Review on state-of-the-art dynamic task allocation strategies for multiple-robot systems

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Abstract

Purpose – This paper aims to present a concise review on the variant state-of-the-art dynamic task allocation strategies. It presents a thorough discussion about the existing dynamic task allocation strategies mainly with respect to the problem application, constraints, objective functions and uncertainty handling methods.

Design/methodology/approach – This paper briefs the introduction of multi-robot dynamic task allocation problem and discloses the challenges that exist in real-world dynamic task allocation problems. Numerous task allocation strategies are discussed in this paper, and it establishes the characteristics features between them in a qualitative manner. This paper also exhibits the existing research gaps and conducive future research directions in dynamic task allocation for multiple mobile robot systems.

Findings – This paper concerns the objective functions, robustness, task allocation time, completion time, and task reallocation feature for performance analysis of different task allocation strategies. It prescribes suitable real-world applications for variant task allocation strategies and identifies the challenges to be resolved in multi-robot task allocation strategies.

Originality/value – This paper provides a comprehensive review of dynamic task allocation strategies and incites the salient research directions to the researchers in multi-robot dynamic task allocation problems. This paper aims to summarize the latest approaches in the application of exploration problems.

Keywords Multiple mobile robots, Dynamic task allocation, Market-based task allocation, Behavior-based task allocation, Task clustering, Heuristic task allocation

Paper type General review

1. Introduction

A cooperative multiple-robot system is one of the most extensive research domains in robotics (Fang *et al.*, 2018; Palmer *et al.*, 2018). A multiple-robot system (MRS) deploys a number of cooperative robots in a coordinated fashion to execute and accomplish tasks (D'Emidio and Khan, 2017). Deployment of a single robot to perform such complicated tasks is time-consuming and exhausting (Li and Li, 2017). Whereas, deployment of multiple robots overwhelms the drawbacks of a single-robot system, are sufficient to perform complex tasks faster than a single robot in a distributed manner. It provides the flexibility to manipulate the robots failure, self-reconfiguration, high fault tolerance and robustness (Palmer *et al.*, 2018). The applications of an MRS are in numerous fields such as manufacturing, construction, mining, inspection (Liu *et al.*, 2017), warehouses (Tsang *et al.*, 2018), surveillance (Farinelli *et al.*, 2017), defence applications (Jha and Nair, 2017) agriculture, exploration of underwater, space and land, search and rescue operations (Rishwaraj and Ponnambalam, 2017).

In the paradigm of the multi-robot system, there are two coordination methodologies: centralized and distributed (Johnson *et al.*, 2016; Semwal *et al.*, 2017). In centralized coordination, a server monitors the essential parameters such as relative position, status of the task, battery capacity of individual robots in the team. The server also identifies the most competent robot to execute a task. This system relies on a central server for successful task allocation; however, it becomes futile when the central server fails (Li *et al.*, 2017a). Therefore, this coordination is befitting to a small team of robots with rigidly connected networks (Liu *et al.*, 2017). In distributed coordination, individual robots allocate their own tasks. It requires neither a globally connected network nor a central server (Hooshangi and Alesheikh, 2017). Every individual robot frequently observes the status of the neighbour robots within its field of view (Sung *et al.*, 2018). It compares its task execution competency from its neighbours' competency and self-allocates profitable tasks (Lerman *et al.*, 2006;

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Luo *et al.*, 2014). This method is suitable for a large team of robots in weak communication environments (Wang *et al.*, 2018). Though the centralized coordination method necessitates a rigid communication network, it ensures the consensus about task allocation among the team of robots. Whereas, distributed coordination is unsusceptible to frail communication, but the consensus of task allocation is difficult to achieve (Giordani *et al.*, 2010). The responsibilities of individual robots in MRS networks are task execution and coordination (Irfan and Farooq, 2016; Xie *et al.*, 2018). The coordination methods have their own advantages and disadvantages. Thus, the proper selection of a coordination method for an application influences successful task allocation and task accomplishment in an MRS.

Multi-robot task allocation (MRTA) problems are categorized into eight types, as shown in Figure 1 (Gerkey and Matarić 2004). Korsah *et al.* (2013) group them into four (Figure 2) based on inter-dependent resources and constraints and refer them as iTax classification. The task allocation strategies are classified with respect to the consequential applications such as search and rescue, surveillance, foraging, flocking, formation, target tracking, cooperative manipulation and exploration (Jia and Meng, 2013; Darmanin and Bugeja, 2017; Jin *et al.*, 2019). Two important task allocation strategies are auction- and optimization-based techniques (Badreldin *et al.*, 2013; Khamis *et al.*, 2015). The evaluation of these task allocation strategies based on the solution optimality, allocation time and problem constraints determine that optimization-based task allocation is faster and produces optimal solutions for complex constrained problems.

