

Bacterial Foraging Optimization Building Block Distribution Algorithm Based Dynamic Allocation in Multiple Robotic System

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Abstract

Robots are effectively utilized in various applications by using ambient assisted living techniques for improving people lifestyle. Especially, in healthcare centers, robots are played a vital role instead of using supporting staff. The healthcare application needs to process multiple tasks at one time, for that reason, multiple robots' systems are designed to handle the tasks. The task must be dynamically allocated for each robot dynamically allocated for each robot for improving the performance of the robots. For achieving this goal, this paper introduces the bacterial Foraging Optimization building block distribution algorithm is used to allocate the work to robots heterogeneously. This algorithm allocates the resources and tasks to the robot for performing their process with a specific time and minimum computation complexity. Then the efficiency of the system is evaluated using experimental analysis and results are compared with existing methods.

1. Introduction

Ambient Assisted Living (AAL)[1] played a vital role in independent life in the developing techniques the AAL consists of various devices that used to provide a safe and healthy life for an older person in their home or place. The AAL includes the various wireless networks, smart devices, medical sensors, software applications which helps to age people lives their life without making any difficulties. In addition to this, AAL smart devices [2] are providing the self-dependent, easier and some extent lifestyle using various developing techniques. The created AAL devices are integrated with the environment because it is one of the users centric one which provides the older adults to maximize their wellness, prevent their difficulties, curing their disease without requiring other people support. Due to the changes in the demographic is the main reason to develop AAL technologies [3] for supporting the people. The created AAL process having several benefits such as switch off the kitchen fires, fan, protect against burglary, turn of light, smart smoke detector, smart thermostat, control music player and self-learning system. In addition to these discussed benefits, the AAL system having several benefits [4] such as provide education to the caregivers via ambient assisted living, emergency response system, mobility, disease management, providing health signals via smartphone, pill dispensers and assistive robots. Among the various AAL technology, assistive robots are one of the important concepts because it successfully eliminates the physical limitation of older persons [5] in-home and other applications. The AAL assistive robot supports the people from carrying their daily routine activities and helps to balance the social life. The created AAL assistive robots guide several basic activities [6] which are listed as follows.

- Guiding daily living activities such as grasping household objects, feeding, dressing, grooming, wheelchair to bed pickup, objects picking, etc.
- IADL activities or instrumental activities of daily living such as consumption of food, medicine, movement, hygiene maintenance, specialization function called stethoscope pick up and so on.
- EDAL activities such as enhanced activities of daily living which include the learning, hobby and another category. In addition to this, the emotional level of interaction also comes under this activity.

- Other activities in which robots are helping in telepresence, monitoring person activities, makes caregiver stress free.

From the listed activities of assistive robots, it depicted that robots need to perform multiple tasks at one time. Due to this reason, robots are created and designed to handle multiple tasks [7]. According to the discussion, the assistive robots doing multiple tasks are described in Fig. 1.

From Fig. 1, it clearly illustrated that the assistive robots having several tasks [8] in healthcare application. Due to the multiple tasks, the robots are instructed to perform their task without making any difficulties. For this purpose, assistive robots are designed and the task needs to be distributed correctly for enhancing their performance. During this process, multiple robots have participated in the healthcare application but it has several problems. The first problem is which robot is assigned to complete the specific task [9] because some robots are busy with some other task. This leads to creating the high execution time so, the optimization process should be considered to reduce the makespan or completion time. To reducing is allocation issues, tasks are allocated to the robot according to their behavior. Then the generalized task allocation for robots is listed in Table 1.

Table 1: Multi-robot task allocation problem based mathematical analysis

S. No	Problem statement- optimization criteria is defined as μ_{ij}
1	$\sum_{i \in N} x_{ij} = 1 \quad \forall i \in M,$
2	$\sum_{j \in M} x_{ij} = 1 \quad \forall i \in N$
3	$x_{ij} = \{0,1\}, \forall i \in N, \forall j \in M$
	N is the number of robots; M is a task present in the hospital environment.

From Table 1, clearly shows that task allocation [10] process must be considered both the number of tasks involved in the system as well as several robots in the environment. In addition to this, the task must be allocated a dynamically by considering the robot behavior. To overcome this task allocation problem in this work bacterial foraging optimization building block distribution algorithm is introduced. The effective computation of robot utilities such as gain, time, combination work the task and resources are allocated with minimum complexity. Then the efficiency of introduced optimized algorithm based simulating results is evaluated using experimental results and discussion which is described in Sect. 4.

The rest of the paper is organized as follows, Sect. 2 analyze the few researcher opinions regarding the task allocation process for robots, Sect. 3 deals about the bacterial foraging optimization building block distribution algorithm-based task allocation process. Section 4 analyzes the introduced system efficiency and concludes in Sect. 5.

2. Related Works

This section discusses the various researchers' work about the robotic task allocation process. (Dong-HyunLee et al., 2018) [11] introducing the resource-based task allocation process for allocating the task to the multi-robot systems. During this process, tasks and respective resources are continuously examined to operate. In this process, task performance is continuously examined by robots for estimating the different combinations of resource level which is performed according to the refill station. The continuous assessment of resources reduces the waste of time for completing the specific task. This process is repeated continuously until to perform the task by multiple robots. Then the efficiency of the system is evaluated using experimental results such as resource consumption rate, task completion time, communication overhead.

(Aranda López et al., 2019) [12] creating an effective multi-task allocation system using assistive robots in a domestic application. The introduced system's ability to resolve the multi-robot task allocation problem by using the heterogeneous collection of robots. During this process, inter-task information is collected and reported to perform the effective task allocation process. The task constraints, resources are allocated according to the auction algorithm which successfully manages the user constraint. With the help of this auction algorithm, AURORA domestic project is createdina flexibly. At last, the efficiency of the system is evaluated using experimental analysis which is integrated with the task assignation process.

