multi-robot collaboration in remanufacturing contexts.
(2) Different objective functions for the Dingo Optimization Algorithm are developed to investigate how human participants perceive task assignments and interpret the disassembly process under varying objectives in MHMRC.
(3) The developed approaches are implemented in real-world MHMRC tasks and evaluated through a user study with comprehensive questions.

II. MODELING METHODOLOGY

A. Overview

In this work, we conduct a user study with fourteen human participants and pair them to collaborate with a multi-robot system in a disassembly task. Specifically, there are four agents in a shared workspace, two humans and two robots forming a multi-human multi-robot collaboration environment. Fig. 1 shows one of the pairs of participants working with robots. These agents are tasked with two rounds of disassembly tasks, removing common computer hardware parts from an open computer case, guided by the developed task scheduling optimization approach using two different objective functions for task assignments. First, the two participants demonstrate a preferred disassembly sequence, then participants complete two rounds of disassembly with optimized task assignments to complete the disassembly collaboratively and effectively. Participants do not know the differences between the objective functions used. This study seeks to compare the two different objective functions in this disassembly context and analyze participant survey results about their experiment experience using the NASA-TLX (Task Load Index) [24], among other questions. Potential insights from the participant survey can be used to inform future research and development, and show how human perception of the disassembly task is influenced by efficient task assignments and different optimization goals. As well as to influence the design and formation of objective functions in HRC and MHMRC contexts. One of the objective functions only considers human-robot distance as a factor, with a few constraints to further help delegate tasks amongst all agents. The other objective function is more complex and considers three factors, including distance, object weight, and object size, along with the same constraints as the first function.

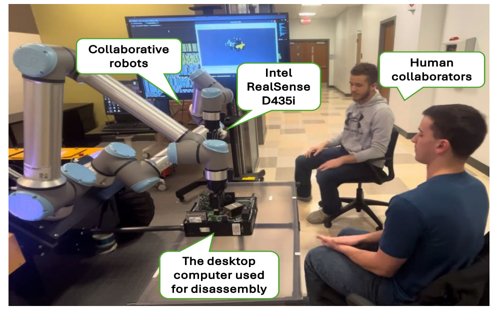


Fig. 1. Multi-human multi-robot collaboration experiment platform.

B. Dingo Optimization Algorithm

Dingo Optimization Algorithm (DOA) is a powerful nature-inspired metaheuristic where search agents emulate behaviors of real-life dingoes, including encircling, chasing, scavenging, and survival, one behavior at a time. This metaheuristic has proven rapid convergence and optimization ability [25, 26]. For the input of the algorithm, we represent the problem encoding as a position array, where each element corresponds to an object, and the value at that element corresponds to the assigned robot or human arm. In our experiment, four arms are assigned (two robot arms and two human arms). Decoding is accomplished through the objective function, which interprets the encoding format, minimizes cost values, and returns a meaningful output for task optimization.

The behavior that the Dingo Optimization Algorithm chooses is probabilistic, with a probability parameter P determines whether the group performs a hunting behavior (i.e., encircling or chasing) or a scavenging behavior. If a hunting behavior is chosen, another probability parameter Q determines whether encircling or chasing is selected for the agents in each new iteration [27, 28]. Encircling involves a few agents coordinating and focusing on the current best fitness solutions found by the group and adjusting by moving toward them. Fitness in this context means how well an agent acts in the optimization problem. The higher the fitness value, the better the agent's performance. Chasing involves individual agents trying to aggressively pursue the best fitness or the highest performing agent among all. On the other hand, scavenging is performed by the weakest agents, who attempt to improve their solutions by exploring new solutions through exploitation or borrowing from known better ones. After any one of these processes, a survival behavior ensues. An agent's survival rate is calculated based on its fitness compared to the best and worst fitness values in the entire population. When this survival rate is too low for a given agent, it is likely to combine its solution with others to allow them to search through new areas of the search space while still maintaining diversity. These behaviors govern how all search agents participate in the optimization process, enabling the algorithm to perform effective optimization.

