Market-Based Task Allocation by using Assignment Problem

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***Abstract*— In this study, a market-based task allocation method is proposed. In the trading process, the energy model of a robot platform is used to calculate the price and cost for a task. In order to determine the winner robot(s), two auction clearing algorithms, which are named as Iterative and Highest-Bid Task for Robots (HBTR), are proposed. Additionally, assignment problem is used to determine instantaneous optimal task-robot matching. The Hungarian algorithm is implemented to solve optimal assignment problem. In the implementation of the algorithms, three types of tasks are used: cleaning, carrying and monitoring. The tasks consist of three important features: delicacy, priority, and the task completion time. These tasks are assigned to the members of a heterogeneous robot team, according to the proposed task allocation method.**

***Keywords*—market-based task allocation, energy model, optimal task assignment .**

I. INTRODUCTION

In many applications, the complex and varied problems may require to use more than one robot because of the faster task completion, increased robustness, higher solution quality and achievement of the tasks that cannot be completed with a single robot. In [1], Dias and Stentz introduced application areas of multi-robot systems and their requirements and they also indicated that in many application areas, a multi-robot system is more efficient than a single-robot system. In order to exploit the advantages of the multi-robot systems, many researches attempt to achieve coordination among the multi robots. In recent years, the multi-robot task allocation problem has become main topic in the coordination of the multi-robot systems. The task allocation problem can be defined as assigning the set of resources to the set of tasks in an efficient way.

Multi-robot task allocation solutions take place in a wide perspective from fully centralized to fully distributed approaches. In the centralized approaches, a single robot (planner) is responsible for assigning the tasks to the robots by using information that is gathered from the team members [2]. These approaches have advantages to obtain the optimal solution because the planner robot reaches all information while generating the plans. However, the centralized approaches suffer from several important disadvantages. One of them is scalability. As the number of members in the team increases, the communication load increases and ability to generate the optimal solution decreases. If the environment is highly dynamic, the response of the planner robot could be very slow. Finally, in the centralized approaches the success of the team tightly depends on the planner robot. If the planner robot fails, then the entire team fails.

In the distributed approaches, each robot is responsible for its own plan generation based on its local information and states. The major limitation of these approaches is producing suboptimal solution. Several multi-robot architectures dealing with multi-robot task allocation problem in a distributed manner have been placed in the literature. ALLIANCE [3] and BLE [4] are behavior-based distributed approaches. In [5] and [6], a negotiation-based task allocation approach which was inspired by Contract Net Protocol (CNP) was presented. M+ [7] is a general distributed multi-robot coordination scheme which consists of task allocation, failure detection, and task execution. MURDOCH [8], [9] is a publish/subscribe communication model and auction-based task allocation method. It is based on a greedy algorithm that the most suitable robot in the team is instantaneously assigned to the task.

Market-based approaches have become more popular in the recent years. The advantages of the centralized and distributed approaches are combined in the market-based approaches. Each individual has the ability of generating its own plan by using local information. However, the members of the team may enter in trading as the tasks are assigned to the robots. In addition, communication is limited to only for certain information such as bid for tasks and award of tasks. Dias and Stentz [1] first introduced a free market approach to coordinate multi-robot systems. They defined some basic terms which are used in the market approaches. The architecture called TraderBots, [10] consists of layers, such as resources, tasks, robots, and RoboTrader. The RoboTrader coordinates activities of the robot and the other robots. In [11], an implementation of the TraderBots for distributed sensing task is represented. Another implementation of the market-based approach is given for multi-robot exploration task [12]. Recently, market-based approaches are used for complex tasks which are represented by task trees [13]. These trees are used for task announcements,

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bid computations and evaluations. The studies mentioned above use currency for trading tasks in the market approaches. However, the only thing the robots have is energy. Therefore, the price and cost of a task should be determined in terms of energy. In this paper, market-based task allocation approach is proposed. In the trading process, energy model of a robot platform is used to calculate the price and cost of a task. The task allocation problem is considered as an optimal assignment problem and using the Hungarian algorithm tasks are allocated to robots. Additionally, two auction clearing approaches are used to allocate tasks to robots. All those three algorithms are implemented and compared for instantaneous task assignment.