In recent years, the researchers have focused on developing dynamic task allocation strategies for complex constraint problems and developing robust strategies with multiple uncertainty conditions. This paper aims to survey the contemporary dynamic task allocation strategies (Nunes *et al.*, 2017). It recognizes the expedient task allocation strategies for variant real-world MRS applications. It performs a review of task allocation strategies by analyzing the problem applications, constraints, objective functions, task allocation and completion time and the uncertainty handling methods. In this paper, the authors have attempted to review, categorize and evaluate the related papers to provide a systematic view of past work and provide various research scopes in this problem domain. This study reviewed published articles from 2010–2020, from high-ranking journals and reputable international conferences, most of which were related to multiple-robot task allocation, swarm robots, scheduling and optimization methods and were extracted from the "Web of Science and Scopus" databases. The performance of various strategies is compared considering the holistic nature of the problem and parameters such as number of robots, tasks, time for task allocation and completion, uncertainty conditions and several other constraints.

This paper is organized as follows: Section 2 defines the multiple-robot dynamic task allocation problem. Section 3 presents a detailed analysis of four distinct task allocation strategies. Section 4 provides a detailed discussion of the analyzed literature, and Section 5 presents the possible research gaps and scope in this area. Section 6 concludes the major findings in this paper.

2. Multi-robot task allocation problem definition

This section outlines the MRTA problem. Let $\mathcal{J} = \{j_1, j_2, j_3 \ldots j_m\}$ be the set of tasks to be allocated, and $R = \{r_1, r_2, r_3 \ldots r_n\}$ be the set of robots in the team. The term A in equation (1) represents that the set of tasks $\mathcal{J}$ are assigned to the set of robots R:

$$A : \mathcal{J} \rightarrow R \tag{1}$$

If a task j is allocated to a robot r, then task allocation $A_{j,r} = 1$ else $A_{j,r} = 0$.

Let $U_{\mathcal{J}} \in \mathbb{R}$ be a matrix of required utility values to execute m tasks by n robots.

Let $U_R \in \mathbb{R}$ be a matrix of available utility values to execute m tasks by n robots.

Let $T = \{T_1, T_2, T_3, \ldots T_m\}$ be the start time of m tasks.

Let $W = \{W_1, W_2, W_3, \ldots W_m\}$ be the waiting time of the tasks to commence.

Let $M = \{M_1, M_2, M_3, \ldots M_m\}$ be the set of time span of the tasks.

Let $D_{j,r}$ be the distance travelled by the robot r to execute the task j.

Let $K = \{K_1, K_2 \ldots K_l\}$ be the set of completed tasks.

Task assignment to the robots is an optimal decision-making problem. It is subject to some essential constraints. The various

Figure 1 Fundamental MRTA taxonomy

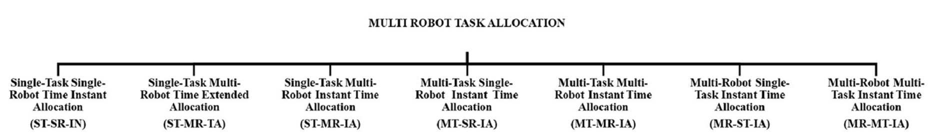


Figure 2 iTax MRTA taxonomy

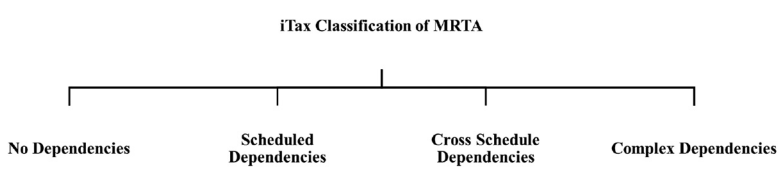


Table 1 Dynamic task allocation constraints with examples

Constraints	Types
Environmental constraints	Moving obstacles, unknown environment, cluttered environment, etc.
Robot constraints	Sensor malfunction, communication loss, uncertainty of robot's travel distance, heterogeneity draining of battery capacity, computational capacity, resource constraint (Chen and Sun, 2011; Notomista *et al.*, 2019; Schillinger *et al.*, 2019)
Task constraints	Time-bounded tasks, multi-agent tasks, hierarchical tasks (Blankenburg *et al.*, 2017), task variants (Cano *et al.*, 2018)

multi-robot problem constraints are listed in Table 1. The basic dynamic task allocation problem consists of resource and time constraints as stated below:

- A task must be allocated to a robot with sufficient utility, as depicted in equation (2):

$$\text{If } U_j > U_r \text{ then } A_{jr} = 0, \ \forall j \in \mathcal{J} \ and \ r \in R \tag{2}$$

