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Integrated Task Assignment and Path Planning for Capacitated Multi-Agent Pickup and Delivery

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Abstract—Multi-agent Pickup and Delivery (MAPD) is a challenging industrial problem where a team of robots is tasked with transporting a set of tasks, each from an initial location and each to a specified target location. Appearing in the context of automated warehouse logistics and automated mail sortation, MAPD requires first deciding which robot is assigned what task (i.e., Task Assignment or TA) followed by a subsequent coordination problem where each robot must be assigned collision-free paths so as to successfully complete its assignment (i.e., Multi-Agent Path Finding or MAPF). Leading methods in this area solve MAPD sequentially: first assigning tasks, then assigning paths. In this work we propose a new coupled method where task assignment choices are informed by actual delivery costs instead of by lower-bound estimates. The main ingredients of our approach are a marginal-cost assignment heuristic and a meta-heuristic improvement strategy based on Large Neighbourhood Search. As a further contribution, we also consider a variant of the MAPD problem where each robot can carry multiple tasks instead of just one. Numerical simulations show that our approach yields efficient and timely solutions and we report significant improvement compared with other recent methods from the literature.

Index Terms—Task assignment, motion and path planning.

I. INTRODUCTION

IN AUTOMATED warehouse systems, a team of robots works together to fulfill a set of customer orders. Each order comprises one or more items found on the warehouse floor, which must be delivered to a picking station for consolidation and delivery. In automated sortation centres, meanwhile, a similar problem arises. Here, the robotic team is tasked with carrying mail tasks from one of several emitter stations, where new parcels arrive, to a bin of sorted tasks, all bound for the same processing facility where they will be dispatched for delivery. Illustrated in Fig. 1, such systems are at the heart of logistics operations for major online retailers such as Amazon and Alibaba. Practical success in both of these contexts depends on computing timely solutions to a challenging optimization problem known in the literature as Multi-agent Pickup and Delivery (MAPD) [1].

In MAPD, we are given a set of tasks (equiv. packages) and a team of cooperative agents (equiv. robots). Our job is twofold: first, we must assign every task to some robot; second, we need to find for each robot a set of collision-free paths that guarantee every assigned task to be successfully completed. Each of these aspects (resp. Multi-robot task assignment (TA) [2] and Multi-agent Path Finding (MAPF) [3]) is itself intractable, which makes MAPD extremely challenging to solve in practice. Further complicating the situation is that the problem is lifelong or online, which means new tasks arrive continuously and the complete set of tasks is a priori unknown.

A variety of different approaches for MAPD appear in the recent literature. Optimal algorithms, such as CBS-TA [4], guarantee solution quality but at the cost of scalability: only small instances can be solved and timeout failures are common. Decentralised solvers, such as TPTS [1], can scale to problems with hundreds of agents and hundreds of tasks but at the cost of solution quality: assignments are greedy and made with little regard to their impact on overall solution costs. Other leading methods, such as TA-Hybrid [5], suggest a middle road: MAPD is solved centrally but as a sequential two-stage problem: task assignment first followed by coordinated planning after. The main drawback in this case is that the assignment choices are informed only by lower-bound delivery estimates instead of actual costs. In other words, the cost of the path planning task may be far higher than anticipated by the task assignment solver.

In this work we consider an alternative approach to MAPD which solves task assignment and path planning together. We design a marginal-cost assignment heuristic and a meta-heuristic improvement strategy to match tasks to robots. The costs of these assignments are evaluated by solving the associated coordination problem using prioritised planning [8]. We then
II. RELATED WORK

A. Task Assignment

The problem studied in this letter requires both the task assignment of robots and the planning of collision-free paths. Nguyen et al. [10] solved a generalised target assignment and path finding problem with answer set programming. They designed an approach operating in three phases for a simplified warehouse variant, where the number of robots is no smaller than the number of tasks and unnecessary waiting of agents exists between the three phases. As a result, the designed approach scales only to 20 tasks or robots.