C. Objective Function for Task Schedule Optimization

Central to this study are the objective functions developed for the Dingo Optimization Algorithm for task optimization. The objective functions specify the factors to be optimized, directly influencing task assignments among the agents in the MHMRC. The first objective function we built in this study is:

$$C(d) = \min \sum_{i=1}^{n} d_{i,a(i)} , \quad (1)$$

where n refers to the total number of parts in the multi-human multi-robot collaborative task, and $d_{i,a(i)}$ refers to the distance between the part i and the assigned agent $a(i)$. The goal of the objective function is to minimize the total cost associated with assigning arms of the robot or human to the disassembly task in order of a human-demonstrated disassembly order. The second and more complex objective function is defined as:

$$C(d,w,s) = \min \sum_{i=1}^{n} [\alpha d_{i,a(i)} + \rho_{a(i)} \beta w_{i,a(i)} + \rho_{a(i)} \gamma s_{i,a(i)}] , \quad (2)$$

$$\rho_{a(i)} = 1 - t_{a(i)}(1-\delta) . \quad (3)$$

The second objective function seeks to minimize the cost of assignments based on three different factors, including distance d, object weight w, and object size s. $\alpha d_{i,a(i)}$ refers to the distance between part i to agent $a(i)$ with a scaling factor α. $\beta w_{i,a(i)}$ refers to the weight of part i with scaling factor β. $\gamma s_{i,a(i)}$ refers to the size of part i with scaling factor γ. The term $\rho_{a(i)}$ in Eq. (3) defines when to apply a further discount to the size and weight terms, $t_{a(i)}$ will be equal to either 0 or 1, depending on whether the agent is assigned or $a(i)$ is a human or robot. For instance, when a human is assigned the task, $t_{a(i)}$ is equal to 0 and no discount will be applied; however, when a robot is assigned the task, $t_{a(i)}$ is equal to 1 and a discount δ is applied to the cost of the size and weight terms. This gives the robot a potentially large advantage in picking up objects that are heavier or larger than those of humans. The final cost of assignments is equal to the sum over all of the parts n of the distance, weight, and size terms. We also define several constraints to help guide our objective function to a balanced and efficient solution for MHMRC:

$$a(i) \neq a(i+1), \forall i \in \{1,2,...,n-1\} , \quad (4)$$

$$\sum_{i=1}^{n} t_{a(i)} \leq [n/m], \forall 1 \in \{1,2,...,m\} . \quad (5)$$

The constraint defined in Eq. (4) applies a penalty to the cost when an agent is being assigned tasks consecutively. By incentivizing the optimization algorithm to seek out answers wherein agents are not assigned over and over again consecutively, this constraint helps minimize the overall downtime of agents in the disassembly process. The constraint defined in Eq. (5) ensures a fair distribution of all tasks amongst all agents in the disassembly process, where $t_{a(i)}$ means the allocated task for agent $a(i)$ at step i in the MHMRC scenario. For n tasks and m agents, no agent should be assigned more than $[n/m]$ tasks. Applying a penalty for assignments that are in violation of this constraint helps prevent one or a small subset of agents from being assigned all of the tasks while others are left idling with no assignments. These constraints are applied to both objective functions utilized in the multi-human multi-robot collaborative task.

III. Experimental Setup

A. Experimental Platform

The experimental platform utilized in this study is the Multimodal Collaborative Robot System (MCROS) [7]. As shown in Fig. 1, the MCROS is equipped with two UR10e arms with Robotiq grippers as end effectors, with an attached Intel RealSense D435i depth camera on each robot arm. The MCROS utilizes the Robot Operating System (ROS), which is a framework with a large collection of libraries that help program robots and build robot applications [29, 30]. Moveit! is utilized for robot path planning and path execution to facilitate the grasping of parts when needed [31]. The MCROS is placed in a shared workspace with human participants sitting across from it, along with a desktop computer to perform the disassembly task, placed upon a table between the humans and the MCROS. A large monitor is also placed nearby to help with the initial setup of the experiment discussed in the following section.

