Market-based Multiagent Framework for Balanced Task Allocation

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Abstract This paper proposes a market-based multiagent task allocation framework for allocating tasks in a balanced manner based on the energy levels of robots. In this framework, a market-based agent is designed for trading tasks considering the robot capabilities, task requirements and energy level of the robot. The framework utilizes a bid weight for distributing the tasks in a balanced manner without frequent using of particular robots. To demonstrate the effectiveness of the proposed framework, a simulation experiment was carried out for a cleaning mission consisting of collecting, carrying, sorting and disposal tasks.

Key words: Multirobot coordination, Market-based task allocation, Balanced task allocation

1 Introduction

Market-based coordination approach for multirobot system has been developed with considerable popularity and it has been widely used in the areas of exploration and dynamic team formation [1, 2, 3, 4]. The concept of the market-based task allocation was started from the contract net protocol [5]. Many approaches have since adopted similar strategies for multiagent task allocation. Beaumont and Chaib-draa proposed to use multiagent planning and coordination techniques for resource management in command and control systems [6]. Dias proposed *Traderbots*, consisting of *OpTrader* and *RoboTrader* [7]. Gerkey and Mataric implemented an auction-based task allocation system, MURDOCH, where the publish/subscribe communication model was used for efficient resource usage [8]. Vokrinek et al. presented an abstract architecture of a multiagent solver consisting of three types of agents, task agent, allocation agent and resource agent [9].

Although there have been various researches on market-based approach, most of the market-based approaches did not take much consideration on distributing tasks in a balanced manner. In the proposed approach, two types of bid weights, global and local bid weights are defined for adjusting the relative importance of the task quality over task cost.

This paper is organized as follows. Section 2 defines atomic tasks and three types of compound tasks. In Section 3 and Section 4, bid and utility generation processes are described. The proposed framework is applied in a cleaning mission and simulation results are discussed in Section 5. Finally, concluding remarks and future work are described in Section 6.

2 Task Definition

In this framework, two levels of tasks, atomic and compound tasks, are defined. The atomic task is the minimum unit of a task which can not be divided into smaller subtasks. The compound task consists of the atomic tasks and three types of compound tasks, i.e., sequential, synchronous parallel, and asynchronous parallel compound tasks, are defined.

The sequential compound task requires the atomic tasks to be performed sequentially. The ith sequential compound task in a mission, $Task^{i,S}$, $i \in \{1, 2, ..., M\}$, is defined as

$$Task^{i,S} = \{task_1^{i,S}, task_2^{i,S}, ..., task_v^{i,S}\} \tag{1}$$

with

$$task_j^{i,S} \in Task^A, \;\; task_j^{i,S} \succ task_k^{i,S} \;\; (j < k)$$

where M and v are the number of compound tasks in the mission and the number of atomic tasks in $Task^{i,S}$, respectively, $Task^A$ is the set of atomic tasks, and $task_j^{i,S} \succ task_k^{i,S}$ denotes that the priority of $task_j^{i,S}$ is higher than $task_k^{i,S}$. The priority of the atomic task in the sequential compound task represents the execution order.

The synchronous parallel compound task consists of the atomic tasks that should be performed in parallel with synchronized manner. The ith synchronous parallel compound task in the mission, $Task^{i,SP}$ is defined as

$$Task^{i,SP} = \{task_1^{i,SP}, task_2^{i,SP}, ..., task_h^{i,SP}\} \tag{2}$$

with

$$task_j^{i,SP} \in Task^A, \;\; task_j^{i,SP} \succeq task_k^{i,SP} \;\; (j < k)$$

where h is the number of the atomic tasks in $Task^{i,SP}$. The priority of the atomic tasks in the synchronous parallel compound task represents the master and slave relationship such that the robot which gets the atomic task with higher priority becomes a master which takes the initiative in task execution.

