Human-On-The-Loop Multi-Robot Demand-Aware Task Scheduling: A Mixed Reality Approach

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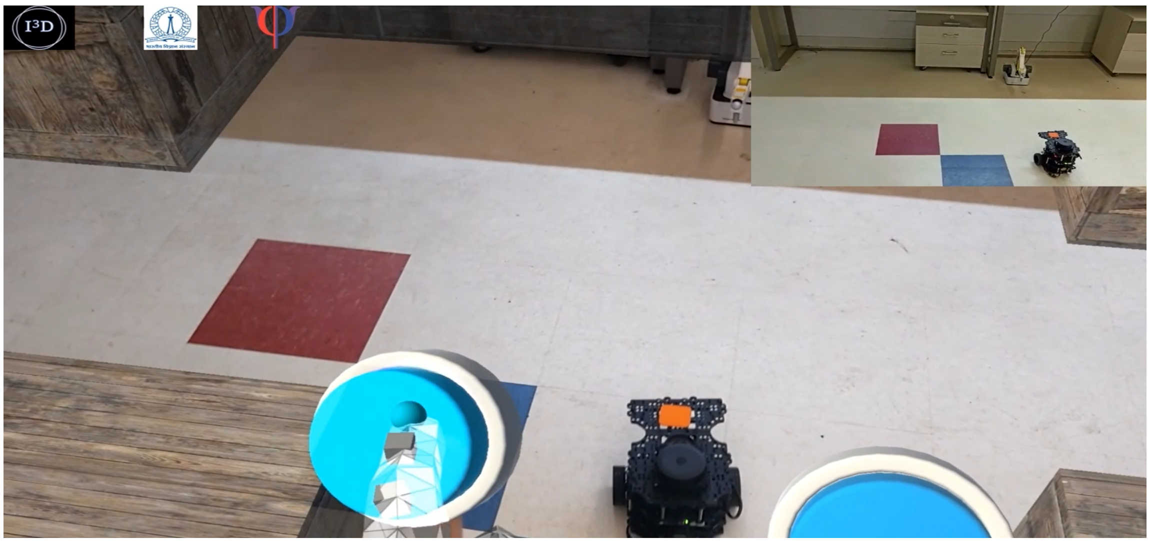

Fig. 1. Load Transportation by Mobile Robot to Stationary Base Robot in Simulated Mixed-Reality Warehouse with Human Supervision.

Scheduling tasks for multiple robots with diverse capabilities becomes challenging due to collaboration under precedence constraints, especially when environmental demands require certain robots to handle heavier workloads. This complexity is compounded when human intervention is needed to allocate limited resources. To address this, we propose the Demand-Aware multi-Robot Task Scheduling (DARTS) approach. Leveraging a multi-agent multi-armed bandit framework to estimate environmental demand, DARTS aims to optimize task scheduling. In a mixed reality-based user study, we explored how human perception influences task scheduling and personalizes the resource allocation process. The study findings reveal that human task schedulers demonstrated improved performance in scenarios involving autonomous agent assistance with DARTS compared to the baseline. Users made optimal choices, instead of focusing on minimizing the time and distance traveled by the mobile robot compared to baseline.

CCS Concepts: • **Human Robot Interaction** → *Human-On-The-Loop*; *Multi-Robot Task Scheduling*; • **Mixed Reality** → *Robot Teleoperation*; *Warehouse Simulation*; • **Reinforcement Learning** → *Multi-Armed Bandit*; *Multi-Agent Learning*.

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1 INTRODUCTION

Multi-robot systems are effective in enhancing task efficiency and scalability by distributing the workload among multiple robots, enabling parallel execution of tasks, and facilitating collaboration and coordination among the robots. In recent years such systems gained popularity due to their potential in various applications such as emergency rescue and care, surveying, manufacturing and logistics as reported by Rajan et al. [18]. Nonetheless, these robotic systems may not possess the robustness to autonomously handle all tasks, necessitating either human involvement within the loop or human supervision, as elucidated by Nahavandi et al. [15]. Achieving efficient task planning, scheduling, motion planning, and control while preserving mission objectives can be intricate, especially in the context of multi-robot systems that involve human intervention, which brings its own set of distinctive challenges. Goodrich et al. [9] explored the spectrum of human-robot interactions and the intricacies within human-supervised and human-in-the loop robotic systems