(Kyle E.C. Booth et al., 2017)[13] analyzing the person's task and planning in residents for supporting the retirement people in a home which is done by using assistive robots. Initially, multi-robot task planning and execution architecture are created to perform the heterogenous task by making the interaction between the users. According to the created architecture, robots are trained to perform the task according to the schedule in a day. After that, the developed robots are continuously questioned the users regarding their availability and interest. Based on the retired person's interest, involvement, activities the robots are performed their task to meet the user's entire requirement effectively. Then the efficiency of the system is evaluated with different user requirements and allocation processes.

(Vinagre M. et al., 2020)[14] creating the multi-robot platform to allocate the resources and perform the task in the intelligent systems. In this process, the system continuously examines the agents, elements present in the environment for predicting the behavior of the task and user needs. Based on the agents and elements, dynamic context and actuation plans are executed. This process is repeated continuously to execute the task by robots and the efficiency of the system is evaluated using simulation results.

(Yuan, Q., et al., 2013)[15] developing the multi-robot task allocation process using contract net protocol along with the neural network approach. During the task allocation process, when the robots are having more bids then robots difficult to execute the task. For overcoming this process, backpropagation neural network with contract net protocol is introduced to manage the robot fuse and decide which robots execute the task effectively. Finally, the system efficiency is evaluated using experimental results.

(Coline Devin et al., 2016)[16] introducing the reinforcement learning algorithm for performing the multi-task and multi-robot transfer process. The reinforcement learning process trains the robotic skills using different policies, classes and training information. Based on the policies robots are trained according to the robot specific modules and task-specific modules. During the training process, task-specific modules are shared by multiple robots and the robot's specific modules are shared by different tasks of robots. This task-sharing detail consists of perception between robots and the sharing robot's information includes the kinematics and dynamics between the tasks. The efficiency of the system is evaluated using the non-visual and visual simulation results.

According to the above researcher's opinion and discussion, the task has been distributed to the robots according to their behavior, elements and so on. By considering the above research opinion, in this work, the bacterial Foraging Optimization building block distribution algorithm is used to allocate the work to robots heterogeneously. The detailed explanation of the work is discussed in Sect. 3.

3. Dynamic Allocation Of The Task In The Assistive Robotic System

This section discusses the dynamic allocation of a task in the assistive robotic system in the health care application. Depending on the research analysis multiple task allocation problem is overcome by applying the optimized building block distribution algorithm. Before allocating the resources and tasks, the robotic utilities [17] are computed. The utility factor computes the fitness of robots for a specific task. In general, every robot has a specific capacity to perform the task which has the utility value that is represented as μ_{rt} . So, the robot utility value for a task is calculated using Eqn (1).

$$\mu_{rt} = \begin{cases} q_{rt} - c_{rt} & \text{if the } t \text{ is executed by robot } r \\ \infty & \text{otherwise} \end{cases} \quad (1)$$

In a (1) μ_{rt} is represented as a utility value of robot (r) on task (t).

q_{rt} is denoted as the quality of task performing by the robot (r)

Cost for performing the task is represented as c_{rt}

From the computation of Eqn (1) μ_{rt} value, the task is allocated to the robot to different categories [18] which are listed as follows.

Category 1:

- The robots are identified according to their utility and the single or several tasks are assigned at the same time.
- The tasks are identified first and it will be allocated to a single robot or several robots at the same time.
- The tasks are allocating to the robot according to the current as well as future needs and information.

Category 2:

- Allocating the task by examining the interdependency between the task and robots.

- Assign the task according to category 1 and considering the interdependency between the task and robot (No-dependency, cross schedule dependence (utility of task and robot does not only depend on schedule), in schedule dependence (utility of task and robot must have dependency in schedule) and complex dependency (the schedules are dynamic)).

Category 3:

- In this category, the task is allocated according to category 1 but divided according to the time extended assignment process.
- The allocation of the task must be considered on time, robot utility and synchronization between tasks and robots.

By considering these three categories, tasks are allocated to robots in a dynamic manner which is done by applying the bacterial Foraging Optimization building block distribution algorithm (BFOBBD). This distribution algorithm is one of the effective probabilistic modeling building stochastic optimized algorithm [19]. The algorithm searches optimized robots from the search space and helps to get the candidate solution. Initially, the robots are analyzed by the utility factor to choose the admissible solution and finally, the globally optimal solution (correct robots) is selected to perform the task. According to the discussion, the general searching process of the distribution algorithm is described in table 2.

Table 2
General Steps for distribution algorithm

Initialize t (task), robots(r), model
T = 0;
Initialize the model to denote the distribution of tasks to get the optimal solution.
While (perform until to meet the termination condition) do
L: generate the candidate solution from model m(t)
G: analyze the solutions present in L
M(t + 1) = adjust model (L,G, m(t))
T:t + 1

Based on the above table 2, the distribution algorithm selects the optimized robots from the multiple robots present in the hospital environment. By considering this algorithm step, the multivariate factorization process is applied to get the dependency [20] between the task and robots and the decisions are taken in the model. During the factorization process, a joint probability distribution is computed which is multiplied with multivariate marginal distribution value. This distribution value helps to determine the interdependence between the task and robots. This dependency computation process satisfies the category 2 type of task allocation process. Let assume $T = \{T_1, T_2, \dots, T_\Psi\}$ is the subset of a task in which every t is belonged to T is linkage set. The task t consists of several variables that are denoted as $|t| \leq K$. Then the factorized joint probability distribution value of t is estimated as follows,

$$p(X_1, X_2, \dots, X_N) = \prod_{t \in T} p(t) \quad (2)$$

During the probability distribution estimation process, the linkage learning process is applied to identify the link between the robots and the task. The linkage learning process is done by two measures such as model complexity and compressed population complexity. The model complexity measure computes the size of bits needed to save the entire marginal probability value of task t which is estimated using Eqn (3).