B. Task Description

We verify and evaluate the proposed approach via a real-world multi-human multi-robot collaborative disassembly task with fourteen participants. After filling out some demographics for the survey, the experiment begins by showing the human participants a picture of the workspace from overhead on a nearby large monitor. Participants are then prompted to select the locations of the parts to be disassembled using a mouse, following the sequence: hard drive, GPU, green RAM, CPU cooler, blue RAM, case fan, and finally the CD-ROM, as illustrated in Fig. 2.

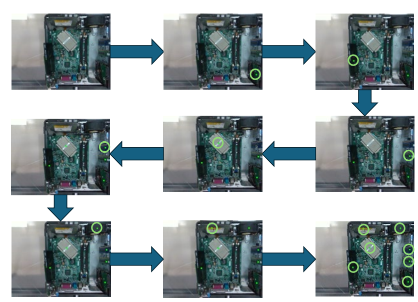


Fig. 2. The process for how a human would select the parts in the disassembly.

To ensure the participants' preferred disassembly sequence is recognized and understood by the robots, we developed a recognition module using the Intel RealSense D435i depth camera. The Intel RealSense D435i attached to one of the robot arms monitors the locations of the objects previously selected by participants in the experiment. For each monitored object, a small region of approximately 5×5 pixels around its location is compared to the baseline frame. If the average pixel difference exceeds a predefined threshold across several consecutive frames, the object is considered removed and is added to the participants' preferred disassembly sequence. Additionally, the module detects contours in the regions of change identified by the background subtractor to estimate object size. These size estimates are later used in the objective function that considers distance, weight, and size. Distance values are measured from participants' seating positions and from robot agent positions to each object location and remain fixed across experiments. Object weights are also measured beforehand and remain constant throughout all trials.

When all parts have been removed from the task, the MHMRC system will run the Dingo Optimization Algorithm with the first objective function in Eq. (1), only considering distance. At the same time, participants will return the parts to their positions. After the DOA returns a disassembly order for all agents to adhere to, they will begin the disassembly. Human agents will place any part assigned to them on the workspace table in front of them, and robot agents will place their assigned parts into bins on either side of the workspace. After the agents complete the disassembly, they will be administered the first part of the survey about their disassembly experience. Once the first-round task is complete, the parts are returned to their locations. The system will run the second objective function in Eq. (2) and return another disassembly order for the agents to adhere to while they begin the disassembly for a second time. After the agents complete the second disassembly, they will be asked the second part of the survey with the same questions about their disassembly experience.

C. Participant Survey

To understand the effectiveness of different objective functions in this multi-human multi-robot collaborative disassembly context, a survey is conducted with a section to be completed before the experiment begins that contains a few demographic questions, including participant sex, age, education, prior robotics experience, and attitude toward robotics. As mentioned in the previous subsection, after each of the two rounds of disassembly, the participants will be given a survey about their disassembly experience. The questions given after each round of the disassembly are from the NASA-TLX and include one more question, "Task Allocation," which asks the participants how they felt about the task assignments. These questions can be seen in Table I. They are administered on a 0-20 continuous scale where endpoints are labeled on the ends as "Very Low" and "Very High". Results from this survey will be analyzed to generate insights about the perception of participants for the developed task optimization approach in the multi-human multi-robot collaborative disassembly task. In this study, we analyze the subscale ratings of each metric instead of creating a single overall workload score that is common in other studies utilizing the NASA-TLX. This will enable a better assessment of the proposed approaches. The study has been approved by the university's IRB (FY23-24-3226).