The rest of the paper is organized as follows. In Section 2, market-based approaches are briefly explained. In Section 3, the assignment problem is discussed. In Section 4, the proposed energy model and algorithms are given. In Section 5 and 6, the implementation of the proposed method and the detailed analysis of the experimental results are presented, respectively. In the final section, conclusions are given.

II. MARKET-BASED APPROACH

In recent years, market-based approaches have become popular to coordinate multi-robot systems. Market-based approaches attempt to present a distributed solution for the task allocation problem. Due to the fact that market-based systems combine the advantages of the centralized and distributed systems, the solutions for the task allocation problem will be more responsive and productive than other methods. Another advantage of the market-based approaches is the necessity of limited communication. In this study, the communication is used just for sending bid and award for tasks. In other words, price encapsulates all factors affecting the producer and the cost is used for the same purpose in the consumer side. Since the price and cost are enough to present positions of both the producer and the consumer in the market, messages do not include additional information.

Assume that a team of robots is responsible for achievement of a set of tasks. In the team, each robot has its self-interest, so each of them tries to maximize its own profit. In order to decrease the cost of the task, the robot should avoid redundancy and pay only the required cost for the task. Since the goal of the team is to complete the missions by minimizing the cost, the self-interested robots improve the profit of the whole team.

In order to determine the required cost for a task, the bidding process is used. A robot (producer) demands services or goods from the other robots in the team. The robot determines a price that is suitable for itself. After that, it announces the task to other members (consumers) in the team. Each consumer calculates a cost for the given task by using its own local information and inner state. Next, a bid, which is a function of the price and the cost, is sent to the producer. After that, the producer must determine the winner robot(s). The allocation problem can be considered as assignment problem. In the next section, the assignment problem is presented.

III. THE ASSIGNMENT PROBLEM

The assignment problem, also known as the maximum weighted bipartite matching problem, is a widely-studied problem in combinatorial optimization literature. It can be stated as follows; choosing an optimal assignment of n task and n resource, assuming that cost of each task-resource assignment is given. An optimal assignment is the one that makes the total assignment cost minimum [14]. Mathematical model of the assignment problem is given below [15].

Indices
i, j: Task and resource index

Sets
v_i: Set of tasks
u_j: Set of resources

Parameters
n: Number of tasks
c_{ij}: Cost of the assignment of v_i to u_j.

Decision Variables

$$x_{ij} = \begin{cases} 1 & \text{If } v_i \text{ is assigned to } u_j \\ 0 & otherwise \end{cases}$$

Model

$$\sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij} \cdot x_{ij} \tag{1}$$

s.t.

$$\sum_{i=1}^{j} x_{ij} = 1, \forall j \tag{2}$$

$$\sum_{j=1}^{n} x_{ij} = 1, \forall \text{i} \tag{3}$$

$$x_{ij} \in \{0,1\}, \forall i,j \tag{4}$$

Equation (1) is the objective function of the model which minimizes the sum of assignment costs. Equation (2) ensures that each resource has to be assigned exactly one task. Similarly, equation (3) ensures that each task has to be assigned exactly one resource. Equation (4) is integrality constraints.

A. Hungarian Algorithm

The Hungarian or Kuhn-Munkres algorithm, originally proposed by Kuhn in 1955 [16] and refined by Munkres in 1957 [14]. The Hungarian algorithm solves the assignment problem in $O(n^3)$ time, where n is the size of one partition of the bipartite graph. The Hungarian algorithm assumes the existence of a bipartite graph, $G = (V, U, E)$ where V and U are the sets of nodes in each partition of the graph, and E is the set of edges. Steps of the Hungarian algorithm are given below [17].

Input: A bipartite graph, $G = (V, U, E)$

where ($|V| = |U| = n$) and $n \times n$ matrix of edge costs C.

