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Battery-aware hierarchical task allocation in multi-robot systems for intelligent warehouse control

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Abstract— **This paper presents a battery-aware hierarchical task allocation (B-HTA) algorithm, which combines a higher-level centralized and lower-level decentralized task allocation layers, for multi-robot systems in warehouse operations. Fully centralized control architectures can provide more equitable task distribution among robots, but also rely extensively on communication which can be costly, hard to scale with number of robots and prone to uncertainties. On the other hand, a decentralized control framework is scalable and robust, however, it cannot achieve similar balanced task allocation as centralized control due to lack of global information. Balanced task allocation for warehouse operations is essential for effective use of the robot resources and minimize time losses in recharging. This paper proposes a blended approach of a hierarchical structure, which is scalable and requires minimal communication, consisting of two layers, i) a centralized layer that does zone wise task allotment, and, ii) a decentralized layer based on market auction algorithm that allots tasks to robots in their respective zones. The decentralized layer of this algorithm takes into consideration the battery level of the robot while allotting it a task, which leads to more balanced task allocation among the robots and fewer recharging instances, as shown through simulation results compared to a completely centralized approach and also outperforms other decentralized market auction based approaches.**

I. Introduction

Warehousing sector has been gaining importance with focus on infrastructure and logistics for e-commerce growth in the country. There is a need for developing technologies that support this growth of warehousing industry. Warehouse automation using mobile robots has been shown to increase operation productivity by 2 to 3 times [1]–[3]. Particularly, one of the most prominent approaches for warehouse automation has been several mobile robots capable of picking shelving unit, called pods, and delivering them from storage area to human operated pick stations, such as the the Kiva system [4]. This approach automates the order picking operation within a warehouse which is otherwise dependent on human labor and manually operated resources. One of the main tasks in operating large fleets of robots for order fulfillment is the task allocation and coordination among the robots [5] in autonomous warehouses. This paper develops a battery-aware algorithm for balanced task allocation among the robots for effective use of available resources and prevent downtime due to frequent charging station visits.

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The existing work in literature for both task allocation and path planning can be categorized as centralized or decentralized. In task allocation, the centralized approaches use optimization-based algorithms, which use all the available global information, about the state of the robots and the warehouse, to arrive at an optimal solution. In [6], an order batch to robot task conversion followed by a centralized adaptive task selection was presented for task allocation for balanced workload among the robots. However, these approaches become computationally very intensive, and do not scale well as the number of robots and tasks increases [7].

On the other hand, decentralized algorithms do not face scalability issues as they can be implemented in a distributed manner. One of the main decentralized approaches available in the literature for decentralized task allocation are market allocation based methods [8]. In [9], task allocation was done via an improved market auction algorithm and multi robot path planning was solved via CBS (Conflict Based Search) algorithm based on D*Lite. In [10], task allocation was done via an auction algorithm and multi robot path planning was done via an improved A* algorithm. In [11], task allocation was implemented via an auction algorithm considering traffic flow prediction. Robot conflicts are resolved via giving priorities to different robots, the less priority robot waits until the higher priority robot moves away. The market auction based algorithms are decentralized, however, they do not generally lead to balanced workload among robots, which can lead to ineffective resource utilization in warehouse operations, frequent recharging instances, and faster wear in robots.

The current work proposes a hierarchical task allocation algorithm, which combines i) a centralized layer of higher-level task distribution into different zones of the warehouse, and, ii) a decentralized layer of lower-level task allocation to individual robots within specific zones. It is shown through example simulations that the use of available battery with each robot in the bid, and therefore in the final task allocation, inherently promotes more equitable task distribution among robots, and significantly reduced number of visits to charging stations. The main contributions of this paper is a battery-aware hierarchical task allocation (B-HTA) algorithm, which leads to a more equitable task allocations among the robots, reduced communication between robots and fewer charging instances of each robot.