TABLE I. QUESTIONS GIVEN TO PARTICIPANTS AFTER EACH DISASSEMBLY TASK

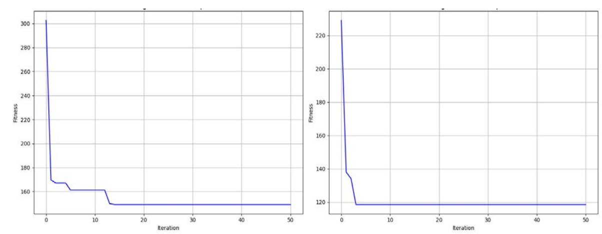
Questions	Descriptions
Mental Demand	How mentally demanding was the task?
Physical Demand	How physically demanding was the task?
Temporal Demand	How hurried or rushed was the pace of the task?
Performance	How successful were you in accomplishing what you were asked to do?
Effort	How hard did you have to work to accomplish your level of performance?
Frustration	How insecure, discouraged, irritated, stressed, and annoyed were you?
Task Allocation	How well do you believe the tasks were assigned amongst you, your partner, and the robots?

IV. RESULTS AND EVALUATIONS

A. Task Schedule Optimization with DOA and Objective Functions

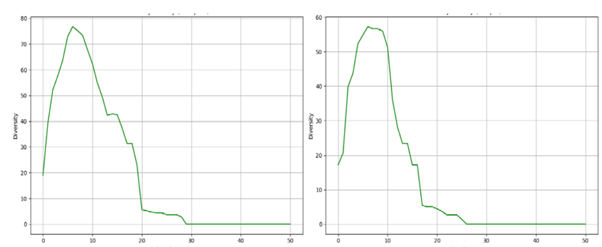
1) Best Fitness per Iteration

The convergence curves shown in Fig. 3 indicate the best fitness obtained by one of the search agents in the DOA for each iteration for both objective functions. For offline testing, 50 search agents are initialized over 50 iterations. In both cases, we can see that the DOA converges on an answer extremely quickly. For the first objective function with only distance considered, it took less than 5 iterations (Fig. 3(b)). For the second objective function with distance, weight, and size considered, we can see that it took slightly longer at under 15 iterations (Fig. 3(a)). These results show that the DOA performed quickly when navigating our search spaces for the best task assignments, which is important for real-world applications. The DOA consistently found viable solutions guided by the objective functions and within the bounds of the constraints defined.



(a) (b)

Fig. 3. The convergence curve shows the best fitness obtained per iteration of the DOA with the developed objective functions. (a) The objective function with distance, weight, and size considered. (b) The objective function with only distance considered.



(a) (b)

Fig. 4. The diversity of all search agents per iteration of the DOA with the developed objective functions. (a) The objective function with distance, weight, and size considered. (b) The objective function with only distance considered.

2) Diversity of Search Agents

Fig. 4 shows the diversity between all search agents per iteration of the DOA with the developed objective functions. Diversity is a measure of the standard deviation of fitness values for the entire population of search agents. It helps visualize the distribution of agents across the search space, even agents that are searching solutions that are in violation of constraints and have had a penalty applied. In both cases, after search agents have been initialized, there is a sharp rise in diversity that peaks before iteration 10, then begins to rapidly decrease, showing convergence on a single or several equally costly optimizations before iteration 30. This is also helpful to show that even after the DOA finds its best solution at about less than 5 for the objective function with only distance considered (Fig. 3(b)) and less than 15 for the objective function with multiple factors considered (Fig. 3(a)), there is still a large diversity amongst the search agents in both cases. This suggests that the DOA is not getting trapped in local optima, as it still has agents in different parts of the search space. The diversity decreasing from iteration 10 indicates that the DOA search agents utilize their various behaviors to converge toward the best solution.