Output: A complete matching, *M.*

Step 1: From each row, subtract the row minimum.

$$c'_{ij} = c_{ij} - \min_{j \in U}(c_{ij}) \ \forall (i \in V, j \in U)$$

Step 2: From each column subtract the column minimum.

$$c''_{ij} = c'_{ij} - \min_{i \in V}(c'_{ij}) \ \forall (i \in V, j \in U)$$

Step 3: Use as few lines as possible to cover all the zeros in the matrix. Consider the following cases where k represents the number of lines.

- If $k < n$, let s be the minimum uncovered number. Subtract s from every uncovered number. Add s to every number covered with two lines. Go back to the start of step 3.
- If $k = n$, go to step 4.

Step 4: Starting with the top row, make an assignment for each row. An assignment can be made when there is exactly one zero in a row. Once an assignment is made, delete that row and column from the matrix C.

IV. THE PROPOSED METHOD

A. Power Model of a Robot Platform

Generally, market-based task allocation algorithms use currency while trading the tasks. However, robots supply services or goods by consuming energy and do not receive any kind of money in return. Therefore, the prices and costs are calculated based on currency become abstract concepts for the robots. To have meaningful quantities, the price and cost of a task should be calculated in terms of energy.

In order to calculate the price and cost for a task, the power model of the robot is required. The robot consumes energy for motion and sensing. The power model of the motors and sonar are developed in Mei *et al.* [18] as follows:

1) Motion Power:

$$P_m(m, v, a) = P_l + m(a + g\mu)v \tag{5}$$

where P_m is the motion power, P_l is the transformation loss, m is mass of the robot, g is the gravity constant, μ is ground friction constant, v and a are the linear speed and acceleration of the robot, respectively.

2) Sonar Power:

$$P_s(f_s) = c_0 + c_1 f_s \tag{6}$$

where P_s is the sonar power, f_s is the sensing frequency, c_0 and c_1 are two positive constants.

B. Market-Based Task Allocation Algorithm and Bidding Process

In this study, each robot $(MR_i, i = 1, \dots, n)$, where n is the number of robot in the team, has two roles in the market which are producer $(P_i, i = 1, \dots, n)$ and consumer $(C_i, i = 1, \dots, n)$. Each producer generates a task, calculates its price and announces the task with this price. Consumers supply goods or services to the producers. After the task announcement, the producer waits a predefined time for receiving the bids from the consumers. Then the producer determines the winner(s) by using auction clearing algorithms. If the task is not assigned to any consumer, it is added to the end of the task list of this producer. If the task is not assigned to any consumer after three announcements, it is removed from the task list. The sequence diagram of the bidding process is given in Fig. 1.

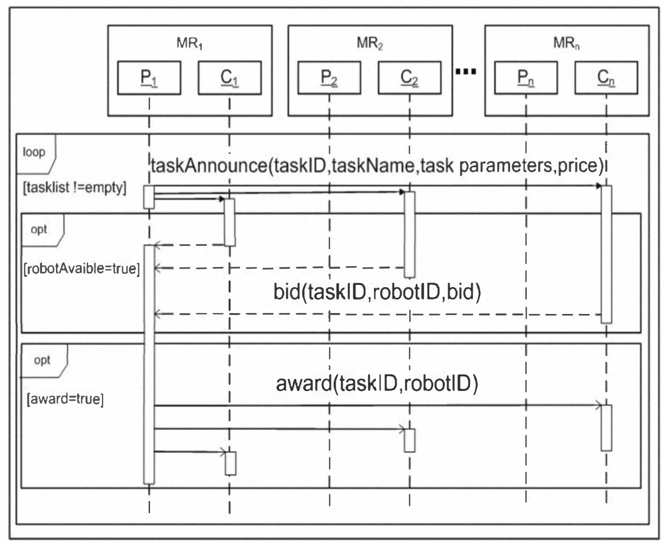

Figure 1. Sequence diagram of Bidding Process

Each consumer receives two kinds of messages (tasks or awards). The consumer evaluates the task messages first by considering the states of the robot whether there is an occupation (currently performing a task or charging). Then, the consumer compares the resources (abilities, tools) required for performing the task and its own resources. If it has enough resources and energy, the consumer calculates the cost of the task. The bid of a task is obtained by subtracting the cost from the price. The consumer starts to perform the task after receiving an award for this task. After the task is accomplished, the consumer controls its energy. If the energy is lower than a specified threshold, the consumer goes to a charging unit. Otherwise, it listens to the new task announcements.