The rest of the article is organized as follows. Section II describes the proposed hierarchical task allocation algorithm. An example warehouse simulation is then presented

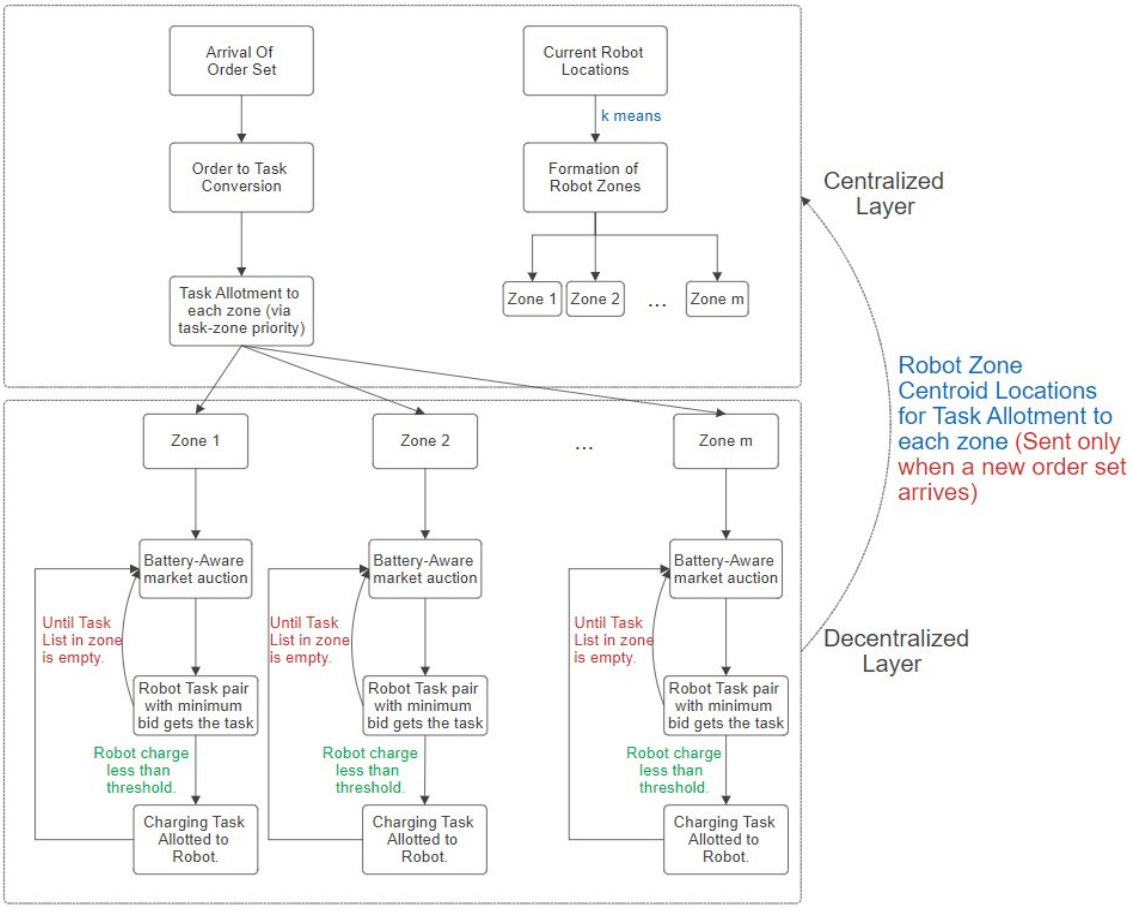


Fig. 1. Flow Chart of the proposed B-HTA algorithm. The zone wise division of robots and the zone wise task allocation based on total priority p of a zone for each task of the order set is done by the Central Controller and this layer is called the centralized layer. The task allotment to robots within each zone done using the battery aware market auction algorithm which is carried out by robots in their respective zones is termed as the decentralized layer. For an order set, the task information flows from the centralized layer to the decentralized layer and when a new order set arrives, robot zone centroid location information flows from the decentralized layer to the centralized layer.

in Section III, which shows comparison with centralized approaches and other market auction based algorithm without considering battery levels in bids. Finally, the main conclusions are highlighted in Section IV.