The asynchronous parallel compound task consists of the atomic tasks that can be performed asynchronously in parallel. Unlike the synchronous parallel compound task, a single robot can perform one or more atomic tasks of the asynchronous parallel compound task as far as it can perform the atomic tasks in parallel. The ith asynchronous parallel compound task in the mission, $Task^{i,AP}$ is defined as

$$Task^{i,AP} = \{task_1^{i,AP}, task_2^{i,AP}, ..., task_y^{i,AP}\} \quad (3)$$

with

$$task_j^{i,AP} \in Task^A, \;\; task_j^{i,AP} \succeq task_k^{i,AP} \;\; (j < k)$$

where y is the number of the atomic tasks in $Task^{i,AP}$. The priority of the atomic tasks in the asynchronous parallel compound task represents the master and slave relationship which is similar to the case of the synchronous parallel compound task.

3 Bid Generation

The bid is defined as the list of the task quality, task cost and normalized energy level of the bidder. The bid of a robot for a task is calculated by the capabilities of the robot and the requirement of the task.

3.1 Robot Capabilities and Task Requirements

To describe the robot capabilities and task requirements, the robot capability matrix and task requirement matrix are provided [10]. The robot capability matrix consists of capability vectors and each capability vector contains the information about the quality and energy consumption rate of the capability which are defined by the hardware resource of the capability. The robot capability matrix of the ith robot, $Robot_i$, R_i^{cap}, $i = 1, 2, ..., n$, is defined as

$$R_i^{cap} = [cap_{i1} \; cap_{i2} \; ... \; cap_{im}] \quad (4)$$

where n and m represent the number of the robots and capabilities, respectively, and the kth capability vector of $Robot_i$, cap_{ik}, $k = 1, 2, ..., m$, is defined as

$$cap_{ik} = [q_{ik} \; e_{ik} \; p_{ik}]^T \quad (5)$$

where q_{ik} ($0 \leq q_{ik} \leq 1$) is the capability quality, and e_{ik} ($e_{ik} \geq 0$) and p_{ik} ($p_{ik} \in \{0, 1\}$) represent the energy consumption rate and its unit, respectively. If p_{ik} is set to one, the unit of e_{ik} is set to J/m, and if p_{ik} is zero, the unit is set to J/s. The robot should be able to monitor its capabilities in real time to make sure they are operating properly.

The task requirement matrix consists of requirement vectors. Each robot has the task requirement matrices such that when one of the tasks is auctioned, the robot searches for the task and gets the task requirement matrix of the task. The task requirement matrix of the jth atomic task, $task_j$, T_j^{req}, $j = 1, 2, ..., l$, is defined as

$$T_j^{req} = [req_{j1} \; req_{j2} \; ... \; req_{jm}] \tag{6}$$

where l represents the number of the atomic tasks, and the kth requirement vector of T_j^{req}, req_{jk}, $k = 1, 2, ..., m$, is defined as

$$req_{jk} = [h_{jk} \; w_{jk}^{cap}]^T \tag{7}$$

where h_{jk} ($h_{jk} \in \{0, 1\}$) denotes the requirement of the kth capability for $task_j$, which is set to one if the kth capability is required for the task and zero if not, and w_{jk}^{cap} ($0 \leq w_{jk}^{cap} \leq 1$) is the capability weight which decides the importance of the capability quality on the task.

3.2 Bid Values

The task quality of a robot represents how well it can perform the auctioned atomic task in terms of the quality. The task quality of $Robot_i$ for $task_j$, Q_{ij} is defined as

$$Q_{ij} = \sum_{k=1}^{m} h_{jk} \cdot w_{jk}^{cap} \cdot q_{ik} \tag{8}$$

where h_{jk} and w_{jk}^{cap} are from (7), and q_{ik} is from (5). The equation implies that if the bidder has high qualities for the required capabilities, it can get high task quality for the task.

The task cost is defined as the estimated energy consumption of the bidder to complete the auctioned atomic task. The task cost of $Robot_i$ for $task_j$, C_{ij} is defined as

$$C_{ij} = \alpha_{ij} \cdot d_{ij} + \beta_{ij} \cdot t_{ij} \tag{9}$$

with

$$\alpha_{ij} = \sum_{k=1}^{m} h_{jk} \cdot p_{ik} \cdot e_{ik} \tag{9.a}$$

$$\beta_{ij} = \sum_{k=1}^{m} h_{jk} \cdot (1 - p_{ik}) \cdot e_{ik} \tag{9.b}$$

where α_{ij} and β_{ij} are the energy consumption rate per meter and per second, respectively, d_{ij} and t_{ij} are the estimated travel distance and estimated time, respectively, h_{jk} is from (7), and p_{ik} and e_{ik} are from (5).