The task assignment aspect of the studied problem is related to multi-robot task allocation problems, which have been widely studied [2], [11]. Most closely related are the VRP [12] and its variants [13], all of which are NP-hard problems. The pickup and delivery task assignment problems have also received attention [14], [15]. In [14], the package delivery task assignment for a truck and a drone to serve a set of customers with precedence constraints was investigated, where several heuristic assignment algorithms are proposed. Cordeau and Laporte [15] conducted a review on the dial-a-ride problem, where the pickup and delivery requests for a fleet of vehicles to transport a set of customers need to respect the customers’ origins and destinations. In [16], the original concept of regret for not making an assignment may be found to assign customers to multiple depots in a capacity-constrained routing, where the regret is the absolute difference between the best and the second best alternative. For the vehicle routing and scheduling problem with time windows in [17], Potvin and Rousseau used the sum of the differences between the best alternative and all the other alternatives as the regret to route each customer. Later on, in [18], agent coordination with regret clearing was studied. In the letter, each task is assigned to the agent whose regret is largest, where the regret of the task is the difference between the defined team costs resulting from assigning the task to the second best and the best agent. But all the methods above avoid reasoning about collisions of vehicles, they assume, quite correctly for vehicle routing, that routes of different vehicles do not interfere. This assumption does not hold however for automated warehouses or sortation centres.

B. Multi-Agent Pickup and Delivery

For warehouses or sortation centres, it is necessary to consider the interaction between agent routes. The MAPD problem describes this scenario. Ma et al. [1] solves the MAPD problem online in a decentralised manner using a method similar to Cooperative A* [8], and in a centralised manner, which first greedily assigns tasks to agents using a Hungarian Method and then uses Conflict Based Search (CBS) [19] to plan collision-free paths. Liu et al. [5] proposed TA-Hybrid to solve the problem offline, which assumes all incoming tasks are known initially. TA-Hybrid first formulates the task assignment as a travelling salesman problem (TSP) and solves it using an existing TSP solver. Then it plans collision-free paths using a CBS-based algorithm.

Researchers have also investigated how to solve this problem optimally. Honig et al. [4] proposed CBS-TA, which solves the problem optimally by modifying CBS to search an assignment search tree. However, solving this problem optimally is challenging, which leads to the poor scalability of CBS-TA. Other limitations of CBS-TA and TA-Hybrid are that they are both offline and hard to adapt to work online, and they don’t allow an agent to carry multiple items simultaneously.

C. Multi-Agent Path Finding

Multi-agent path finding (MAPF) is an important part of MAPD problem and is well studied. Existing approaches to solve MAPF problems are categorised as optimal solvers, bounded-suboptimal solvers, prioritised solvers, rule-based solvers, and so on. Optimal solvers include Conflict Based Search (CBS) [19], Branch-and-Cut-and-Price (BCP) [20], A* based solvers [21] and Reduction Based Solvers [22]. These solvers solve the problem optimally and their weakness is the poor scalability. Bounded-suboptimal solvers such as Enhanced CBS (ECBS) [23] can scale to larger problems to find near optimal solutions. Prioritised solvers plan paths for each agent individually and avoid collisions with higher priority agents. The priority order can be determined before planning as in Cooperative A* (CA) [8], or determined on the fly as in Priority Based Search (PBS) [24]. Rule-base solvers like Parallel Push and Swap [25] guarantee to find solutions to MAPF in polynomial time, but the quality of these solutions is far from optimal. Some researchers focus on the scalability of online multi-agent path finding in MAPD problem. Windowed-PBS [26] plans paths for hundreds of agents in MAPD problem, however it assumes that tasks are assigned by another system.

D. Practical Considerations

This research focuses on the task assignment and path planning for real world applications. However, it also needs to consider plan execution and kinematic constraints necessary to achieve a computed plan in practice.

One issue that can arise in practice is unexpected delays, such as those that can be caused by a robot’s mechanical differences, malfunctions, or other similar issues. Several robust plan execution policies were designed in [27] and [28] to handle unexpected delays during execution. The plans generated by our algorithms can be directly and immediately combined with these policies. Furthermore, $k$-robust planning was proposed in [29], which builds robustness guarantees into the plan. Here an agent can be delayed by up to $k$ timesteps and the plan remains valid. Our algorithms can also adapt this approach to generate a $k$-robust plan.