II. PROPOSED HIERARCHICAL TASK ALLOCATION ALGORITHM

This section delineates the proposed battery-aware hierarchical task allocation (B-HTA) algorithm, which integrates a centralized higher-level task distribution layer with a decentralized lower-level task allocation layer. The algorithm's structure is designed to optimize task distribution among robots while considering their battery levels, thereby enhancing overall system efficiency and longevity.

A. Centralized Layer

The centralized layer of the B-HTA algorithm employs a two-step process: zone-based robot division and priority-based task allocation.

1) Zone-based Robot Division: Initially, the algorithm utilizes the k-means clustering method to partition the robots into distinct zones based on their spatial distribution within the warehouse. The value k, denoting the number of clusters, depends on the distribution of robots on the warehouse floor, which is dynamic. Therefore a recursive approach is developed to select k such that the centroid of the robot zones are well separated by a minimum distance. The choice of the minimum distance is a hyperparameter that can be chosen according to the dimension of the warehouse space.

2) Priority-based Task Allocation: For each task, the algorithm computes a priority score for every zone. This priority score, p, is a weighted sum of two metrics: distance priority (d) and number priority (f).

The distance priority, d, is calculated as:

$$d = \frac{1}{1 + e^{(d_{c,i}/100)}} \tag{1}$$

where $d_{c,i}$ represents the Manhattan distance between the centroid of robots in the i-th zone and the task location.

The number priority, f, is defined as:

$$f = \frac{n}{n_T} \tag{2}$$

where n denotes the number of robots in a given zone, and n_T is the total number of robots in the warehouse.

The total priority, p, for each zone is then computed as:

$$p = \beta \times d + f \tag{3}$$

where β is a weighting parameter that balances the influence of distance and robot distribution.

Tasks are subsequently assigned to zones based on these priority scores, with each task allocated to the zone exhibiting the highest priority for that particular task.

B. Decentralized Layer

Within each zone, task allocation is managed through a decentralized, battery-aware market auction algorithm. This approach allows for efficient, localized decision-making while accounting for the current state of each robot.

1) Bid Calculation: Each robot calculates its bid for every task assigned to its zone. The bid value is derived from a cost function that considers both the Manhattan distance to the task location and the robot's remaining battery charge after task completion.

Let the robot move from point (x_A, y_A) to point (x_B, y_B), then the Manhattan distance is given by:

$$D = |x_A - x_B| + |y_A - y_B| \tag{4}$$

Then the battery left in the robot is given by:

$$C' = C - k \times D \tag{5}$$

2) Cost Function: The cost function incorporates two components: self cost and relative cost. The self cost for doing a task t_i is given by:

$$C(t_i) = 2 \times (|x_P - x_O| + |y_P - y_O|) \tag{6}$$

where (x_P, y_P) and (x_O, y_O) are the pick station location and pod location w.r.t a task t_i.

The relative cost for moving between two task locations t_A and t_B, that is moving between the pod location of the recently completed task to the pod location of the next task, is given by:

$$R(t_A, t_B) = |x_A - x_B| + |y_A - y_B| \tag{7}$$

Considering the battery and distance, the net self cost becomes:

$$\begin{aligned} C(t_i) =& \alpha \times 2 \times (|x_P - x_O| + |y_P - y_O|) - \\ & (1-\alpha) \times (C - k \times 2 \times (|x_P - x_O| + |y_P - y_O|)) \end{aligned} \tag{8}$$

Similarly the net relative cost becomes:

$$\begin{aligned} R(t_A, t_B) =& \alpha \times (|x_A - x_B| + |y_A - y_B|) - \\ & (1-\alpha) \times (C - k \times (|x_A - x_B| + |y_A - y_B|)) \end{aligned} \tag{9}$$

3) Task Assignment: The total cost for a robot r_i to complete a sequence of tasks S_i is calculated as:

$$Cost(r_i, S_i) = \sum_{j=0}^{n-1} R(t_j, t_{j+1}) + \sum_{j=1}^{n} C(t_j) \tag{10}$$

For a new set of tasks $T = \{T_1, T_2, ..., T_k\}$, each robot r_i computes its bid for each task T_z as:

$$bid(r_i, T_z) = Cost(r_i, S_i \cup T_z) - Cost(r_i, S_i) \quad \forall z \in [1, k] \tag{11}$$

which simplifies to:

$$bid(r_i, T_z) = R(t_n, T_z) + C(T_z) \quad \forall z \in [1, k] \tag{12}$$

The task T_p is allocated to the robot r_j where j and p are determined by:

$$j, p = argmin(bid(r_i, T_z)) \quad \forall i \in [1, m] \text{ and } \forall z \in [1, k] \tag{13}$$

This process continues until all tasks in T are allocated within each zone.