The normalized energy level of the robot is used to consider the energy level of the robot in task allocation. The auctioneer is able to consider the normalized energy level of each bidder or the sum of the normalized energy levels of the bidders to adjust the relative importance between the task quality and task cost, and distribute tasks in a balanced manner. Since the robots might have different energy capacities, the energy level of each robot is normalized. The normalized energy level of $Robot_i$ for $task_j$, L_{ij} is defined as

$$L_{ij} = \frac{E_i - C_i(A_i, j) - E_i^{Min}}{E_i^{Max} - E_i^{Min}} \tag{10}$$

where E_i, E_i^{Min} and E_i^{Max} are the current, minimum and maximum energy level of $Robot_i$, respectively, and $C_i(A_i, j)$ represents the estimated energy consumption of the robot for the tasks in the set A_i and $task_j$.

4 Utility Generation

Utility represents the bidder's fitness on the auctioned atomic task. The utility is the weighted sum of task quality and task cost. The bid weight is used to adjust the relative importance of task quality over task cost.

4.1 Bid Weight

The proposed framework provides two types of bid weights, global and local bid weights. The function type of the global bid weight for $task_j$, $w_{glo}^{bid}(G_j)$ is defined as

$$w_{glo}^{bid}(G_j) = \alpha \cdot exp(\lambda \cdot (G_j - 1)) \tag{11}$$

with

$$G_j = \frac{\sum_{i=1}^{b} L_{ij}}{b} \tag{11.a}$$

where α is the initial value of the bid weight, λ is the decrease rate, b is the number of the bidders, and L_{ij} is the normalized energy level of $Robot_i$ for $task_j$ from (10).

When the local bid weight is used, the bid weight generation module calculates each bidder's bid weight based on the bidder's normalized energy level. The local bid weight of $Robot_i$ for $task_j$, $w_{loc}^{bid}(L_{ij})$ is defined as

$$w_{loc}^{bid}(L_{ij}) = \alpha \cdot exp(\lambda \cdot (L_{ij} - 1)) \tag{12}$$

where α and λ are the initial value of the bid weight and the decrease rate, respectively. In the system with the local bid weight, if the bidder has higher normalized energy level than others, the auctioneer considers that the bidder has not worked as much as others and the bidder is able to perform a task qualitatively since it still has energy to spare. This enables the system to allocate tasks in a balanced manner.

4.2 Utility

The utility is generated by using the bid values and the bid weights. The utility of $Robot_i$ for $task_j$, U_{ij} is defined as

$$U_{ij} = 0.5 \cdot (w^{bid} \cdot \hat{Q}_{ij} - (1 - w^{bid}) \cdot \hat{C}_{ij} + 1.0) \tag{13}$$

with

$$\hat{Q}_{ij} = \frac{Q_{ij}}{\sum_{i=1}^{b} Q_{ij}} \tag{13.a}$$

$$\hat{C}_{ij} = \frac{C_{ij}}{\sum_{i=1}^{b} C_{ij}} \tag{13.b}$$

where w^{bid} ($0 \leq w^{bid} \leq 1$) is the bid weight which can be set either as the global or local bid weight, $\hat{Q}_{ij}$ and $\hat{C}_{ij}$ are the normalized task quality and normalized task cost, respectively, and b is the number of the bidders. In the equation, 0.5 and 1.0 are used to set the range of the utility as $0 \leq U_{ij} \leq 1$.

5 The Case of a Cleaning Mission

To demonstrate the effectiveness of the proposed framework, a simulation experiment was carried out for a cleaning mission. The cleaning mission consists of several compound tasks and the robots work together to allocate and execute the compound tasks.