In a mixed reality based user study involving eight participants (six male and two female), we investigated the influence of human perception on human-supervised resource allocation. This study encompassed various scenarios, including independent scheduling, autonomous agent assistance, and simulated scheduling environments. The user study enables us to achieve a deeper understanding of human preferences, facilitating further customization of the resource allocation process. Another significant contribution is the introduction of the Demand-Aware multi-Robot Task Scheduling (DARTS) approach, which addresses multi-robot task scheduling by taking into account environmental demands and precedence constraints, promoting effective collaboration and coordination among robots. Environmental demand estimation is achieved through a multi-agent multi-armed bandit approach, as elucidated by Sandula et al. [21]. In this context, the DARTS approach utilizes the bandit solver to frame the task scheduling problem as a multi-armed bandit problem, considering the precedence constraints among robot coalitions.

Human-robot interaction can be classified into two primary categories. The first category is human-in-the-loop (HIL) [5, 6, 13, 16, 17] where a human operator actively collaborates with or controls the robot during task execution. The second category is human-on-the-loop (HOL) [1, 2, 18] interaction, where a human operator supervises the task performed by the robotic system. Our research centers on HOL robotic systems, with a particular emphasis on human task scheduling for multi-robot systems. The literature on robotics has investigated task scheduling in various scenarios for both single [3, 9, 22] and multi robot [5], [4, 7, 10–12, 16, 22]systems. Previous studies have investigated task scheduling for a single and multiple robot task scheduling in applications industrial automation, assembling, and palletizing tasks etc. Dhanaraj et al. [5] have proposed a human-in-the-loop task scheduling with focus on fault recovery. Zhang et al. [22] proposed heuristic based task scheduling approaches for a generalized scenario where robots form a coalition to accomplish a task. However, a human-on-the-loop demand aware scheduling strategy considering the precedence constraints is not investigated in the current literature. Therefore, to address this gap, we introduce a novel approach: DARTS - a Demand-Aware multi-Robot Task Scheduling algorithm. This algorithm leverages a multi-agent multi-armed bandit [12] framework, as elucidated by Sandula et al. [21], to estimate environmental demand.

In brief, our research makes two notable contributions. First, we propose a novel approach known as DARTS (Demand-Aware multi-Robot Task Scheduling) for multi-robot task scheduling. This approach takes into account environmental demand and precedence constraints. Second, we have conducted a mixed reality based user study to investigate how human perception influences human-guided task scheduling. We observed that human task schedulers demonstrated improved performance in scenarios involving autonomous agent assistance compared to situations with lesser autonomy of the robotic systems.

2 SYSTEM WORKFLOW

In this section we explain the mathematical formulation of the problem and the proposed human in the loop task scheduling and explanation of mixed reality user study.

2.1 Multi-robot task scheduler with demand awareness

A set of independent robots is denoted as $R = [r_1, r_2, \ldots, r_i, \ldots, r_n]$. These robots act as independent agents assigned to execute tasks or sub-tasks. The set of tasks is represented by $T = [T_1, T_2, \ldots, T_j, \ldots]$. All tasks, along with their respective sub-tasks, are assumed to be non-pre-emptive, requiring the complete attention of the robot until execution.

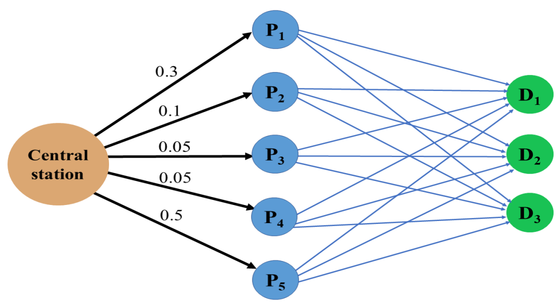


Fig. 2. Probabilities at which tasks have been generated. A central station receives the packages and then transfers them to the pickup points based on the type of packages.

Let an ordered coalition C be an ordered set from R, and $P(R, k)$ represent all ordered sets with k distinct elements from R. For any set ζ, $\zeta = P(R, 1) \cup P(R, 2) \cup \ldots \cup P(R, |R|)$, covering all ordered sets with distinct elements from R. An element $C \subset \zeta$, denoted as $C = (r_a, r_b, \ldots, r_*)$, signifies an ordered coalition of robots. In the context of a task T_j, if accomplished by C, robots $r_a, r_b, \ldots, r_*$ execute sub-tasks in sequence. Task T_j can be achieved by a single or multiple ordered coalitions. The set $C_j \subseteq \kappa$ represents ordered coalitions capable of accomplishing T_j.