- The task execution time T of the tasks allocated to a robot must not overlap with each other. Equation (3) depicts this constraint. It includes starting time, waiting time and time span of the tasks:

$$T_{j_p} \geq T_{j_q} + \left(W_{j_q} + M_{j_q}\right) \text{ where, } j_p \ and \ j_q \epsilon \ \mathcal{J} \ and \ j_p j_q;$$
$$\text{the task } j_p \text{ must be scheduled after the task } j_q \tag{3}$$

- The task assignment must be conflict-free. Equation (4) specifies that a task must be allocated to a single robot:

$$\sum\nolimits_{r \in R} T_{j,r} = 1 \ \forall j \in \mathcal{J} \tag{4}$$

The most common objective functions (equation (5)–(7)) of dynamic task allocation strategy are: minimize the travel distance (d), the waiting time (W) and to maximize the task completion rate (K):

$$min : \sum\nolimits_{j \in \mathcal{J}} \sum\nolimits_{r \in R} D_{j,r} \tag{5}$$

$$min \sum\nolimits_{j \in \mathcal{J}} W_j \tag{6}$$

$$max : \sum\nolimits_{l \in \mathcal{J}} |K_l| \quad l \leq m \tag{7}$$

This multi-robot dynamic task allocation problem is a combinatorial optimization problem. In this paper, the existing strategies for solving this problem are comprehensively reviewed and will be discussed in detail in the remaining sections of the paper.

3. Dynamic task allocation strategies

The objective of multi-robot dynamic task allocation problems is mapping of the tasks with the robots by satisfying the constraints such a way that the cost function is minimal (Sarkar *et al.*, 2018a). The prominent part of real-world multi-robot applications is that the constraints are irregular and diverse in nature. Hence, a rational task allocation strategy necessitates robust handling of the distinct constraints occurs at the time of task execution. There are various task allocation methods reported in the literature, and Figure 3 shows the four broad classifications of multi-robot dynamic task allocation strategies. This section discusses the task allocation strategies in detail.

In this study, the concepts of numerous MRTA strategies form the literature are discussed. The discussion is based on the problem application, the objective function, additional constraints involved, coordination type, the problem taxonomy, task reallocation feature, uncertainty handling method. In addition to these points, the number of tasks and robots considered in the implementation stage, the resultant average task allocation time, task completion time and the implementation method, either simulation or real experimentation, are considered. This way of analysis helps the reader to identify the suitable strategy to be considered for the problem scenario.

3.1 Market-based task allocation

Market-based task allocation is a prominent multiple-robot task allocation strategy (Schneider *et al.*, 2017). It imitates the market trading concept (Luo *et al.*, 2015). The process of market-based task allocation strategy is illustrated in Figure 4. An auctioneer robot advertises tasks information to other robots in the team and requests for bids. Every individual robot

Figure 3 Classification of dynamic task allocation strategies

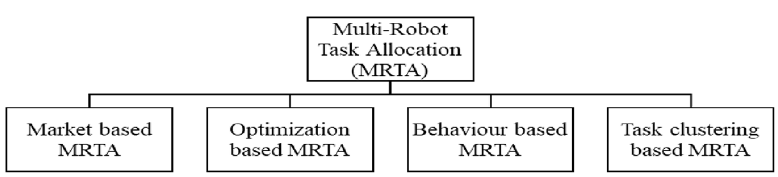
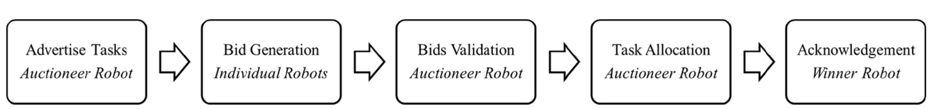


Figure 4 Process of market-based task allocation



in the team prepares bid based on its capability to execute the tasks and then forwards the bids to the auctioneer robot. The auctioneer robot allocates the tasks to the least quoted robots. This strategy is implemented in both centralized and distributed robot's coordination network (Schneider *et al.*, 2017).

Market-based task allocation is broadly divided into single-item auctioning and combinatorial auctioning. The single-item auctioning (Otte *et al.*, 2020) method conducts task-wise auctions. Whereas, combinatorial auctioning conducts auctions for a group of tasks. Researchers develop multiple variants of these two methods. Table 2 illustrates a detailed discussion of various market-based task allocation strategies from the literature. To handle uncertainty, the task allocation list and cost estimate are periodically updated. With respect to the updated cost estimate, the tasks are reallocated (Turner *et al.*, 2017; Turner, 2018). Search and rescue tasks incorporate several uncertainties such as risk level of the victims, cluttered path and robot energy level (Talebpour and Martinoli, 2018). The interval uncertainty theory handles these uncertainties. It updates the bid estimates within a periodical interval and reallocates the tasks. This approach improves the task completion rate and increases the number of life-saved victims in search and rescue applications (Hooshangi and Alesheikh, 2017). However, task reallocation handles uncertainty and improves robustness, task switching increases computation time and it indirectly increases the robot energy consumption (Talebpour and Martinoli, 2018). The procedural process of auctioning consumes much time. In common, all the market-based task allocation strategies result in less robot travel distance. The market-based task allocation strategies rely on strongly connected robots' networks. The task completion rate of market-based strategies during communication loss or weak communication environments is poor.