5.1 Heterogeneous Robots

For the mission, the eight heterogeneous robots with different kinds of capabilities are defined. There are five capabilities, localization, color recognition, mobility, gripper, and block storage. Each of them has different characteristics depending on the hardware resource as shown in Table 1. In the table, q, e and p are the capabil-

Table 1 Five Capability Vectors With Different Hardware Resources

Capability	Hardware resource	q	e	p
LOC	*LRF*	0.9	30.0	0
	USS	0.6	10.0	0
COL	*HQC*	0.9	3.0	0
	LQC	0.6	1.5	0
MOB	*OD*	0.9	210.0	1
	DD	0.6	150.0	1
$GRIP$	*RH*	1.0	2.0	1
$STOR$	*RS*	1.0	0.0	0

ity quality, energy consumption rate and its unit, respectively from (5), and LOC, COL, MOB, $GRIP$ and $STOR$ are the localization, color recognition, mobility, gripper and storage capabilities, respectively, and *LRF*, *USS*, *HQC*, *LQC*, *OD*, *DD* *RH* and *RS* are the laser range finder, ultrasonic sensors, high quality camera, low quality camera, omni-directional drive, differential drive, robot hand and robot storage, respectively. The gripper capability is used to pick up a block, and the block storage capability enables a robot to store the blocks. Since the storage capability does not use any kinds of active actuators, it does not consume any energy.

The hardware resources of the robots for their capabilities are shown in Table 2.

Table 2 Hardware Resources of The Robots

	LOC	COL	MOB	$GRIP$	$STOR$
$Robot_1$	*LRF*	*HQC*	*OD*	*RH*	N/A
$Robot_2$	*LRF*	*LQC*	*OD*	*RH*	N/A
$Robot_3$	*LRF*	*HQC*	*DD*	*RH*	N/A
$Robot_4$	*LRF*	*LQC*	*DD*	*RH*	N/A
$Robot_5$	*USS*	N/A	*DD*	N/A	*RS*
$Robot_6$	*USS*	N/A	*OD*	N/A	*RS*
$Robot_7$	*LRF*	N/A	*DD*	N/A	*RS*
$Robot_8$	*LRF*	N/A	*OD*	N/A	*RS*

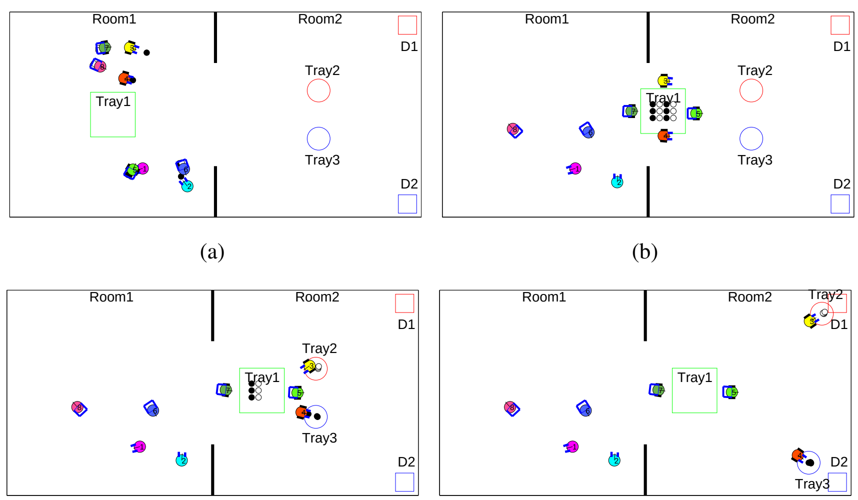
5.2 Compound Tasks

There are four compound tasks in the mission, block collecting task ($Task^{1,AP}$), tray carrying task ($Task^{2,SP}$), white block cleaning task ($Task^{3,S}$), and black block cleaning task ($Task^{4,S}$). The descriptions of the atomic tasks of the four compound tasks are summarized in Table 3. To complete the mission, the mixed blocks should be sorted by their color, and the trays with the sorted blocks, $Tray_2$ and $Tray_3$, should be carried in designated zones, D_1 and D_2, respectively, as shown in Fig. 1(c) and 1(d). Since the block sorting task should be completed before the tray carrying task, the white and black block cleaning tasks are defined as the sequential compound tasks, $Task^{3,S}$ and $Task^{4,S}$, respectively. The white and black block sorting atomic tasks are defined as $task_1^{3,S}$ and $task_1^{4,S}$, respectively, and $Tray_2$ and $Tray_3$ carrying atomic tasks are defined as $task_2^{3,S}$ and $task_2^{4,S}$, respectively.