B. Real-World Implementation

Fig. 5 presents one of the real-world multi-human multi-robot collaborative disassembly implementations in our user study. After the selection of parts previously discussed in Fig. 2 using the large display besides one of the participants is finished, the DOA outputs its task assignments to the display. In Fig. 5, the participants' chosen disassembly order is: CDROM, blue RAM, hard drive, GPU, case fan, CPU cooler, and green RAM. Fig. 5(1) shows that the participants are ready for the disassembly, with respect to the agent's perspective of the computer. In Figs. 5(2)-(3), the right participant grasps the CD-ROM while the left participant grasps the blue RAM. Next, Fig. 5(4) shows the left robot grasping the hard drive, followed by Fig. 5(5), where the right robot grasps the GPU. Fig. 5(6) depicts the left participant grasping the case fan, and Fig. 5(7) shows the right robot grasping the CPU cooler. Following this, Fig. 5(8) shows the left robot grasping the green RAM. Fig. 5(9) presents a participant taking the survey for this round in the study, while the other puts some of the parts back in their position for the next round of collaboration. For each pair of participants, there would be two rounds of this example shown in Fig. 5.

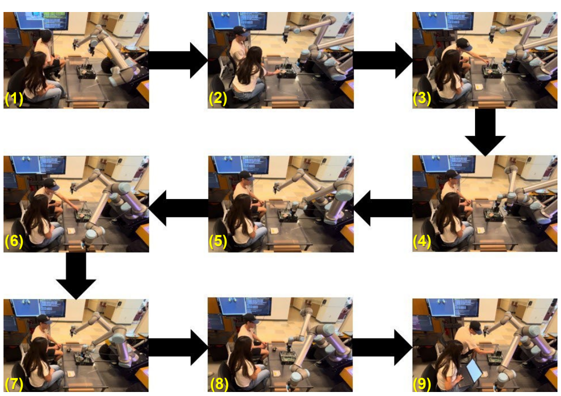


Fig. 5. The real-world multi-human multi-robot collaborative disassembly implementation.

C. Evaluation Results and Analysis

1) Participants' Age and Sex

For our real-world experiments and survey, we gathered fourteen participants and split them into pairs of two. Part of the initial part of the survey is demographic information about age and sex. The study had a slightly higher number of male participants (9) compared to female participants (5). Most participants (8) are in the 18-21 age range, followed by 3 participants aged 22-25, 2 participants aged 26-29, and 1 participant in the 36-40 age range.

2) Robotics Experience and Attitude

The other part of the demographic information gathered is prior participant experience with robotics and their attitude toward robotics. As presented in Fig. 6, most participants reported "Little" prior experience with robotics, and the majority selected "Like" to indicate a positive attitude toward robotics. This provides useful context for relating participants' responses to their prior experience and attitudes. Recognizing potential biases and predispositions linked to robotics experience can further contextualize the results. These findings suggest that, among the participants in our experiment, there is an association between lower levels of prior robotics experience and greater interest in working with robots. This insight has potentially important implications for the design and deployment of multi-human multi-robot collaborative systems. It highlights the need to account not only for skill levels and technical expertise but also for prior attitudes and predispositions toward robotics when evaluating system usability and effectiveness.

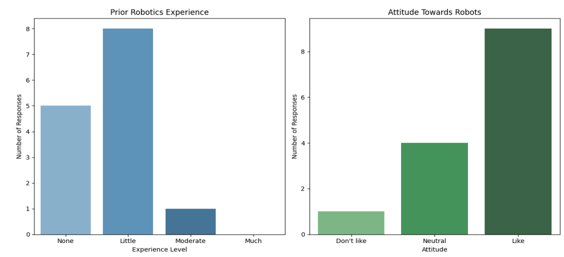


Fig. 6. Participants' prior experience and attitude toward robotics.

3) Mental Demand Evaluation and Analysis

Mental demand ratings from participants are presented in Fig. 7. Overall, ratings for the mental demand of Objective Function 1 (OF1, which considers only distance) tended to be higher than those for Objective Function 2 (OF2, which incorporates distance, weight, and size). This suggests that OF2 provides a more effective optimization framework than OF1 in the context of multi-human multi-robot collaborative disassembly. A possible reason is that OF1 oversimplifies the decision-making process by considering only distance, which may lead to less balanced task allocations. As a result, participants may perceive the process as cognitively demanding because they must compensate for suboptimal assignments or adapt to uneven task distributions. In contrast, OF2 integrates multiple factors, including distance, weight, and size, which may result in more intuitive and equitable task allocation across humans and robots. This alignment likely reduces unnecessary cognitive load and allows participants to focus more effectively on the disassembly task.