Actual robots are further subject to kinematic constraints, which are not considered by our MAPF solver. To overcome
Then, the objective to minimize the total travel delay (TTD) for the robots to transport all the tasks while avoiding collisions is to minimise
\[
TTD = \sum_{i \in P} (a(g_i) - r_i - t(s_i, g_i)),
\]
subject to
\[
\begin{align*}
\sum_{j \in J} \sigma_{j s, k} &= \sum_{j \in J} \sigma_{s j k}, \forall i \in P, \forall k \in R; \\
\sum_{j \in J} \sigma_{j s, k} &= \mu_{i k}, \forall i \in P, \forall k \in R; \\
\sum_{k \in R} \mu_{i k} &= 1, \forall i \in P; \\
\sigma_{i j k} \cdot (p_k(a(i)) - i) &= 0, \forall i, j \in I, \forall k \in R; \\
\sigma_{i j k} \cdot (p_k(a(j)) - j) &= 0, \forall i, j \in I, \forall k \in R; \\
r_i &\leq a(s_i), \forall i \in P; \\
\sigma_{i j k} \cdot (a(i) + t(i, j)) &\leq a(j), \forall i, j \in I, \forall k \in R; \\
k_e(t) &\leq C, \forall k \in R, \forall t; \\
p_k(t) &\neq p_w(t), \forall k, w \in R, k \neq w, \forall t; \\
(p_k(t), p_k(t + 1)) &\neq (p_w(t), p_w(t)), \forall k, w \in R, \forall t; \\
\sigma_{i j k}, \mu_{i k} &\in \{0, 1\}, \forall i, j \in I, \forall k \in R.
\end{align*}
\]
Constraint (2) requires that the same robot drops off the task picked up by it; (3) denotes that a task will be transported by a robot if the robot picks up the task; (4) implies that each task is transported by exactly one robot; (5) and (6) require that vehicle \(k\) will visit all the locations, planned to be visited, at certain time instants; (7) guarantees that the earliest time for the robots to pickup every task is the time when the task is released; (8) ensures that there is no shorter time for each robot to move between two arbitrary locations \(i\) and \(j\) compared with \(t(i, j)\); (9) guarantees that the robots’ capacity constraint is always satisfied; (10) and (11) require that there is no collision between any two robots.

### IV. Task Assignment and Path Planning

Existing MAPD algorithms perform task assignment and path planning separately. Here we propose several algorithms for simultaneous task assignment and path planning, and path costs from planning are used to support the task assignment.

#### A. Task Assignment Framework

Fig. 2 shows the overall process of how task assignment and path planning are performed simultaneously. The key component of this approach is a current assignment set \(A\) and a priority heap \(H\). \(A\) stores a set of assignments \(a_k\) which contains \(a_k\), an ordered sequence of actions (pick-up and drop-off each task) assigned to each robot \(k \in R\), \(k\)’s current collision-free path, and the TTD for \(k\) to transport the assigned tasks. \(a_k\) is initialized as \(\{s_k\}\), and \((o_k)\) is used to denote the TTD for robot \(k\) to transport all the tasks by following \(o_k\). The priority heap \(H\) stores a set of potential assignment heaps \(h_i\), one for each unassigned task \(i \in P\). A potential assignment heap \(h_i\) for task \(i\) stores all
potential assignments of \( i \) to each robot \( k \in \mathcal{R} \) based on \( k \)'s current assignment \( a_k \). An entry in the heap \( h_i \) is a potential assignment \( p_a^i \) of task \( i \) to robot \( k \) which includes updated versions of \( a_k \) and a revised path and cost for the agent under the addition of task \( i \) to robot \( k \). The algorithm continues assigning tasks from the unassigned task set \( \mathcal{P}^u \) initialized as \( \mathcal{P} \), and keeps updating \( \mathcal{H} \) until all tasks are assigned.

Algorithm 1 shows the pseudo-code for task assignment framework. At the start of the algorithm, \( \mathcal{A} \) has no assigned tasks and paths. \( \mathcal{H} \) is initialized to include one potential assignment heap for each task. Each potential assignment heap tries to assign the task \( i \) to every robot based on \( \mathcal{A} \).