For each compound task, the task requirements of the atomic tasks are defined using the task requirement matrices as in Table 4. In the table, $task_{All}^{2,SP}$ represents all of the atomic tasks in $Task^{2,SP}$. Since they require the same capabilities, the task capability matrices of them are also identical.

Table 3 Descriptions of The Atomic Tasks In The Mission

		Description
$Task^{1,AP}$	$task_1^{1,AP}$	Finding and picking up blocks in $Room_1$
	$task_2^{1,AP}$	Carrying blocks to $Tray_1$
$Task^{2,SP}$	$task_1^{2,SP}$	Carrying the front of $Tray_1$ to $Room_2$
	$task_2^{2,SP}$	Carrying the back of $Tray_1$ to $Room_2$
	$task_3^{2,SP}$	Carrying the left of $Tray_1$ to $Room_2$
	$task_4^{2,SP}$	Carrying the right of $Tray_1$ to $Room_2$
$Task^{3,S}$	$task_1^{3,S}$	Sorting white blocks to $Tray_2$
	$task_2^{3,S}$	Carrying $Tray_2$ to D_1
$Task^{4,S}$	$task_1^{4,S}$	Sorting black blocks to $Tray_3$
	$task_2^{4,S}$	Carrying $Tray_3$ to D_2



(a) (b)

(c) (d)

Fig. 1 (a) Robots collect the blocks in $Room_1$ to $Tray_1$. (b) Four robots work together to carry $Tray_1$ to $Room_2$. (c) Two robots sort white and black blocks. (d) After sorting, trays are carried to designated places.

5.3 Simulation Results

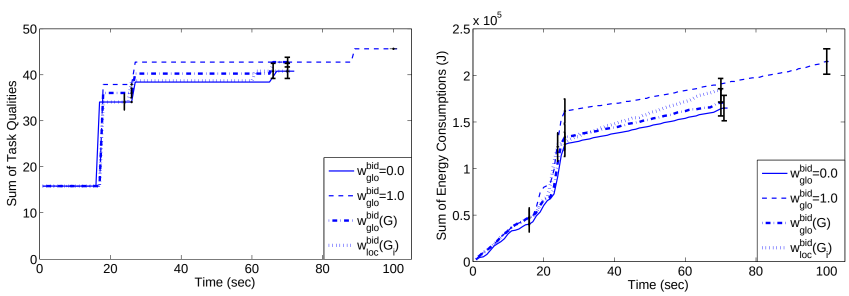
In the simulation experiment, robots completed the mission with four different types of bid weights, $w_{glo}^{bid} = 0.0$, $w_{glo}^{bid} = 1.0$, $w_{glo}^{bid}(G)$ and $w_{loc}^{bid}(G_i)$. In the experiment, α and λ from (11) and (12) were set to 0.9 and 6.0, respectively. For each bid weight,

Table 4 Task Requirement Matrices of The Atomic Tasks

		LOC	COL	MOB	$GRIP$	$STOR$
$task_1^{1,AP}$	h	1	1	1	1	0
	w^{cap}	0.5	0.8	0.5	1.0	0.0
$task_2^{1,AP}$	h	1	0	1	0	1
	w^{cap}	0.7	0.0	0.5	0.0	1.0
$task_{All}^{2,SP}$	h	1	0	1	0	0
	w^{cap}	1.0	0.0	0.8	0.0	0.0
$task_1^{3,S}$	h	1	1	1	1	0
	w^{cap}	0.5	0.8	0.5	1.0	0.0
$task_2^{3,S}$	h	1	0	1	0	0
	w^{cap}	0.8	0.0	0.8	0.0	0.0
$task_1^{4,S}$	h	1	1	1	1	0
	w^{cap}	0.5	0.8	0.5	1.0	0.0
$task_2^{4,S}$	h	1	0	1	0	0
	w^{cap}	0.8	0.0	0.8	0.0	0.0

the mission was performed five times, and the blocks in $Room_1$ were randomly scattered for each trial.