C. Auction Clearing Algorithms

The determination of the winner is at the heart of the task allocation problems. This process is called auction clearing. In this study, two auction clearing methods are presented.

The first auction clearing algorithm is iterative auction clearing algorithm and was introduced by Gerkey and Mataric [19]. Each consumer submits a bid only for the task with the maximum bid value. Then the producer determines the maximum bid for each task. The new price of a task is calculated as old price minus maximum bid for that task. The new price is announced; new bids are received from the consumers. This process continues until the consumer and producer agree on the same price. Once the market is reached the equilibrium the awards are sent to winner consumers. The details of the algorithm are given in Fig. 2.

Iterative Auction Clearing Algorithm

```
while the market does not reach equlibrium then
  hold new prices as old prices
  for each task do
    find the maximum bid
    find the new price as old price minus maximum bid
  end for
  if all old prices and new prices are equal then
    find  minimum-profit robots for these tasks
    send awards
    delete the tasks from the task list
  else
    announce the tasks with new prices
  end if
end while
if there is a nonassigned task then
  push the task to the end of task list
end if
```

Figure 2. Iterative Auction Clearing Algorithm

The second one is the Highest-Bid Task for Robot (HBTR). In this algorithm, consumers send bid for each task that are available for them. Producer determines the task that having the highest bid is determined for each robot. Then, the bids are sorted from the highest to lowest. The robot and the task according to the highest bid are determined. If this robot has no assigned task or it is not at the charging unit, and the task is not assigned to another robot, the task is assigned to this robot. This procedure is applied for all bids. The proposed algorithm is given in Fig. 3.

HBTR Auction Clearing Algorithm

```
while there is at least one bid to evaluate do
  for each robot do
    find the maximum bid
  end for
  sort the bids from highest to lowest
  for each bid do
    find the task and robot corresponding to this bid
    if the robot has no assigned task then
      if the task is not assinged to another robot then
        send award to the robot
        update the award list
      end if
    end if
  end for
  remove the used bids
end while
if there is a nonassigned task then
  push the task to the end of task list
end if
```

Figure 3. HBTR Auction Clearing Algorithm

D. Hungarian Algorithms in Task Assignment

In this study, Hungarian algorithm is used to assign tasks to robots. In the task assignment, differently from assignment problem the objective function is in maximization form. The input matrix represents profits instead of costs and not all tasks can be performed by all robots. An example for profit matrix is given in Fig. 4.a. In this matrix, positive values represent the profit value if task v_i is assigned to robot u_j , and "0"s represents the task v_i that cannot be assigned to robot u_j. First, all positive values are subtracted from the greatest value of the matrix to transform the matrix maximization to minimization form. In the example matrix, greatest value is 6.5 and all positive values are subtracted from 6.5. Secondly, it is necessary to avoid undesired assignment. For this purpose a big number (∞) is assigned to unwanted assignment places. The transformed matrix of the example profit matrix is given in Fig. 4.b.

$$
\begin{bmatrix} 0 & 1.3 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 6.5 & 0 & 5 & 0 & 0 & 0 \\ 1.2 & 0 & 3 & 4 & 0 & 0 \\ 3.4 & 2 & 0 & 0 & 0 & 5 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}
\qquad
\begin{bmatrix} \infty & 5.2 & \infty & 4.5 & \infty & \infty \\ \infty & \infty & \infty & \infty & \infty & \infty \\ 0 & \infty & 1.5 & \infty & \infty & \infty \\ 5.3 & \infty & 3.5 & 2.5 & \infty & \infty \\ 3.1 & 4.5 & \infty & \infty & \infty & 1.5 \\ \infty & \infty & \infty & \infty & \infty & \infty \end{bmatrix}
$$

(a) (b)

Figure 4. **a)** Example profit matrix. **b)** Transformed matrix

For the sample matrix, assignments (task-robot) 1-2, 3-1, 4-4, 5-6 are obtained by using the Hungarian algorithm and the total profit for the given assignment is 16.8.