In pickup-dispatch tasks, a coalition involves a mobile robot transporting a load to a fixed-base robot, which performs the pick-and-place operation. For example, a pickup-dispatch task T_j requires a unique coalition with a fixed-base robot $[r_a]$ and mobile robots $[r_b, r_c, r_d]$. All possible ordered coalitions for task T_j are represented as $C_j = [(r_b, r_a), (r_c, r_a), (r_d, r_a)]$. Here, mobile robots r_b, r_c, or r_d transport the load, and the fixed-base robot performs the pick-and-place operation. Equitable task allocation in C_j can be achieved through an auction-based approach, as outlined in [8].

After task allocation to the robots, establishing a well-defined execution sequence becomes crucial, contingent upon task priorities to achieve the desired objective. In the context of dispatching pickup tasks, priority assignment for sub-tasks of a fixed-base robot is essential. Consider a pickup-dispatch scenario involving pickup points $(P_1, P_2, P_3, P_4, P_5)$ and drop points (D_1, D_2, D_3). Tasks are represented by $T = [T_1, T_2, \ldots, T_{15}]$, where T_1 denotes the pickup-dispatch task from P_1 to D_1. Tasks like $T_1 =< P_1, D_1 >$ are defined, encompassing all pickup-dispatch combinations. These tasks are generated based on a probability distribution (Figure 2) from the *central station* due to environmental demand. Each pickup point has specific load constraints, limiting the set of mobile robots capable of picking up loads. At drop points, the fixed-base resource can handle loads from any approaching mobile robot. Mobile robots collaborating with fixed-base robots and carrying loads from P_i are denoted by Ψ_i. Thus, Ψ_i represents a set of homogeneous robots executing sub-tasks for tasks $< P_i, D_j >$. Scheduling is crucial at drop points when multiple mobile robots from Ψ_{1-5} approach, aiming to reduce waiting time for mobile robots handling tasks with higher probability.

2.2 DARTS - Demand Aware multi-Robot Task Scheduling

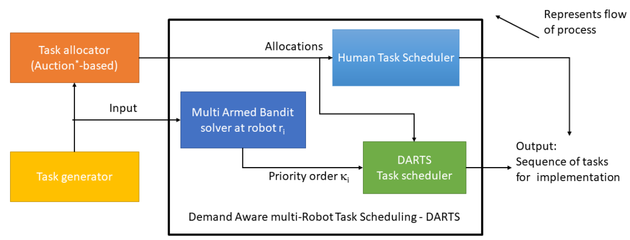


Fig. 3. Individual modules of the proposed architecture

In this section, we present the DARTS approach for multi-robot task scheduling, considering environmental demand. Figure 3 illustrates the overall architecture of DARTS. The task generator module simulates tasks using predefined probabilities to mimic environmental demand. Tasks are fairly allocated to robot coalitions by the task allocator module, employing an auction-based approach [8]. Importantly, other modules remain unaware of these probability distributions. The proposed DARTS algorithm incorporates two key components. To monitor environmental demand, we integrate a multi-agent multi-armed bandit approach, as suggested by Sandula et al. [21]. A combination of epsilon-greedy and Thompson sampling algorithms is employed to address the bandit problem.

2.2.1 Bandit solver. We employed a multi-agent multi-armed bandit solver [21] at each robot to assess demand and establish a priority order. In cases where a robot (denoted as r_i) collaborates with others and awaits their sub-task completion, a bandit solver is deployed. Consider a group of homogeneous robots, represented as $\psi_1, \psi_2, \ldots, \psi_k$, with which r_i collaborates. A bandit solver at r_i assesses demand, deriving a priority order κ_i among ψ_{1-k}. Agents share information on their choices (Ψ_i) and rewards (1 or 0) for collaborative problem-solving. The bandit algorithm employed combines Thompson sampling and ϵ-greedy strategies. *Beta* distribution is used to estimate the expected reward of the arms Ψ_{1-k}.