The main while loop of the algorithm keeps selecting and assigning the top potential assignment \( p_a^i \) of the top potential assignment heap of \( \mathcal{H} \). The potential assignment \( p_a^i \) assigns task \( i \) to robot \( k \). Then the \( a_k \in \mathcal{A} \) is replaced by \( p_a^i \), \( h_i \) is deleted from \( \mathcal{H} \) and \( i \) deleted from \( \mathcal{P}^u \). When the action sequences \( a_k \) and path for robot \( k \) in \( \mathcal{A} \) change, all other potential assignment's action sequence \( a_k \) on robot \( k \) in any \( h_j \), \( j \in \mathcal{P}^u / \{ i \} \), must be recalculated based on the new path for agent \( k \).

The behaviour of \( \text{insert}(\cdot) \) function in Algorithm 1 will be explained in Section IV-B and Section IV-C. The \( \text{planPath}(\cdot) \) function uses prioritised planning with space-time A* [8], which is fast and effective, to plan a single path for agent \( k \) following its ordered action sequence \( a_k \) while avoiding collisions with any other agents’ existing paths in \( \mathcal{A} \). As a result, the overall priority order for path planning is decided by the task assignment sequence. It is worth noting that the path planning part of Algorithm 1 might be incomplete as the prioritised planning is known to be incomplete [24].

For the remaining potential assignments on robot \( k, k' \neq k, k' \in \mathcal{R} \) in any \( h_j \), the recalculation of action sequence \( a_k \) is not necessary since the assigned tasks \( a_k \in \mathcal{A} \) do not change. However their current paths may collide with the updated agents path \( a_k \). To address this issue, we could check for collisions of all potential assignments for agents other than \( k \) and update their paths if they collide with the new path for agent \( k \). A faster method is to only check and update the paths for assignments at the top \( v \) elements of each potential assignment heap using the \( \text{updateHeapTop}(\cdot) \) function shown in Algorithm 2. Using the second method saves considerable time and it only slightly influences the task assignment outcome.

A potential assignment heap sorts each potential assignment in increasing order of marginal cost. The sorting order of \( \mathcal{H} \) is decided by the task selection methods defined below.

### B. Marginal-Cost Based Task Selection

We now introduce the marginal-cost based task assignment algorithm (MCA). The target of MCA is to select a task \( i^* \) in \( \mathcal{P}^u \) to be assigned to robot \( k^* \in \mathcal{R} \), with action sequences \( q_{1}^{i^*} \) and \( q_{2}^{i^*} \) for \( k^* \) to pick up and deliver, while satisfying:

\[
(k^*, i^*, q_{1}^{i^*}, q_{2}^{i^*}) = \arg \min_{k \in \mathcal{R}, i \in \mathcal{P}^u, 1 < q_{1} < |o_k|, q_{2} < q_{1} + 1} \left\{ t((o_k \oplus q_{1}^{i}, s_i) \oplus q_{2}^{i}, g_i) - t(o_k), \right\}
\]

where operator \((o_k \oplus q_{1}^{i}, s_i) \oplus q_{2}^{i}, g_i\) means to first insert location \( s_i \) at the \( q_{1} \)th position of the current route \( o_k \), and then insert location \( g_i \) at the \( q_{2} \)th position of the current route \( a_k \). If \( q_{1} = |o_k|, s_i \) is inserted to the second last of \( o_k \) where \( |o_k| \) is the length of \( a_k \) and the last action should always be go back to start location. After assigning task \( i^* \) to robot \( k^* \), the unassigned task set \( \mathcal{P}^u \) is updated to \( \mathcal{P}^u = \mathcal{P}^u \setminus \{i^*\} \), and \( k^* \)'s route is updated to \( o_{k^*} = (o_{k^*} \oplus q_{1}^{i^*} s_i) \oplus q_{2}^{i^*} g_i \).