C. Algorithm Considerations

The B-HTA algorithm incorporates several key considerations to ensure robust and efficient operation:

1) **Order Processing:** Orders are processed at fixed time intervals, with tasks assigned based on the B-HTA algorithm. Each robot maintains its own task list.
2) **Task Definition:** A task encompasses the entire process of navigating to a pod, retrieving it, transporting it to the picking station, and returning it to its original location.
3) **Replenishment:** The algorithm assumes that pod replenishment is managed separately and does not interfere with the task allocation process.

By integrating these centralized and decentralized approaches while accounting for battery levels, the B-HTA algorithm aims to achieve a more balanced workload distribution among robots, potentially reducing the frequency of recharging events and optimizing overall warehouse operations.

III. Simulation Results

This section presents a comparative simulation study using an example warehouse system (Figure 2), to showcase the effects of decentralization and battery considerations on task allocation among robots for warehouse operations. The implementation is available at `https://github.com/anujtiwari9/taskallocation_icc2024`.

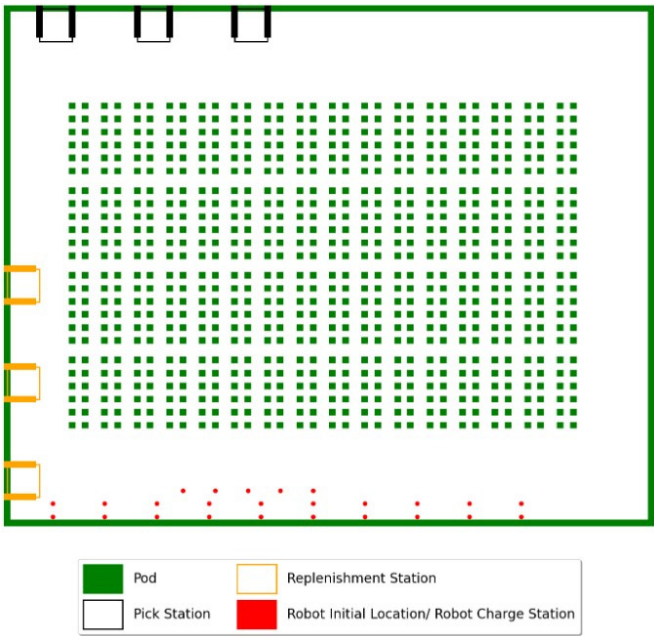


Fig. 2. This is the Warehouse Floor Plan (80m X 100m), It has 3 pick stations, 3 replenishment stations and a total of 768 pods. The 25 robots are shown at their starting locations and the charging stations of each robot is assumed to be at its starting location.

Approach	σ_d **(Eq.** (14)**)**	N_c **(Eq.** (15)**))**
CTA (Baseline)	2803.2	26
B-CTA (*% improv. w.r.t. baseline*)	2551.8 (*9 %*)	17 (*35 %*)
DMTA (*% improv. w.r.t. baseline*)	1613.8 (*42 %*)	21 (*19 %*)
B-HTA (Proposed Approach) (*% improv. w.r.t. baseline*)	769.2 (*73 %*)	9 (*65 %*)

TABLE I

COMPARISON OF STANDARD DEVIATION OF DISTANCES TRAVELLED BY ALL ROBOTS AND TOTAL NUMBER OF CHARGING STATION VISITS BY ALL ROBOTS FOR THE TASK ALLOCATION APPROACHES FROM SECTION III-A. CENTRALIZED APPROACHES (CTA AND B-CTA) HAVE HIGHER VARIANCE IN DISTANCE TRAVELLED COMPARED TO DECENTRALIZED APPROACHES (DMTA AND B-HTA) WHICH INDICATES A MORE EQUITABLE TASK ALLOCATION IN THE DECENTRALIZED APPROACHES. BATTERY UNAWARE APPROACHES (CTA AND DMTA) HAVE MORE NUMBER OF CHARGING STATION VISITS COMAPRED TO BATTERY AWARE APPROACHES (B-CTA AND B-HTA) WHICH INDICATES BETTER UTILIZATION OF THE BATTERY OF THE ROBOTS.