$$\text{Model complexity} = \log_2(\lambda + 1) \sum_{t \in T} (2^{|t|-1}) \quad (3)$$

After computing the model complexity of the task, the entropy value of the task is estimated using the number of tasks involved in the search area λ , $|t|$ is denoted as the number of decision variables in a linkage set. So, the entropy value of the task set is computed as using Eqn (4).

$$\text{compressed population complexity} = \lambda \sum_{t \in T} H(t) \quad (4)$$

In ,and (4) H(t) is represented as the joint entropy variable of task t.

From the computed linkage learning process, allocate the task to the robot and verify the schedule of the robot continuously. By adding these two-measure value, the task-related robots are computed in saved in the search space effectively. Based on the discussion, the robots and task allocation process are demonstrated in figure 2.

From figure 2, it depicted that each robot assists the user request according to different sensors such as sound, light, ultrasonic and touch sensor. These sensors are used to monitor the patient's activities continuously and provide the proper guides to the patient. Here task 1 is allocated according to the computation of interdependency between the robots and task. Based on the above discussion, the task is allocated to specific robots. Further, the optimized task allocation process is done by applying the bacterial foraging optimization algorithm [21]. It is one of the metaheuristic optimization algorithm works according to the bacteria characteristics. It used to solve the computational intelligent problem called which robots are chosen to perform the task in the hospital environment. As discussed earlier, the robots are selected based on utility factors, inter-dependency and other cost factors. Among that information, optimal robots are selected via this optimization algorithm. This algorithm selects the right robot based on three function such as chemotaxis (comparing the one robot with other robot based on the utility factor, cost and so on), reproduction (perform the comparison process and produce the next generation information) and elimination -dispersal (eliminate the old robot and check the probability or possibility of next robots in the list). So, the interaction between the robots is analyzed and the bacterial cost derated is estimated. To obtain the value, the interaction [22] between the cells (robots) are computed using Eqn (5).

$$\begin{aligned} g(\text{cell}_k) &= \sum_{i=1}^S \left[-d_{attr} * \exp(-w_{attr} * \sum_{m=1}^P (\text{cell}_m^k - \text{others}_m^i)^2) \right] \\ &+ \sum_{i=1}^S h_{repeal} * \exp(-w_{repeal} * \sum_{m=1}^P (\text{cell}_m^k - \text{others}_m^i)^2) \end{aligned} \quad (5)$$

In Eqn (5) given robot or cell is denoted as cell_k

Attraction coefficients are d_{attr}, w_{attr}

Repulsion coefficients are h_{repeal}, w_{repeal}

Number of robots in search space is S

The number of dimensions on a cell is denoted as P.

Based on the interaction, the optimized robots are selected, when the robots having the highest fitness value. According to the discussion, the pseudocode for the robot's selection process [23] is depicted in table 3.

Table 3: Pseudocode for optimization algorithm

<p>Initialization:</p> <p>$Cells_{num}$: number of cells maintained in the search space</p> <p>N_{ed}: number of elimination dispersal steps</p> <p>N_{re}: number of reproduction steps</p> <p>N_C: number of chemotaxis steps</p> <p>N_s: number of swim steps for given cell</p> <p>$Step_{size}$: random vector (same number of dimension)</p> <p>P_{ed}: probability of cell subjected to N_{ed}</p> <p>Attraction coefficients: d_{attr}, w_{attr}</p> <p>Repulsion coefficients: h_{repeal}, w_{repel}</p> <p>Number of robots in search space: S</p> <p>The number of dimensions on a cell is denoted: P.</p> <p style="text-align: center;"><i>for (Cell \in population)</i></p> <p>$Cell_{fitness} \leftarrow cost (cell) + Interaction (cell, pollution, d_{attr}, w_{attr}, h_{repeal}, w_{repel})$</p> <p>$Cell_{health} \leftarrow Cell_{fitness}$</p> <p>$Cell' \leftarrow \emptyset$</p> <p style="text-align: center;"><i>for (i = 0 to N_s)</i></p> <p style="text-align: center;"><i>randomstep direction \leftarrow createstep (Problem_{size})</i></p>
<p>$Cell' \leftarrow takestep (randomstepdirection, Step_{size})$</p> <p>$Cell'_{fitness} \leftarrow cost (Cell') + interaction (Cell', population, d_{attr}, w_{attr}, h_{repeal}, w_{repel})$</p> <p><i>if (Cell'_{fitness} > Cell_{fitness})</i></p> <p>$i \leftarrow N_s$</p> <p>Else</p> <p>$cell \leftarrow Cell'$</p> <p>$C_{health} \leftarrow C_{health} + C'_{fitness}$</p> <p>End</p> <p>End</p> <p>End</p>

Based on table 3, the optimized robots are selected by the continuous optimization process. During the computation process, by default, , values are 0.1 and 0.2, value is equal to the and the value is 10. Then the step size is 0.1 which is a small fraction of search space. Along with this, half of the robots are selected for the searching process and remaining populations are discarded. Then the elimination

dispersal probability value 0.25. Thus the bacterial optimization algorithm successfully selects the best robots and allocates the task to the robot successfully. This allocation process considering the above category by computing different computation numerical factors. Then the efficiency of the introduced system is evaluated using experimental analysis discussed in section 4.