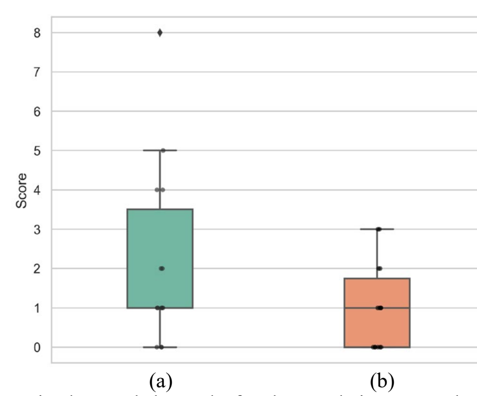


Fig. 7. Perceived mental demand of task completion across both objective functions. (a) The objective function with only distance considered. (b) The objective function with distance, weight, and size considered.

4) Physical Demand Evaluation and Analysis

Physical demand ratings, as shown in Fig. 8, further demonstrate that OF2 generally outperforms OF1. By incorporating both size and weight in addition to distance, OF2 generated task allocations in which robot agents handled larger and heavier components, such as the hard drive and CPU cooler, while human participants managed lighter and smaller parts like the RAM. This division of labor appears to reduce the physical burden on participants compared to OF1, which considered only distance in its assignments. The data reflect this trend clearly; aside from two outliers (rated 4 and 3), all physical demand scores for OF2 remained between 0 and 1. In contrast, OF1 produced ratings ranging from 0 to 4, indicating greater variability and generally higher perceived physical effort. These results suggest that OF2's more comprehensive factor integration leads to more efficient and balanced task distributions, minimizing unnecessary exertion for human collaborators.

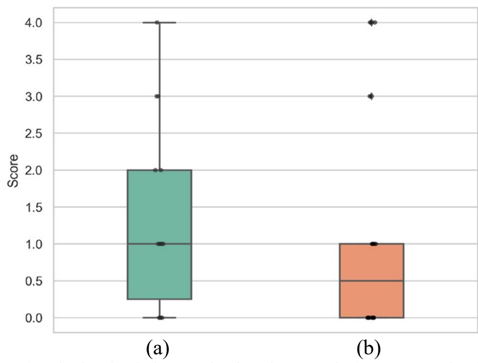


Fig. 8. Perceived physical demand of task completion across both objective functions. (a) The objective function with only distance considered. (b) The objective function with distance, weight, and size considered.

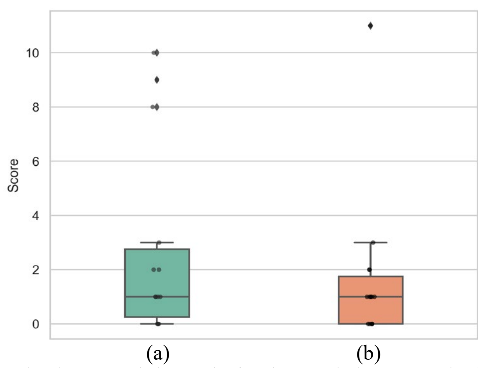


Fig. 9. Perceived temporal demand of task completion across both objective functions. (a) The objective function with only distance considered. (b) The objective function with distance, weight, and size considered.

5) Temporal Demand Evaluation and Analysis

Temporal demand ratings, as shown in Fig. 9, are generally similar across both objective functions. Because the robot agents moved at the same speed in both scenarios, participants experienced comparable pacing during the disassembly process. Most ratings for both OF1 and OF2 fell within the 0-3 range, indicating relatively low perceived temporal demand overall. However, OF1 exhibited three outliers with ratings of 8, 9, and 10, while OF2 had only a single outlier at 11. These results suggest that participants were generally comfortable with the pace of disassembly in both conditions, but OF1 occasionally produced situations where certain participants felt more time pressure or pacing misalignment. By contrast, OF2's results, despite having one extreme outlier, indicate a more consistent perception of manageable temporal demand across the group.