To satisfy equation (12), the \( \text{insert}(\cdot) \) function in Algorithm 1 tries all possible combinations of \( q_{1}^{i} \) and \( q_{2}^{i} \) and selects \( q_{1}^{i*} \) and \( q_{2}^{i*} \) that minimise the incurred marginal TTD by following \( o_k \).
ignoring collisions for transporting task \( i^* \), where \( k \)'s load is always smaller than capacity limit \( C \). Then the \( \text{planPath}() \) function uses an \( A^* \) algorithm to plan a path following \( o_{k'} \), while avoiding collision with any \( a_k \). \( \text{path}, a_k, k' \in \mathcal{A}, k' \neq k \), and calculates the real marginal cost in terms of TTD. Finally, the \( \text{updateHeapTop}() \) function (Algorithm 2 with \( v = 1 \)) updates the potential assignment heaps. The heap of potential assignment heaps \( \mathcal{H} \) sorts potential assignment heaps based on marginal cost of the top potential assignment \( p_{i}^{top} \) of each potential assignment heap \( h_i \) in increasing order, where \( i \in \mathcal{P}^u \).

C. Regret-Based Task Selection

This section introduces a regret-based MCA (RMCA), which incorporates a form of look-ahead information to select the proper task to be assigned at each iteration. Inspired by [16], [18], RMCA chooses the next task to be assigned based on the difference in the marginal cost of inserting the task into the best robot’s route and the second-best robot’s route, and then assigns the task to the robot that has the lowest marginal cost to transport the task.

For each task \( i \) in the current unassigned task set \( \mathcal{P}^u \), we use \( k_i^* \) to denote the robot that inserting \( i \) into its current route with the smallest incurred marginal travel cost while avoiding collisions, where

\[
(k_i^*, q_i^1, q_i^2) = \arg \min_{k_i \in \mathcal{R}, q_i^1 < q_i^1 \leq |o_k|, q_i^2 < q_i^2 \leq |o_k| + 1} \{ t((o_k \oplus q_i^1 s_i) \oplus q_i^2 g_i) - t(o_k) \}
\]

(13)

The second-best robot \( k_2^* \in \mathcal{R} \setminus \{k_i^*\} \) to serve \( i \) is

\[
(k_2^*, p_i^1, p_i^2) = \arg \min_{k_2 \in \mathcal{R} \setminus \{k_i^*\}, p_i^1 < p_i^1 \leq |o_k|, p_i^2 < p_i^2 \leq |o_k| + 1} \{ t((o_k \oplus p_i^1 s_i) \oplus p_i^2 g_i) - t(o_k) \}
\]

(14)

Then, we propose two methods for RMCA to determine which task \( i^* \in \mathcal{P}^u \) will be assigned.

The first method, \( \text{RMCA}(a) \), uses absolute regret which is commonly used in other regret-based algorithms. The task selection satisfies:

\[
i^* = \arg \max_{i \in \mathcal{P}^u} t((o_k^2 \oplus p_i^1 s_i) \oplus p_i^2 g_i) - t((o_k^1 \oplus q_i^1 s_i) \oplus q_i^2 g_i).
\]

(15)

The second method, \( \text{RMCA}(r) \), uses relative regret to select a task satisfying the following equation:

\[
i^* = \arg \max_{i \in \mathcal{P}^u} t((o_k^2 \oplus p_i^1 s_i) \oplus p_i^2 g_i) / t((o_k^1 \oplus q_i^1 s_i) \oplus q_i^2 g_i).
\]

(16)

Both RMCA(r) and RMCA(a) use the same \( \text{insert}() \) function in Section IV-B to select an insert location for each potential assignment. The main difference between RMCA and MCA is that the heap \( \mathcal{H} \) sorts the potential assignment heaps \( h_i, i \in \mathcal{P}^u \) by absolute or relative regret. RMCA uses Algorithm 2 with \( v = 2 \) to ensure that the top two elements of each heap are kept up to date.

D. Anytime Improvement Strategies

After finding an initial solution based on RMCA, we make use of an anytime improvement strategy on the solution. This strategy is based on the concept of Large Neighbourhood Search (LNS) [9]. As shown in Algorithm 3, the algorithm will continuously destroy some assigned tasks from the current solution and reassign these tasks using RMCA. If a better solution is found, we adopt the new solution, and otherwise we keep the current solution. We keep destroying and re-assigning until time out. We propose three neighbour selection strategies to select tasks to destroy.