4. Results And Discussion

This section discusses the efficiency of the multiple robotic task allocation [24] process. We assume that entire tasks need to be allocated to the robots a dynamically because most of the time, the emergency patient task also handled by robots. Then considered the numerical data for performing the task. During the simulation results, the system randomly generates the cells 100*100 cells, in which 10 resources are used and the above-defined parameters are having default values. After that, the dataset is spilled into different categories such as dataset 1 (10 to 50 robots and 100 tasks), dataset 2 (10 to 100 task and 10 robots) and dataset 3(10to 100 task and 50 robots). After dividing the dataset, the task needs to be allocated to single or multiple robots which are done according to the robot utility and another numerical measurement. Based on the discussion, the task is provided by the user in the format of task ID, location, duration and resources. Here sample task is mentioned in Table 4

Table 4
Example of task

Task Id	Resource	Location	Duration
T1	[1,1,1,0]	(3,3)	15
T2	[1,0,1,1]	(7,3)	10

Here above table represented only the sample numerical based task allocation process according to the task requirement, robots are allocated to perform the specific task in duration. Then the dataset is chosen according to the task and the number of robots is decided to perform the task effectively. Here dataset 2 and dataset 3 is chosen to perform the task because multiple numbers of a task and the multiple numbers of robots need to complete the task effectively. Then the excellence of introducing system is compared with the fireflies-power set theory multi-robot task allocation technique (FA-POWERSET-MART) [25] and firefly algorithm quantum artificial bee colony multi-robot task allocation (FA-QABC-MART) [26]. By considering this existing algorithm, the efficiency of the system is evaluated in terms of using some allocated tasks and allocation time. From these two metrics, the bacterial Foraging Optimization building block distribution algorithm (BFOBBDD) attains the effective results while solving the multi-robot task allocation issues. Initially, the distribution of robots is identified and the respective task is chosen for the selected robots. Then the optimized robots are selected according to the bacterial optimization function. Then tasks are allocated to the robot effectively. Based on the discussion, the utility value and allocation time for three algorithms such as FA-POWERSET-MART, FA-QABC-MART and BFOBBDD algorithm efficiency being demonstrated in Figs. 3 and 4. During the estimation process, dataset 1 is selected in which 1 to 100 tasks are considered which is performed by the 10 to 50 robots. From dataset 1, it depicted that the number of robots is not provide an effective result which means, number of tasks are performed by fews

fewer robots which are clearly shown in Figs. 3 and 4. Due to the high utility factor and efficiency of the robots complete the task faster. From the results, it demonstrated that the BFOBBDD method consumes minimum task allocation time (4.23s) compared to other methods such as FA-POWERSET-MART (20.19s), FA-QABC-MART (5.26s). So, the maximum number of tasks is assigned to the minimum number of robots. So, it clearly shows that the BFOBBDD approach attains effective results compared to the other two methods such as FA-POWERSET-MART and FA-QABC-MART. In addition to this, task allocation time, we need to compare the efficiency of the utility factor to examine the quality of task allocation to optimal allocation. Then the comparison of the robot utility value is depicted in Fig. 4 which demonstrated that selected robots having the skill to complete the task perfectly.

Further, the efficiency of the system is evaluated in terms of task allocation and the obtained results are compared with the FA-POWERSET-MART and FA-QABC-MART. Considering the dataset 2 and dataset 3, in which the number of robots is low in which number of tasks are used. Based on the results the task-related obtained results are depicted in Figs. 5 and 6 which depicted that the maximizing number of robots does not affect the execution of a task. In addition to this, it clearly shows that, when the number of tasks maximizes the allocation time also increased.

From the figures, it depicted that the introduced BFOBBDD approach successfully recognize the right robots for the task and allocate the multiple tasks with minimum task allocation time. In addition to this, the number of robots used on the number of assigned tasks to be examined in different iteration which is demonstrated using Fig. 7.

From Fig. 7 illustrated that the number of tasks allocated with the number of robots in the search space. During the computation process, 100 tasks are taken which are examined using 10 to 50 robots. The introduced algorithm effectively assigns the task to the robots and the maximum number of robot's utilization directly indicates that maximize the number of tasks allocated in the iterated manner. Even though utilizing a maximum number of robot's allocation time is depends on the task completion time. Thus, the introduced algorithm effectively allocates the task with available resources and minimum allocation time.

5. Conclusion

Thus, the paper analyzes the bacterial Foraging Optimization building block distribution algorithm (BFOBBDD) based task allocation process in the multiple assistive robotic systems. Initially, robots and tasks are arranged in the search space. From the collected robots, interdependency between the task and robots are computed by using joint and marginal distribution value. By considering the dependency and utility factor list of robots are selected. Then the bacteria optimization algorithm characteristics are used to select the optimal robots for the task completion. The robots are selected according to the cell fitness value and the other operations such as chemotaxis, reproduction and elimination -dispersal. These steps successfully select the right robot according to the cost factor, utility, attractive value and so on. Then the efficiency of the system is evaluated using simulation results in which the different number of tasks are

taken to examine the system. In which system allocate the greater number of task with minimum allocation time (4.23s) for the different number of robots. In the future, the task allocation time is optimized by using a meta-heuristic neural network because it trains the system regularly that improves the overall task allocation system efficiency