A. Compared Approaches

The following four approaches are implemented on the example warehouse system.

1) **Approach 1 - Centralized Task Allocation (CTA):** This is a completely centralized approach where the entire task allocation is done through a central controller, without battery level considerations. This approach can be obtained from the proposed algorithm in Section II when the number of zones is restricted to 1 (and hence centralized) and the cost function for the auction algorithm in Eq. (8) and Eq. (9) is used with $\alpha = 1$, that is the cost function does not include the battery of the robot but solely relies on the distance metric. Note that the CTA approach is very close to the state of the art market auction based approaches such as the approaches used in [9] and [10].
2) **Approach 2 - Battery-aware Centralized Task Allocation (B-CTA):** The second approach is centralized task allocation obtained by considering only one zone in Section II, however this approach considers battery levels in the cost function for auction in Eq. (8) and Eq. (9).
3) **Approach 3 - Decentralized Market Task Allocation (DMTA):** This is a decentralized market auction based algorithm, however the battery considerations are not taken during task allocation. Here the robots are divided into zones based on their location but the cost function for the auction algorithm has α set to 1, i.e., the cost function does not include the battery of the robot.
4) **Approach 4 - Battery-aware Hierarchical Task Allocation (B-HTA):** This is the proposed approach for task allocation in this paper, where the robots are divided into zones based on their location and the cost function includes battery state of robot, as described in Section II.

B. Metrics for Comparison

The following two metrics were used to compare the different approaches.

- **Standard deviation of distance travelled by robots (σ_d)**:

$$\sigma_d = \sqrt{\frac{\sum_{i=1}^{N}(d_i - \mu)^2}{N}} \tag{14}$$

Where d_i is the distance travelled by a robot, μ is the mean of distances travelled by all robots and N is the total number of robots. A higher standard deviation signifies unequal task distribution where few robots are allocated most of the tasks. On the other hand smaller σ_d indicates a balanced task allocation.

- **Number of charging stations visits by robots (N_c)**:

$$N_c = \sum_{j=1}^{N} n_i \tag{15}$$

where n_i is the number of times a robot visited its charging station and N is the total number of robots.

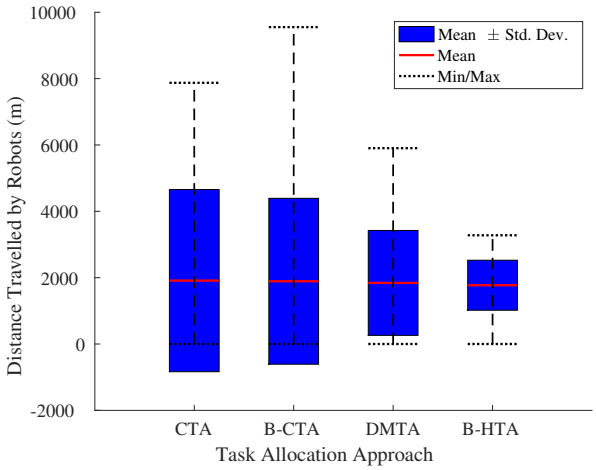


Fig. 3. Distance travelled by robots during task execution for the task allocation approaches from Section III-A have similar mean however different variances indicating different levels of equitable task allocation. Centralized approaches (CTA and B-CTA) consideration leads to higher variance, and hence less balanced task allocation compared to the decentralized and hierarchical approaches (DMTA and the proposed B-HTA). Furthermore, including battery level considerations into the bidding algorithm leads to more balanced task allocation compared to battery unaware cases. The proposed approach B-HTA has the least variance of robot travelled distances.