1) \( \text{Destroy Random} \): This method randomly selects a group of tasks from all assigned tasks. The selected tasks are removed from their assigned agents and re-assigned using RMCA.

2) \( \text{Destroy Worst} \): This strategy randomly selects a group of tasks from the agent with the worst TTD. The algorithm records the tasks that are selected in a tabu list to avoid selecting them again. After all tasks are selected once, we clear the tabu list and allow all tasks to be selected again.

3) \( \text{Destroy Multiple} \): This method selects a group of agents that have the worst sum of TTD. Then it randomly destroys one task from each agent. It also makes use of a tabu list as in the previous strategy.

V. EXPERIMENTS

We perform our experiments on a 21 x 35 warehouse map as shown in Fig. 3, where black tiles are static obstacles, white tiles are corridors, blue tiles represent potential origins and destinations (endpoints) of the tasks, and orange tiles represent starting locations of the robots.

For the experiments, we test the performance of the designed algorithms under different instances. Each instance includes a set of packages/tasks with randomly generated origins and
A. One-Shot Experiment

We first evaluate the designed algorithms in an offline manner to test their scalability. Here, we assume that all the tasks are initially released. This helps us to learn how the number of tasks and other parameters influence the algorithms’ performance, and how many tasks our algorithm can process in one assignment time instant.

1) Relative TTD and Runtime: The first experiment compares variants of methods for different numbers of agents and different capacities of agents. We compare two decoupled versions of the algorithms, where we first complete the task assignment before doing any route planning. In these variants we use optimal path length as the distance metric while performing task assignment. We consider two variants: decoupled MCA (MCA-pbs) where we simply assign tasks to the agent which will cause the least delay (assuming optimal path length travel), and decoupled RMCA (RMCA(r)-pbs) where we assign the task with maximum relative regret to its first choice. The routing phase uses PBS [24] to rapidly find a set of collision-free routes for the agents given the task assignment. We compare three coupled approaches: MCA uses greedy task assignment, while RMCA instead uses maximum (absolute or relative) regret to determine which task to assign first. For each number of tasks, each number of agents (Agents) and each capacity (Cap), we randomly generate 25 instances. Each task in each instance randomly selects two endpoints (blue tiles in Fig. 3) as the start and goal locations for the task.

Fig. 4 shows the algorithms’ relative TTD. The relative TTD is defined as real TTD minus the TTD of RMCA(r) when ignoring collisions. The reason we use relative TTD as a baseline is that the absolute TTD values in one-shot experiment are very large numbers varying in a relative small range. If using absolute TTD values, it is hard to distinguish the performance difference of algorithms in plots. Overall we can see that the decoupled methods are never the best, thus justifying that we want to solve this problem in a coupled manner instead of separate task assignment and routing. For Cap = 1, MCA is preferable since we cannot modify the route of an agent already assigned to a task to take on a new task and regret is not required. For Cap = 3, RMCA(r) eventually becomes the superior approach as the number of agents grows. When Cap = 5, RMCA(r) is clearly the winner. Interestingly, the absolute regret based approach RMCA(a) does not perform well at all. This may be because the numbers of tasks assigned to the individual agents by RMCA(a) are far from even, and the resulting travel delay changes greatly when agents are assigned with more tasks. In other words, RMCA(a) prefers to assign tasks to agents with more tasks. The relative regret is more stable to these changes.

Fig. 5 shows the average runtime for the above experiment. The results show that decoupled approaches are advantageous in runtime, especially for instances with a large number of tasks and small capacity. Although RMCA and MCA require more runtime than the decoupled approaches, we demonstrate below that MCA and RMCA are still competitive in runtime compared with other algorithms.

2) Anytime Improvement Methods: The second experiment uses any time improvement algorithm to improve the solution from RMCA(r) for 60 seconds with three neighbourhood destroy strategies: Destroy random (DR), Destroy worst (DW) and Destroy multiple (DM). For each destroy strategy, we run experiments on different destroy group sizes (how many tasks to destroy each time). The experiment is performed on 25 instances that each have 500 tasks with different capacity values and agents’ numbers.