V. IMPLEMENTATION OF THE PROPOSED METHOD

A. Definitions of Tasks and Robots

The proposed method is applied by using three different tasks and six robots. The tasks are cleaning a room, carrying an object from one room to another, and monitoring a room for a specified time interval. Each type of task has three important features. The first feature is delicacy of the task. For example, the delicacy of a carry task varies according to the type of the object, such as, a crystal or a plastic object. The second feature is the priority of the task. The last feature is defined as the task completion time. Some tasks must be finished in a pre-specified time interval. In this study, tasks have two delicacy levels as low and high and three priorities as low, normal, and high. The high-level delicacy tasks are 30% of all tasks. Similarly, 30% of all tasks have task completion time feature. The normal-priority, low-priority and high-priority tasks are 60%, 20% and 20% of all tasks, respectively. In order to respond to these different kinds of tasks; the robot team must have high-degree heterogeneity. The robot team and the tasks used in the experiments are given in Table I. Clean1 and Clean2 represent the clean task with low and high delicacy, respectively. Carry and Monitor tasks are divided using the same notation to represent the tasks.

TABLE I. TASKS AND ROBOTS

Robots / Tasks	MR_1	MR_2	MR_3	MR_4	MR_5	MR_6
Clean1	✓	X	X	✓	X	X
Carry1	X	✓	X	X	✓	X
Monitor1	X	✓	✓	X	✓	✓
Clean2	✓	X	X	X	X	X
Carry2	X	✓	X	X	✓	X
Monitor2	X	X	✓	X	X	X

B. Determination of Price and Costs

The prices are determined by using the worst-case parameters. This ensures that all available robots bid for a task. The price of the task is calculated as the multiplication of the time required to perform the task and the total power of all resources on the robot. If the robot has any feature such as high delicacy or priority, the price is multiplied by a constant to increase the price. Because of the high price, the task requiring a feature becomes more attractive than the other tasks for the consumer. The cost of a task is calculated in the same manner except that the consumer uses its own parameters.

C. Applications

The algorithms in the proposed approach are coded in C++ and tested for the experimental environment (Fig. 5). In Fig. 5, there are seven rooms $(R_i, i = 1, \ldots, 7)$ and six mobile robots $(MR_j, j = 1, \ldots, 6)$. The dimension of each room is given in meters as $x \times y$. Each dot ($\bullet$) represents a node in the environment. The numbers above the dashed lines represent the distance between two nodes. Initially, the robots are at the rooms indicated by their names inside circles.

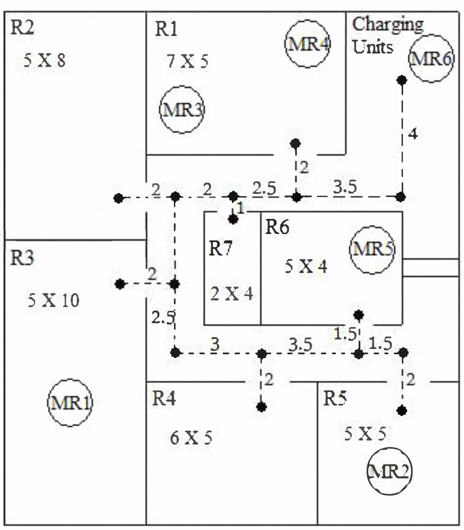

Figure 5. Experimental Enviroment

In the experiments, Pioneer 3-DX robots are used as the robot platform. There may be a SICK LMS200 laser rangefinder, Canon PTZ VC-C4 camera and gripper on a robot. Motion and sonar power are calculated using equations (5) and (6), respectively. The value for the parameters of these equations are $a = 0.6\, m/s^2$, $g = 9.8\, m/s^2$, $\mu = 0.02$, $P_l = 0.25\, W$, $c_0 = 0.51$, $c_1 = 0.0039$, $f_s = 40\, Hz$. The weight of the Pioneer 3-DX Robot Platform with batteries is 9 Kg, the laser rangefinder is 4.5 Kg, the camera is 0.375 Kg, and the gripper is 1.125 Kg. The power of the laser [20], camera [21], and gripper [22] are obtained from the official sites of the manufacturers of these devices. The powers of laser, camera, and gripper are 20, 12, and 12 Watts, respectively.