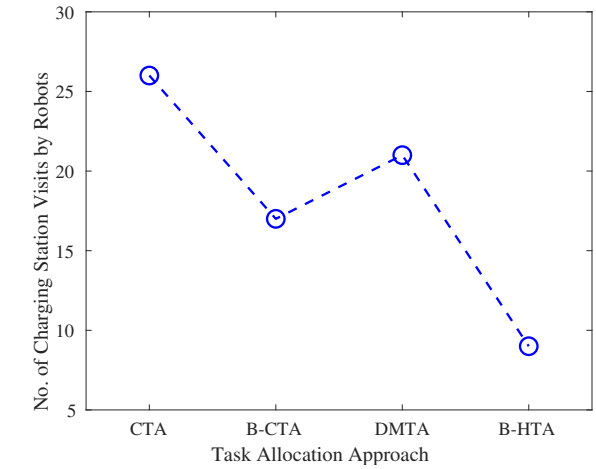


Fig. 4. Total number of charging station visits by robots for the task allocation approaches from Section III-A. A fall in number of charging station visits is observed when moving from CTA to B-CTA. A similar fall is observed when moving from DMTA to B-HTA. This implies that battery aware approaches (B-CTA and B-HTA) utilize the battery of all the robots more efficiently compared to battery unaware approaches (CTA and DMTA).

C. Results

Matlab was used to simulate the proposed Battery-aware Hierarchical Task Allocation (B-HTA) algorithm. Note that, to plan the paths taken by all robots, a path planning function in MATLAB called plannerHybridAstar with MinTurningRadius set to 3 was used but collisions among the robots were not considered and the simulations were done considering the robots as point masses and hence robot dynamics has not been considered. The value of k is set to be 0.05. The parameters α and β were found to be 0.1 and 4 respectively via simulation for most equitable task allocation. The algorithm was simulated for 5 set of orders with a total of 290 tasks. Order batch to robot task conversion was not done but assumed that it was done and then 50 random tasks (pod locations) were chosen for the first order set, 60 for the second, 70 for the third , 60 for the fourth and 50 tasks for the last order set. Order sets were released at constant time intervals. The warehouse layout used for simulation is given in Figure 2.

Centralized Task Allocation (CTA), Battery-aware Centralized Task Allocation (B-CTA) and Decentralized Market Task Allocation (DMTA) algorithms were simulated for 5 set of orders of a total of 290 tasks with number of tasks per order set same as for the simulation of B-HTA. They were also simulated in the same Warehouse Environment as given in Figure 2.

Standard deviation of distances travelled by the robots in each approach and the total number of charging station visits by the robots in each approach were chosen as metrics of comparison between the task allocation approaches from Section III-A. This Comparison is given in Table I. It is evident from Figure 3 and Figure 4 that the centralized approaches (CTA and B-CTA) have higher variance in distance travelled by the robots compared to decentralized approaches (DMTA and B-HTA), which indicates better workload distribution in the decentralized approaches. Here the centralized approaches do not have balanced workload because the cost function for bidding does not directly optimize for it. Also, the battery unaware approaches (CTA and DMTA) have more number of charging station visits compared to battery aware approaches (B-CTA and B-HTA), which shows that battery aware approaches utilize the battery of all robots more efficiently compared to battery unaware approaches.

IV. Conclusions

This article developed a Battery-aware Hierarchical Task Allocation (B-HTA) algorithm which is a blend of centralized and decentralized approaches, and considers robot battery states. The proposed B-HTA algorithm is able to achieve a more equitable task allocation with very less number of charging station visits for the robots compared to Centralized approaches (CTA and B-CTA) and Battery unaware decentralized approaches (DMTA), as shown through example simulations. So the B-HTA algorithm leads to a more balanced task allocation, better utilization of the charge of robots and can lead to reduction in wear of the robots which can occur due to unbalanced workload among the robots. Furthermore, the B-HTA algorithm has a decentralized layer, therefore it is scalable to a larger number of robots and tasks compared to centralized approaches. Future work will focus on extending the algorithm to consider lower level control of robot paths for conflict-free planning and coordination among robots for warehouse operations and will also consider robot dynamics, uncertainities in the environment and a realistic battery model of the robot.

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