2.2.2 DARTS task scheduler. Algorithm 1 outlines the pseudocode for the DARTS algorithm at robot r_i. After establishing the priority order κ_i among ψ_{1-k}, this module determines the task execution sequence. Input [T, R] denotes task allocations, where T corresponds to tasks allocated to indices in set R. For instance, T_i represents the tasks allocated to robot r_i. The scheduler avoids unnecessary computations during task execution and computes the sequence for the next task only when the current task is completed. It organizes tasks in T_i based on the priority order κ_i for collaborative robot coalitions $\psi_a, \psi_b, \ldots$.

ALGORITHM 1: DARTS Task Scheduler ($[T_i, R_i]$,κ)

```
if Task is being executed then
    return
end
λ = Empty_list;
while κ ≠ ϕ do
    ψ_j = κ → pop;
    for k < length(T_i) do
        if R_i[k] → robot_type = ψ_j then
            Append(R_i[k]) → λ;
        end
    end
end
if λ ≠ ϕ then
    cur_robot_task = λ → pop;
    execute T → (cur_robot_task);
    T_i → pop(T_i → (cur_robot_task));
    Update current status (task is being executed);
end
```

2.3 User Study

(a) Mixed Reality setup for single robot scheduling.

(b) Mixed reality setup for multi-robot scheduling.

Fig. 4. Mixed Reality User Study

We conducted a user study to understand the impact of human perception on task scheduling in a human-on-the-loop robotic system. Employing a mixed-reality setup, we simulated a realistic warehouse scenario for a pickup-dispatch task. The study involved three scenarios: (1) Single-robot scheduling, (2) Multi-robot scheduling, and (3) Simulated scheduling with zero robots, each described below. Data were collected from all participants across these scenarios.

2.3.1 Material. We established a mixed reality environment by utilizing Microsoft Hololens [14], Unity [23], Turtlebot [19] and ROS [20] platforms. In this environment, we introduced three distinct scenarios aimed at investigating the influence of human perception on task scheduling.

2.3.2 Participants. We recruited 8 participants (6 males, 2 females) from our university, with an average age of 24.37 years and a standard deviation of 2.99. None of the participants had color blindness, and they all provided the necessary permissions and consent for the study.

2.3.3 Setup. In Case 1 (single-robot scheduling, Figure 4a), participants operate a single robot, aiming to deduce rewards for maximizing collection. Using virtual buttons, participants control the robot, and upon reaching a designated station, the reward is revealed in green text. Measurements include robot travel distance, task completion times, and calculated rewards based on confidential probability distributions unique to each station.

Case 2 (multi-robot scheduling, Figure 4b) introduces an autonomous agent using the DARTS algorithm. Participants observe the agent's actions and can incorporate its strategies into their scheduling. Two rewards are displayed: one for the autonomous agent (yellow) and one for the user-controlled robot. Participants optimize their scheduling using agent reward data.

Case 3 (simulated scheduling with zero robots) maintains the mixed reality setup without physical robots. Participants instantly observe rewards upon interacting with virtual buttons.

In all the mentioned cases, we created a multi-armed bandit-based task scenario [21] featuring five reward stations. Users could observe rewards which are generated based on preset probabilities. The rewards are displayed after the tasks are completed by the tele-operating robot in cases 1 and 2. In case 3, the rewards are instantly displayed.

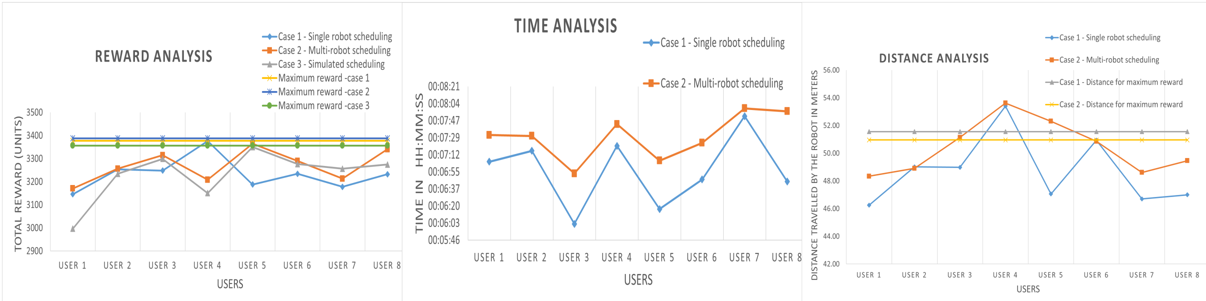
2.3.4 Design. The user interface, illustrated in Figures 4a and 4b, includes five virtual buttons for task scheduling. In Cases 1 and 2, pressing each button prompts the tele-operated robot to execute a pickup-dispatch task. The robot autonomously navigates to the base location and then to the corresponding station. Upon task completion, a reward is displayed on the respective station. For the tele-operated robot, the reward is presented in green text, while for the autonomous robot, it is displayed in yellow text. In the simulated scheduling scenario (Case 3), rewards instantly appear on the corresponding station when users press the virtual button, as no robots are involved.