Each producer generates 30 tasks during the experiments. Each producer randomly generates approximately the same number of tasks for each type (cleaning, carrying and monitoring). The initial consumer parameters are given in Table II.

TABLE II. INITIAL ROBOT PARAMETERS

Robots / Parameters	MR_1	MR_2	MR_3	MR_4	MR_5	MR_6
Current Charge	20%	10%	40%	60%	50%	30%
Max Charge(kW-s)	300	300	300	300	300	300
Average Speed(m/s)	0.15	0.1	0.3	0.1	0.3	0.2
Grabbing Time(s)	0	5	0	0	5	0
Dropping Time(s)	0	5	0	0	5	0
Robot Location (Room)	3	5	1	1	6	0

VI. EXPERIMENTAL RESULT

The proposed auction clearing algorithms and Hungarian algorithm are compared in terms of percentage of completed tasks and communication overhead.

A. Percentage of Completed Tasks

The algorithms in the proposed approaches are tested over three hours. For each algorithm, tests are repeated 10 times. The percentages of the completed tasks are given in Fig. 6 to Fig. 8 for two auction clearing algorithms and Hungarian algorithm, respectively. In these figures, TCT represents the Task Completion Time. Priority1, priority2 and priority3 represent the priority orders as low, normal and high, respectively.

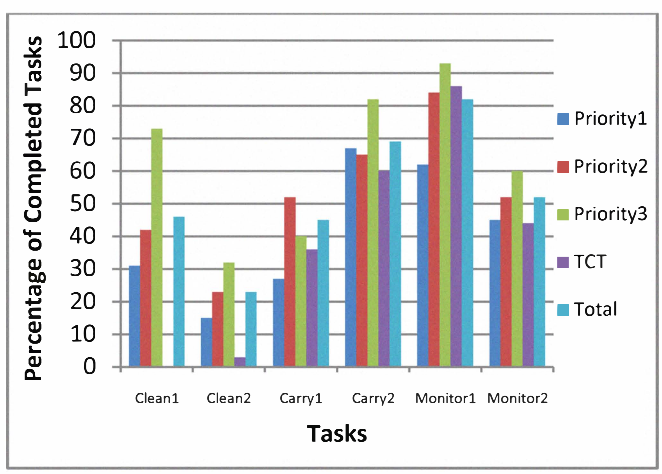

Figure 6. Test results for Iterative Auction Clearing Algorithm

In Fig. 6 and Fig.7, the results for iterative and HBTR auction clearing algorithms are shown, respectively. The results given in Fig. 6 and Fig. 7 are very similar. The only difference between these two algorithms is that the iterative algorithm approaches the solution slower than the HBTR. In the iterative algorithm, the auction clearing process continues task announcement sequences till both the consumer and the producer agree on the same price. During this process, the consumer that sends bid for a task may miss the possible tasks announced by other producers. In contrast, the HBTR assigns all the tasks at once and the robots with no assignments may send bids to the remaining tasks.