Fig. 2 shows the sum of the task qualities and the sum of energy consumptions of the robots with different types of bid weights. In the case of using $w_{glo}^{bid} = 0.0$, the

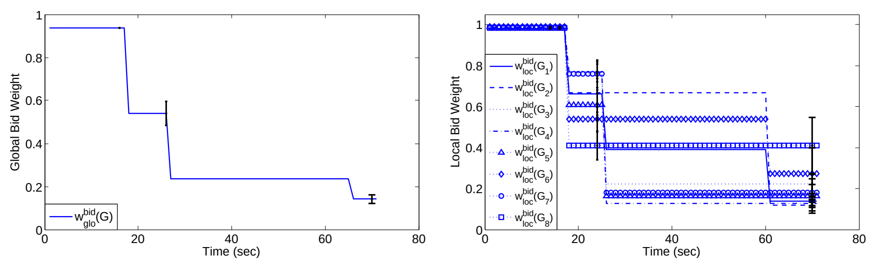


(a) (b)

Fig. 2 The result of the mission with different types of bid weights. (a) Sum of the task qualities. (b) Sum of the energy consumptions.

system tried to minimize the sum of task costs such that it was able to minimize the sum of the energy consumptions as shown in Fig. 2(b). However, the sum of task qualities was worse than any other cases as shown in Fig. 2(a). It implies that the auctioneer allocated tasks to the bidder which can perform the task with lowest task cost regardless of its task quality. Likewise, the system using $w_{glo}^{bid} = 1.0$ was able to maximize the sum of task qualities, while it consumed more energy than any other cases.

To compare the results with $w^{bid}_{glo}(G)$ and $w^{bid}_{loc}(G_i)$, the changes of the bid weights during the mission were measured as shown in Fig. 3. When $w^{bid}_{glo}(G)$ was used, the result was similar to the case with $w^{bid}_{glo} = 1.0$ during the early stage of the mission. As the mission progressed, however, the result was getting close to the result with $w^{bid}_{glo} = 0.0$. It was because of the decrease of the sum of the normalized energy levels caused the decrease of the global bid weight as shown in Fig. 3(a). The result with w^{bid}_{loc} did not show any specific tendency like the other cases. This was because the local bid weight was decided by each bidder's normalized energy level. Fig. 3(b) shows the changes of the local bid weights of the robots during the mission where the differences between the local bid weights were reduced as the mission progressed. The reduction of the differences between the local bid weights



(a) (b)

Fig. 3 The changes of bid weights. (a) $w^{bid}_{glo}(G)$. (b) $w^{bid}_{loc}(G_i)$.

implies that the tasks were distributed in a balanced manner such that most of the robots were assigned tasks and worked with consuming their energy.

The energy levels of the robots with four types of bid weights were measured as shown in Fig. 4. In the case of using $w^{bid}_{glo} = 0.0$, when robots performed $Task^{AP}_1$, the robots with next to each other organized a team to minimize energy consumptions. As a result, four sub-teams, $Robot_1$ with $Robot_5$, $Robot_2$ with $Robot_6$, $Robot_3$ with $Robot_7$, and $Robot_4$ with $Robot_8$ were organized and worked together to complete $Task^{1,AP}$. Likewise, the robots which could minimize the overall cost for $Task^{SP}_2$ worked together to complete the task. For $Task^{S}_3$, $Robot_3$ and $Robot_4$ which had performed $Task^{SP}_2$ worked together until the mission was completed since they were the closest robots which can perform block sorting and tray carrying. As a result, $Robot_3$ and $Robot_4$ worked more than others.