2.3.5 Procedure. Participants were briefed about the objectives of the study. Their goal was to maximize rewards. We documented the total reward of each participant, task execution time, and robot travel distance for all scenarios. The outcomes are detailed in Section 3.

3 DISCUSSION

The user study comprises three conditions: (1) Single-robot (no autonomous agent), (2) Multi-robot scheduling (with autonomous agent), and (3) Simulated scheduling with no robots. Participants scheduled 45 tasks in total: 15 tasks independently in case 1, 15 tasks with autonomous agent assistance in case 2, and an extra 15 tasks in a simulated environment with instant user reward observation and no robots. Our analysis considered three key aspects. Reward obtained, time taken and distance travelled by the mobile robot.

From figures 5a and 5c, users prioritized lower rewards to minimize robot travel, particularly in case 1, with an exception for *user 4.* Autonomous agent assistance led to improved reward performance, and users were less concerned about robot travel distance. There was no significant difference in user reward performance between cases 1 and 3.From Figure 5b, it is clear that participants favored completing tasks quickly over optimal scheduling in independent scheduling (Case 1). However, in Case 2, with autonomous agent assistance, participants took more time to complete tasks while achieving higher rewards. Figure 5c illustrates participants' scheduling preferences. In Case 1, they aimed to minimize the robot's travel distance, considering it efficient. Conversely, Case 2 presented a different scenario. With



(a) Reward Analysis (b) Time Analysis (c) Distance Analysis

Fig. 5. Analysis of Results

the autonomous agent employing the DARTS algorithm, participants shifted their focus toward maximizing rewards. This adjustment occurred after observing the rewards acquired by the autonomous agent, even if it meant the robot had to cover a greater distance. Notably, in Case 2, the robot covered significantly more distance compared to Case 1, except for User 4.

We conducted a one-way ANOVA to compare the *total rewards* of users across the three cases: 1, 2, and 3. The analysis did not reveal any statistically significant differences. However, paired T-tests on other dependent variables, namely *total task completion time* and *total distance* traveled by the tele-operated robot, showed statistical significance between cases 1 and 2. The paired T-test for total task completion time indicated that users took more time to complete tasks in case 2, while case 1 had a significantly lower duration ($t = -4.693$, $p < 0.050$, Cohen's $d = -1.369$) than case 2. Similarly, the paired T-test for *total distance* traveled by the tele-operated robot indicated that the tele-operated robot covered significantly more distance to complete tasks in case 2, while case 1 had a significantly lower distance ($t = -2.759$, $p < 0.050$, Cohen's $d = -0.787$) than case 2. In conclusion, the data suggests significant differences between the means of distances traveled by the tele-operated robot and the time taken by users across the different cases.

In summary, participants initially prioritized task completion speed and minimizing travel distance when scheduling tasks independently. However, when an autonomous agent was introduced, task scheduling improved, resulting in higher rewards but with increased time consumption. Participants also learned that minimizing robot travel distance did not always yield the best task scheduling outcomes, a finding supported by statistical analysis.

4 FUTURE WORK & CONCLUSION

This paper introduces the DARTS algorithm, a human-on-the-loop multi-robot task scheduling approach designed to accommodate environmental demands and precedence constraints among the robots. The mixed reality user study underscores the advantages of incorporating an autonomous agent into the human-on-the-loop multi-robot task scheduling process. The study reveals enhanced demand-aware performance with assistance from autonomous agent employed with DARTS algorithm. Future work will delve into further advancements, specifically exploring the effects of robot planning under human supervision and its impact on multi-robot scheduling.

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