6) Performance Evaluation and Analysis

Performance ratings captured participants' perceptions of how successfully they completed the disassembly task. All participants were able to fully complete the process, confirming that both objective functions allowed task completion. However, as shown in Fig. 10, participants generally rated their performance higher when using OF2 compared to OF1. For OF1, the ratings exhibited an outlier at 12 and a lower whisker at 16, indicating some variability in perceived performance. In contrast, OF2's ratings were consistently higher, with an outlier at 18 and all other ratings clustered between 19 and 20. This pattern suggests that participants felt more confident and satisfied with their performance under OF2, likely reflecting the algorithm's more balanced task allocations that considered distance, weight, and size.

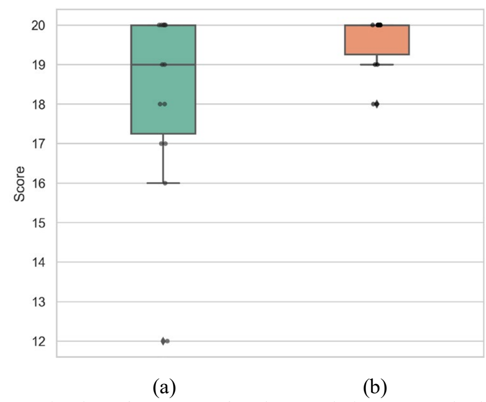


Fig. 10. Perceived performance of task completion across both objective functions. (a) The objective function with only distance considered. (b) The objective function with distance, weight, and size considered.

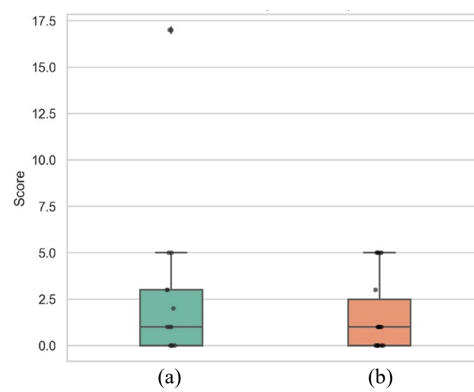


Fig. 11. Perceived effort required for task completion across both objective functions. (a) The objective function with only distance considered. (b) The objective function with distance, weight, and size considered.

7) Effort Evaluation and Analysis

Effort ratings capture how hard participants felt they had to work to complete the disassembly task under OF1 and OF2. As shown in Fig. 11, the ratings for effort were largely similar across both objective functions, suggesting that the overall workload felt comparable between the two conditions. However, OF1 exhibited a single outlier with a rating of 17, indicating that one participant perceived the task as substantially more effortful. This outlier may be attributed to minimal prior experience or even first-time exposure to working with robots, which could have amplified the perceived difficulty of collaboration under OF1. In contrast, OF2 did not display such variability, suggesting that its more balanced allocation of tasks with distance, weight, and size considered may help mitigate excessive perceived effort.

8) *Frustration Evaluation and Analysis*

Frustration ratings, as shown in Fig. 12, indicate that participants tended to report higher frustration with OF1 compared to OF2. With the exception of a single outlier, all OF2 ratings were either 0 or 1, reflecting consistently low frustration levels. This suggests that OF2's task assignments, which account for object weight, size, and distance rather than relying solely on distance as in OF1, helped to minimize participant frustration during the collaborative disassembly task. This reduction in frustration is meaningful because emotional factors such as trust, comfort, and stress can strongly influence how humans evaluate the developed approaches and collaborative robots.