In the case of using $w^{bid}_{glo} = 1.0$, the robots with high task qualities organized a team for $Task^{1,AP}$ and $Task^{2,SP}$. $Robot_1$ worked together with $Robot_8$ and $Robot_4$ worked together with $Robot_5$ although the initial positions between them were not close. After completing $Task^{2,SP}$, $Robot_1$ took the rest of the tasks since it had the highest task qualities for the tasks although its energy level was relatively

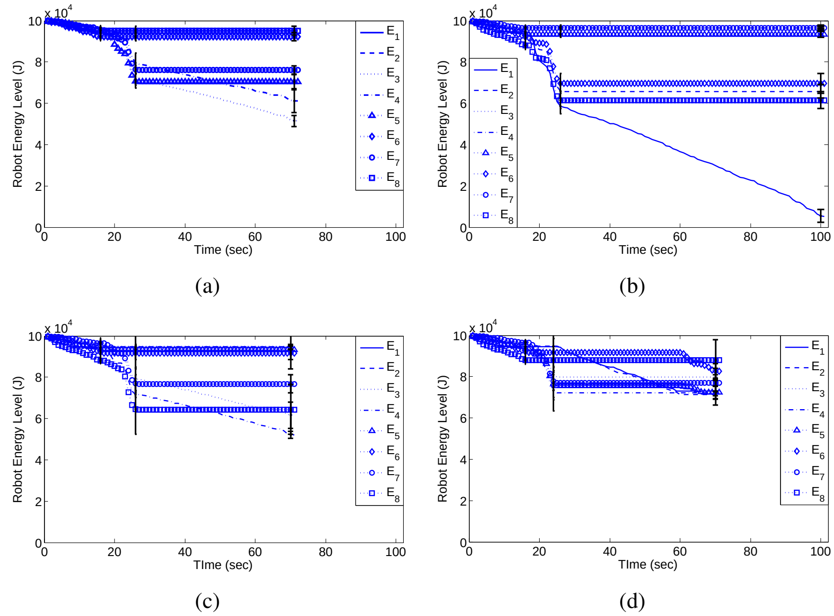


Fig. 4 The energy levels of the robots. (a) $w_{glo}^{bid} = 0.0$. (b) $w_{glo}^{bid} = 1.0$. (c) $w_{glo}^{bid}(G)$. (d) $w_{loc}^{bid}(G_i)$.

lower than others. As a result, the differences of the energy levels of the robots were increased at the end of the mission as shown in Fig. 4(b). In the case of using the function type global bid weight, the results of task allocations were similar to the case with $w_{glo}^{bid} = 1.0$. However, as the mission progressed, the result of task allocations became similar to the case with $w_{glo}^{bid} = 0.0$. This was because of the decrease of the sum of the normalized energy levels of the robots. As a result, the differences of the energy levels of the robots at the end of the mission was similar to the result from $w_{glo}^{bid} = 0.0$ as shown in Fig. 4(c). In the case of using the local bid weight, most of the normalized energy levels of the robots were decreased evenly as shown in Fig. 4(d). There was no remarkable energy decrease of any specific robot such as $Robot_1$ in the case with $w_{glo}^{bid} = 1.0$ or $Robot_3$ and $Robot_4$ in the case with $w_{glo}^{bid} = 0.0$ and $w_{glo}^{bid}(G)$, and the size of the differences between the energy levels of the robots was lower than any other cases. It implies that the system with the local bid weight is able to distribute the tasks in a balanced manner.

6 Conclusion

This paper proposed a market-based multiagent task allocation framework for bid adjustment and balanced task allocation. The proposed framework was applied to the cleaning mission and the results with different types of bid weights were compared in a simulation experiment. In the case of using the global bid weight, the system was able to adjust the relative importance between maximizing the sum of task qualities and minimizing the sum of energy consumptions, while it did not guarantee the balanced task allocation since the identical global bid weight was applied to calculate all of the utilities of the bidders. On the other hand, the system with the local bid weight was able to distribute the tasks in a balanced manner considering each individual's normalized energy level, while the overall profits such as maximizing the sum of task quality and minimizing the sum of energy consumptions were not as good as the system with the global bid weight.

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