Table I shows the results of relative TTD of RMCA(r)/MCA (Relative to the TTD of RMCA(r) that ignores collisions, and
the lower the better) under different anytime improvement strategies. The results show that all of the three neighbourhood destroy methods improve the solution quality of RMCA(r) and MCA. We still see that MCA performs better than RMCA(r) when capacity and number of agents are low (the relative TTD of MCA smaller than 0 means its TTD is smaller than TTD of RMCA(r) that ignores collisions.), even the anytime improvement strategies can not reverse this trend. Overall, destroy random and destroy worst performs better than destroy multiple. This is not unexpected as simple random neighbourhoods are often very competitive for large neighbourhood search.

**B. Lifelong Experiment**

In this part, we test the performance of RMCA(r) in a lifelong setting compared with the TPTS and CENTRAL algorithms in [1]. The MAPD problem solved by TPTS and CENTRAL assumes that each agent can carry a maximum of one package at a time, and the objective is to minimize the makespan. This objective is somewhat misleading when we consider the continuous nature of the underlying problem where new tasks arrive as the plan progresses. As a result, minimizing TTD might be a better objective since it may help in optimizing the total throughput of the system by trying to make agents idle as soon as possible, whereas makespan minimization all agents can be active until the last time point.

At each timestep, after adding newly released tasks to the unassigned task set \(P_u\), the system performs RMCA(r) on current assignments set \(A\), and runs the anytime improvement process on all released tasks that are not yet picked up. The RMCA(r) uses the anytime improvement strategy of destroy random with a group size of 5. As the anytime improvement triggers at every timestep when new tasks arrive, and involves all released yet unpicked up tasks, we set the improvement time as 1 s in each run.

We generate 25 instances with 500 tasks. For each instance, we use different task release frequencies (\(f\)): 0.2 (release 1 task every 5 timestep), 2 and 10 (10 tasks are released each timestep). For each task release frequency, we test the performance of the algorithms under different agent capacities (\(Cap\)) and different numbers of agents (\(Agents\)).

1) **Result:** Table II shows that RMCA(r) not only optimizes TTD, its makespans are overall close to CENTRAL, and are much better than TPTS. Comparing TTD, CENTRAL and TPTS perform much worse than RMCA(r). This supports our argument that makespan is not sufficient for optimizing the total throughput of the system. In addition, the runtime per timestep (\(T/TS\)) shows that RMCA(r) gets a better solution quality while consuming less runtime on each timestep compared with CENTRAL. A lower runtime per timestep makes RMCA(r) better suited to real-time lifelong operations. Furthermore, by increasing the capacity of robots, both total travel delay and makespan are reduced significantly, which increases the throughput and efficiency of the warehouse.

2) **T-Test on TTD and Makespan:** We evaluate how significant is the solution quality of RMCA(r) with respect to CENTRAL and TPTS by performing t-test with significance level of 0.1 on the normalized TTD and normalized makespan for experiments with robots’ \(Cap = 1\). The normalized TTD is defined as \(\frac{TTD \times N_a \times f}{N_t}\) where \(N_t\) is the number of tasks, \(N_a\) is the number of agents and \(f\) is the task frequency. This definition is based on the observation that increasing \(N_a\) decreases TTD, and increasing \(N_t\) and \(f\) increases TTD. Similarly normalized makespan is \(\frac{makespan \times N_a \times f}{N_t}\) (where now increasing \(f\) decreases
Table III shows the t-score and p-value for the null hypotheses that RMCA(r) and the other methods are identical. The results show that RMCA(r) significantly improves the normalized TTD compared with CENTRAL and TPTS and improves the normalized makespan compared with TPTS.

VI. CONCLUSION

In this letter, we have designed two algorithms MCA and RMCA to solve the Multi-agent Pickup and Delivery problem where each robot can carry multiple packages simultaneously. MCA and RMCA successfully perform task assignment and path planning simultaneously. This is achieved by using the real collision-free costs to guide the multi-task multi-robot assignment process. Further, we observe that the newly introduced anytime improvement strategy improves solutions substantially. Future work will extend the anytime improvement strategies to refine the agents’ routes, and improve the algorithms’ completeness on path planning.

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