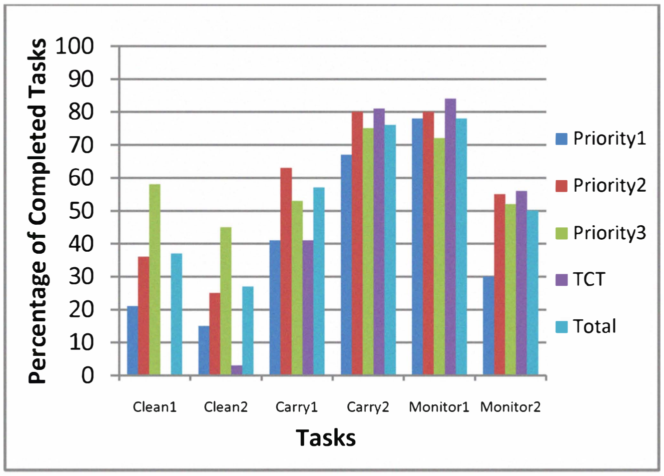

Figure 7. Test results for HBTR Auction Clearing Algorithm

Fig. 8 shows the results for the Hungarian algorithm. Since the HBTR attempts to assign the robots to the high-feature tasks, the percentage of the completed clean tasks for HBTR is better than the Hungarian algorithm as the task features increase. On the other hand, percentage of the total completed clean tasks is improved by the Hungarian algorithm. The same explanation is valid for carry tasks. However, the difference between the HBTR and the Hungarian algorithm in terms of percentage of completed tasks is smaller than clean tasks as the task features increase. Furthermore, improvement in the percentage of total completed tasks is greater for the Hungarian algorithm. For monitor tasks, the Hungarian algorithm improves both the total and high-feature completed tasks.

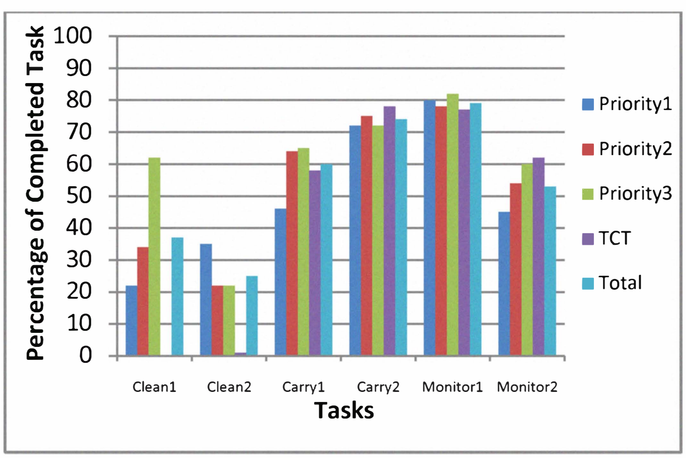

Figure 8. Test results for the Hungarian Task Assignment Algorithm

Finally, some of the tasks were not executed due to the lack of the resources. Clean tasks take more time than carry or monitor tasks. Additionally, the number of robots to perform all of the clean tasks is not enough. Therefore, a high percentage of clean tasks were not performed. Similarly, since monitor2 can be performed only by one robot (R3), the percentage of completed monitor2 tasks is low. Generally, the HBTR produces better solutions than the Hungarian algorithm as task features increase, except the monitor2 task. Since monitor tasks are less profitable than clean and carry tasks, the HBTR produces worse solutions than the Hungarian algorithm. In contrast, the percentage of total completed tasks by the Hungarian algorithm is higher than that of the HBTR.

B. *Communication Overhead*

Communication overhead is another criterion to evaluate the task allocation algorithms. Due to the fact that the iterative algorithm announces the task and receives the bids until the market reaches the equilibrium, the communication load increases. In contrast, the HBTR and the Hungarian algorithm generate the solutions for task allocation problem at the end of the one cycle. Therefore, the number of messages used in the HBRT and the Hungarian algorithm is less than the number of the messages used in the iterative algorithm. For each algorithm, the number of messages is given in Table III.

TABLE III. MESSAGES USED IN TRADING

Name of algorithm	Number of Message
Iterative	619
HBTR	410
Hungarian	413

VII. CONCLUSION

In this paper, market-based task allocation method is proposed. In the trading process, the energy model of the Pioneer 3-DX mobile robot platform is used. In the winner determination process, two auction clearing algorithms (Iterative and HBTR) and the Hungarian algorithm were presented and applied to the task allocation problem over three-hour-long scenario. The results show that the HBTR algorithm produces better solutions than the Iterative auction clearing algorithm and the Hungarian algorithm as the task features increase. However, the Hungarian task assignment algorithm improves percentage of completed total tasks. The communication load of the Hungarian algorithm and the HBTR is also better than the iterative auction clearing algorithm.

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