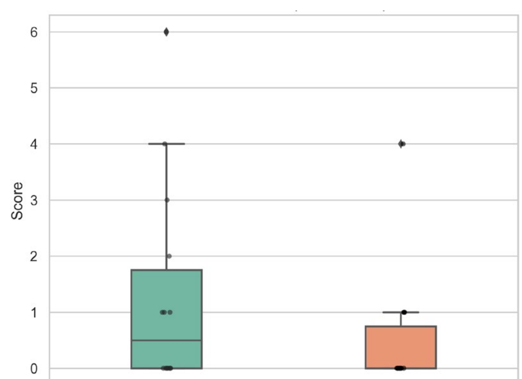


Fig. 12. Perceived frustration of task completion across both objective functions. (a) The objective function with only distance considered. (b) The objective function with distance, weight, and size considered.

9) *Task Allocation Evaluation and Analysis*

Participants' evaluations of task allocation based on both objective functions are shown in Fig. 13. The results indicate that OF2 consistently scored higher than OF1. Subjective evaluation ratings for OF1 ranged between 9 and 20, reflecting a broader and less consistent distribution of perceived effectiveness. In contrast, the majority of ratings for OF2 clustered tightly between 18 and 20, with only two outliers at 11 and 14. This suggests that OF2 was generally perceived to generate better and more reliable task assignments than OF1, leading to greater participant confidence and satisfaction in the MHMRC process.

From the above evaluation results, we can conclude that incorporating multiple task factors, such as distance, weight, and size, into the objective function leads to more effective and user-preferred task allocations in multi-human multi-robot collaboration. The strong clustering of high ratings for OF2 highlights not only its technical effectiveness but also its ability to enhance participant satisfaction, reduce variability in experiences, and facilitate trust in the MHMRC system.

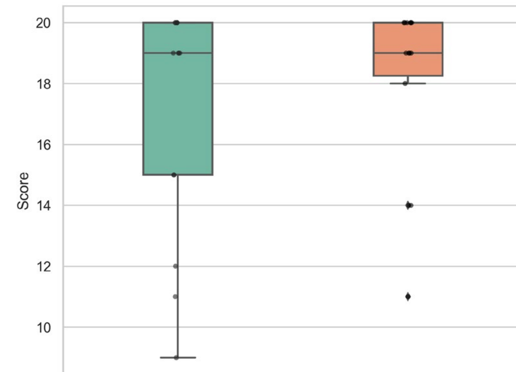


Fig. 13. Participants' evaluation for task allocation based on both objective functions. (a) The objective function with only distance considered. (b) The objective function with distance, weight, and size considered.

V. Conclusions and Future Work

A nature-inspired, objective function-constrained task scheduling optimization solution has been developed for multi-human multi-robot collaborative remanufacturing. We designed two different objective functions for the Dingo Optimization Algorithm to investigate how human participants perceive task assignments and interpret the disassembly process under varying objectives in MHMRC. The developed approach was implemented in real-world disassembly tasks and evaluated through a user study incorporating the NASA-TLX and additional survey questions. The evaluation results demonstrated that the objective function incorporating distance, weight, and size consistently outperformed the distance-only function across several metrics. Participants generally perceived this more comprehensive objective function to generate better task assignments, resulting in improved satisfaction and reduced workload. These findings suggest that objective functions that integrate task-specific constraints and human-centered considerations can enhance the quality of MHMRC tasks, supporting the broader goals of Industry 5.0. Importantly, the convergence behavior of the optimization algorithm showed that this added complexity did not hinder performance, as the algorithm continued to find high-quality solutions.

Our future work will extend this study by testing more complex disassembly scenarios with larger participant groups to further validate the generalizability of the proposed approach. In addition, we plan to incorporate further objective performance criteria, such as task completion time, error rates, and collaboration fluency, to gain deeper insights into the interplay between optimization strategies, human experience, and system performance. These enhancements will potentially contribute to a more comprehensive understanding of task allocation and scheduling in multi-human multi-robot collaboration contexts.

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