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Figures

Assisting food habits, medicine & routine activities



Lifting patients



Relaxing patients



Analyzing patients



Health Care



Providing treatment to patients



Performing surgery to patients

Figure 1

Assistive Robots Tasks in Healthcare Applications

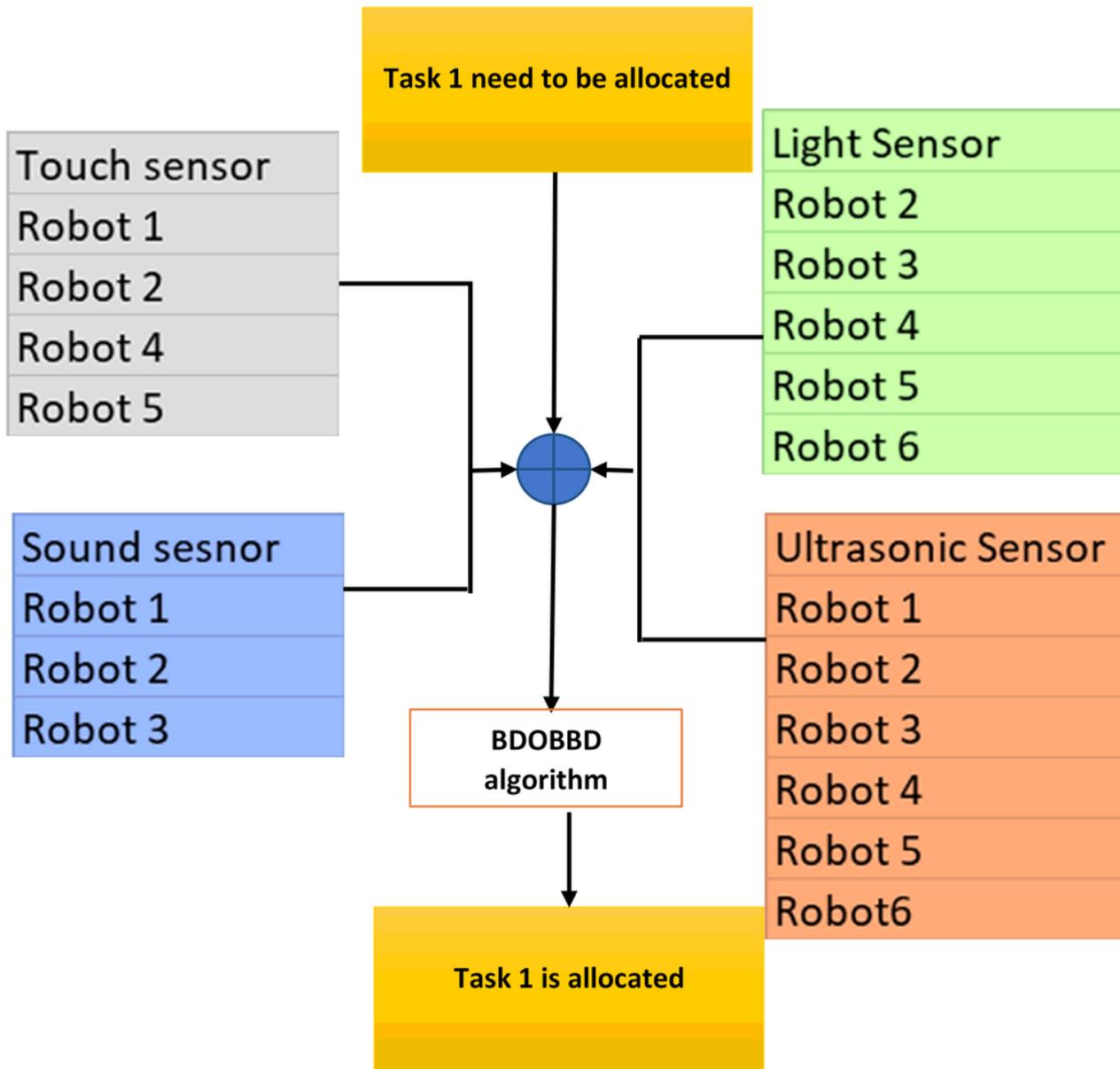


Figure 2

Task allocation process

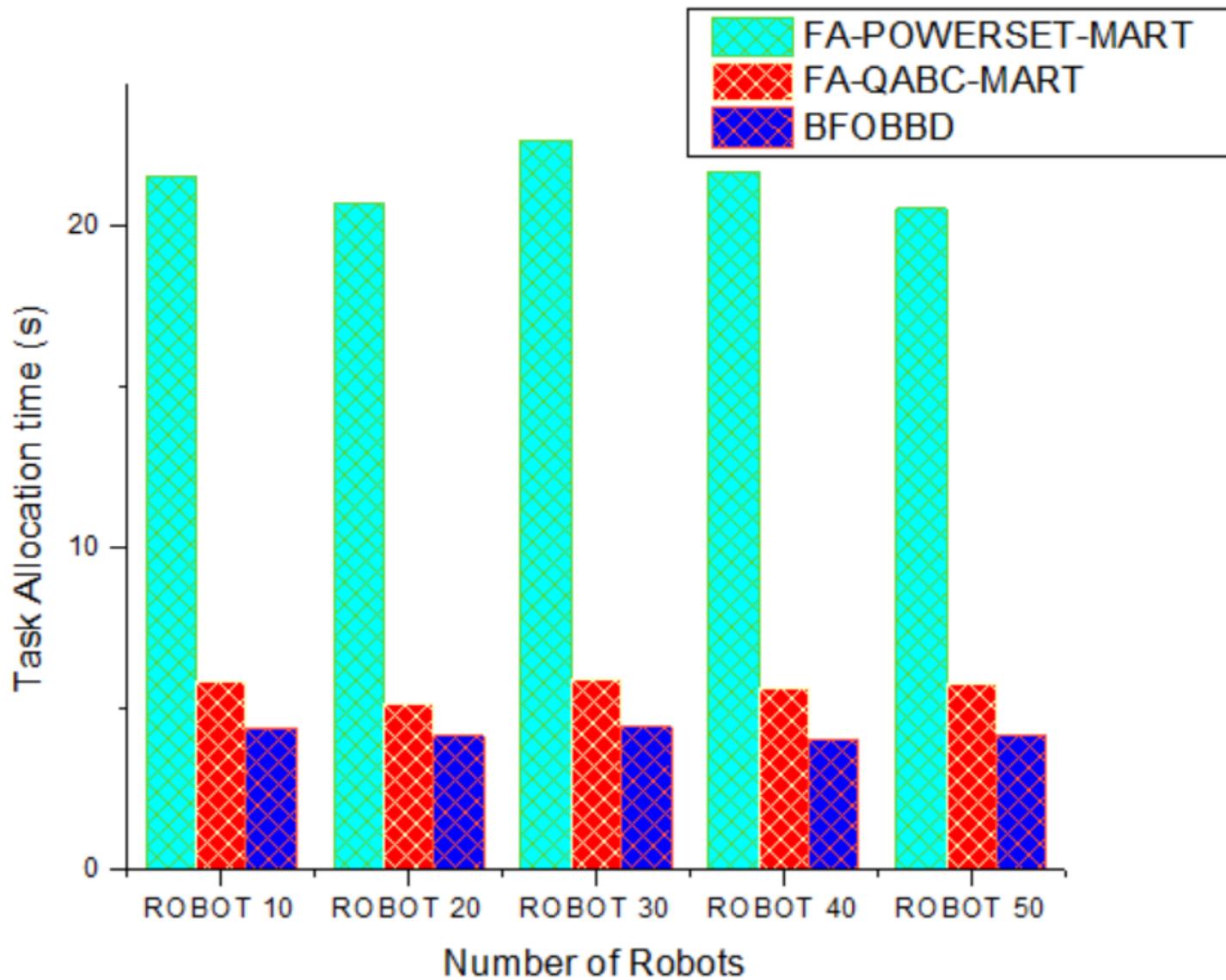


Figure 3

Task Allocation time (s)

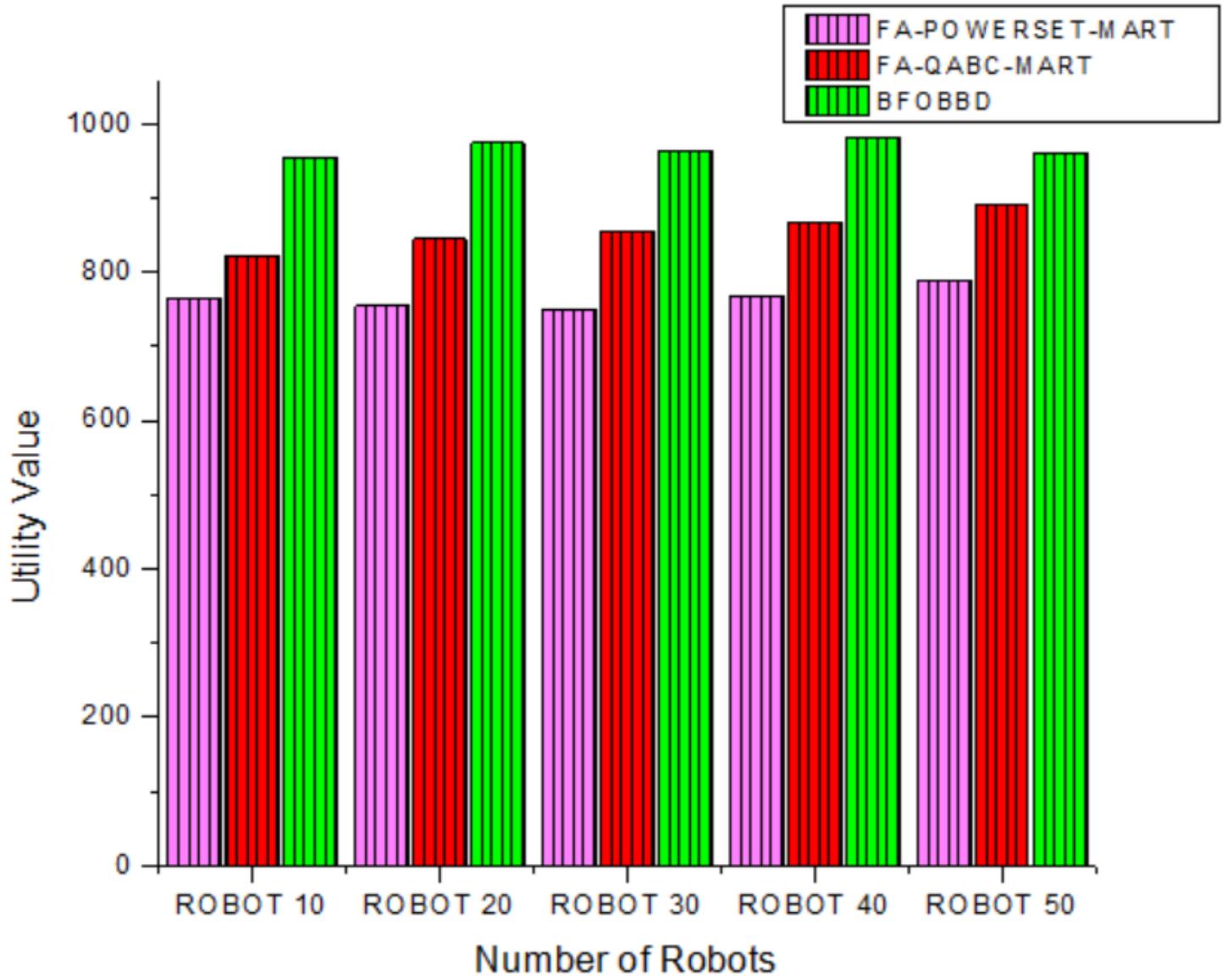


Figure 4

Utility value

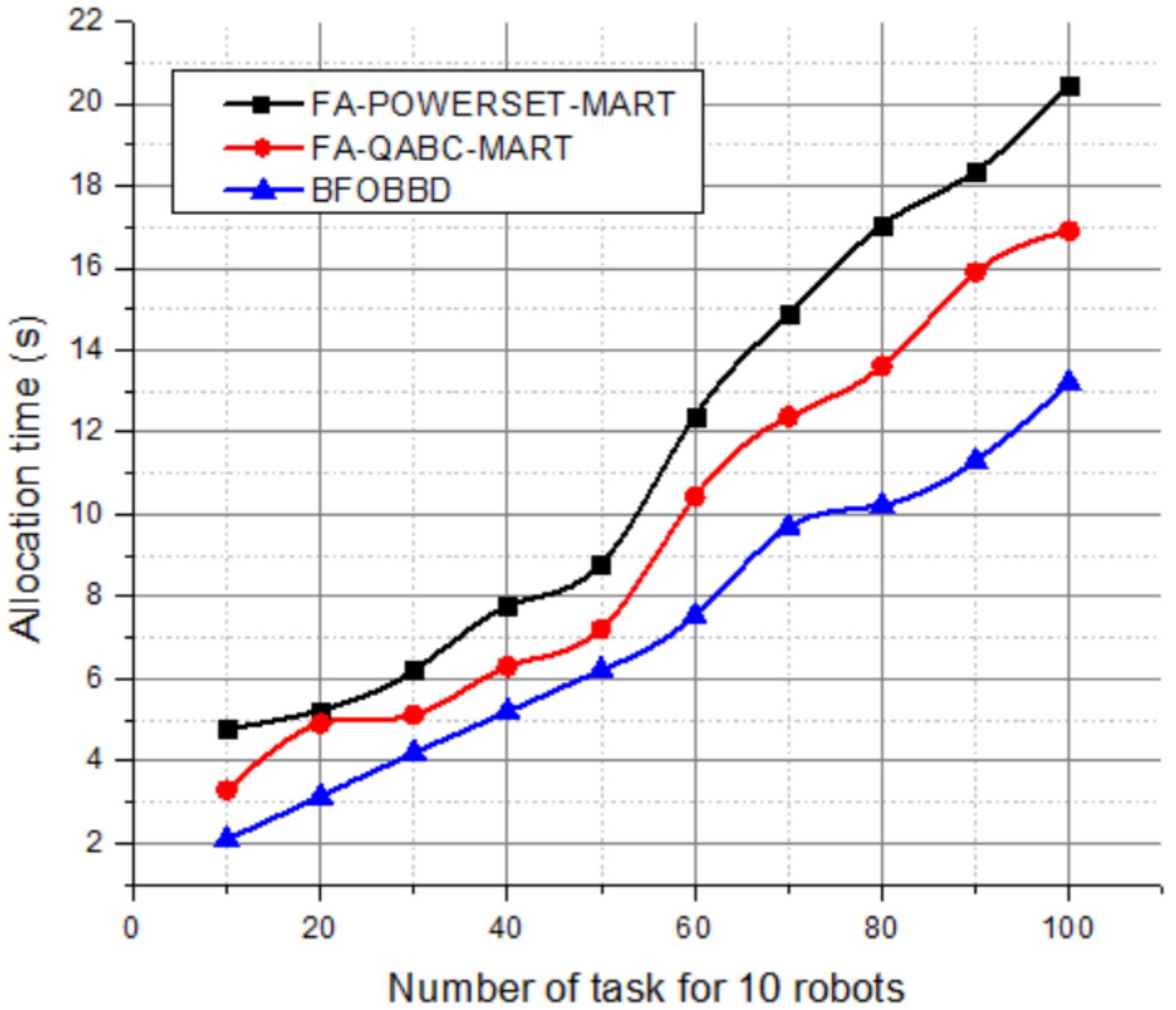


Figure 5

Task allocation time (10 robots)

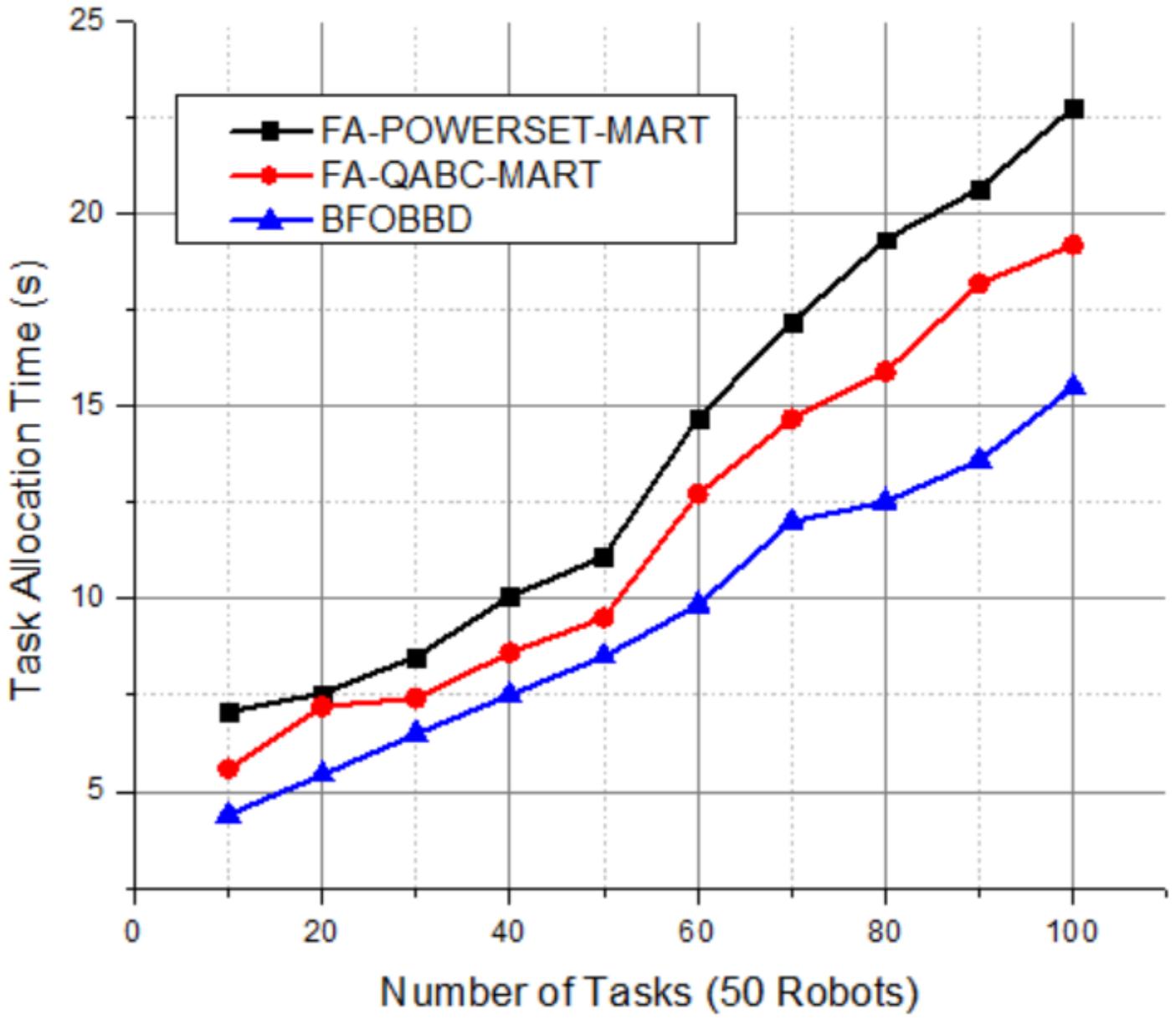


Figure 6

Task Allocation time (50 Robots)

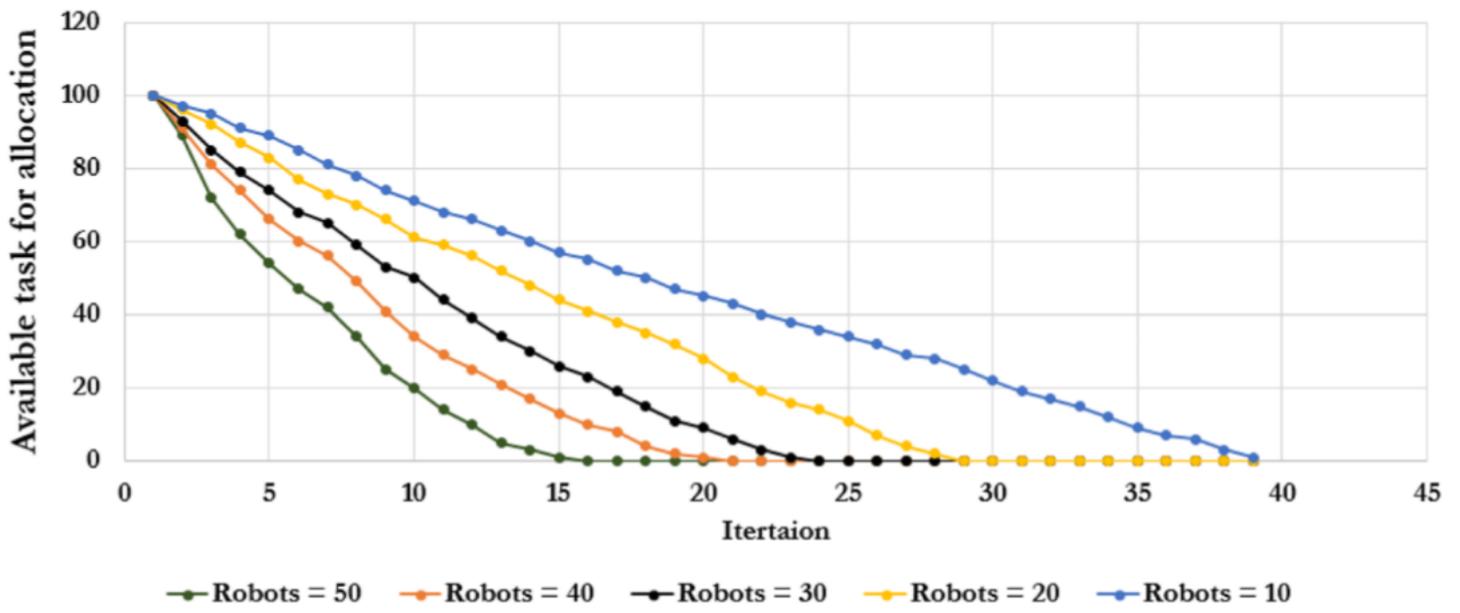


Figure 7

Representation of the allocated task with robots