The variants of single-item auctioning and combinatorial auctioning are found in the literature. It supports all kinds of coordination. Most of the authors used single-objective functions, and it is observed that task allocation strategies are implemented in simulation than in real experiments as can be seen (S shows simulation, R shows real-time experiments). There exists a large gap to identify the difference between the simulation results and the real-time execution results.

3.2 Optimization-based task allocation

Real-world multiple robot problems are bounded with multiple uncertain constraints. Therefore, the mathematical modelling of dynamic task allocation problems is formidable (Li and Yang, 2018). However, heuristic modelling of dynamic task allocation problems furnishes contiguous optimal solutions. The multiple mobile robots' dynamic task allocation problem is generalized as multiple travelling salesman problem (Arif and Haider, 2017) and classified as a combinatorial optimization problem (dos Reis and Bastos, 2017). It is solved by evolutionary optimization algorithms: genetic algorithm (Arif and Haider, 2017; Arif and Haider, 2018; Bänziger *et al.*, 2018), particle swarm optimization (PSO) (Alshawi and Shalan, 2017), ant colony optimization (ACO) (Li *et al.*, 2017b), the variants of PSO and ACO algorithms (Muhuri and Rauniyar, 2017).

The essential objective functions of dynamic task allocation problems are minimization of: task completion time, robot travel distance, battery resource utilization; maximization of: task distribution rate and task completion rate. Table 3 lists the features of various optimization strategies. Similar to market-based strategy, most of the optimization strategies consider single-objective optimization only. Several methods have been used in the literature for this. Few researchers considered integer programming (Li and Li, 2017; Su *et al.*, 2018; Zhou *et al.*, 2019) and various search algorithms (Zhao *et al.*, 2015; Kartal *et al.*, 2016; Mitiche *et al.*, 2019). Many researchers used metaheuristic algorithms (Liu and Kroll, 2012; Alshawi and Shalan, 2017; Li *et al.*, 2017b, Z. Zhu *et al.*, 2017; Arif and Haider, 2018; Chen *et al.*, 2018b, Padmanabhan Panchu *et al.*, 2018; Wang *et al.*, 2018; Zhou *et al.*, 2019) to solve this optimization problem, and this could be because of the ease of implementation of such algorithms.

Generation of multiple solutions for a problem instance enhances the robustness of single-objective optimization (Huang *et al.*, 2018). Though this technique theoretically enhances the robustness, there is a gap for systematic switching between multiple solutions. An optimization strategy consumes high computational resources (Shenoy and Anupama, 2017). Multi-objective optimization approach improves the task completion rate with less time utility. The issue in multi-objective optimization is framing the proper fitness function. As some of the objective factors of dynamic task allocation have a functional trade-off, the weight value of each objective factor must be precisely given. In future, it is recommended to perform a study on regularity and adoption of fitness factors for distinct task allocation problems.

The task distribution rate of multi-objective optimization is higher than the single-objective optimization strategy. This approach has better scalability. However, the robustness is low because of the poor adaptability to multiple performance objective factors. However, there is an open research gap to identify differences between the simulation and real implementation of optimization-based dynamic task allocation.

3.3 Behaviour-based task allocation

Behaviour-based dynamic task allocation is a unique strategy. This strategy exerts multiple prorated solutions to solve distinct problem instances taking place in a single application. The problem solutions are in any form of mathematical model, heuristic or optimization functions. This strategy is highly reactive to the problem. Multi-robot exploration problems consist of two-layered behaviour-based control architecture (Chetty *et al.*, 2010; Chetty *et al.*, 2011). Tasks identification and inter robot communication are classified under higher-level behaviours, whereas obstacle avoidance, navigation and task switching are categorized into lower-level behaviours. In addition to the basic low-level behaviours, problem-specific behaviours are developed to incorporate robustness (Schillinger *et al.*, 2018).

Table 4 summarizes the analysis of various behaviour-based task allocation techniques. Unlike other task allocation strategies, this approach is adaptable and reactive to the problem's specific constraints. Thus, this strategy leads to high robustness and scalability features. This approach is adaptable for centralized and distributed coordination. Distributed

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Table 2 Analysis of market-based task allocation

Source	Application	Method	Objective function	Additional constraint	Problem type	Coordination	Reallocation	Uncertainty	Maximum no.: tasks	Maximum no.: robots	Average task allocation time (s)	Average task completion time	Real time/ simulation
Chen and Sun (2011)	Generic	Leader–follower coalition algorithm	Maximize utility	Heterogeneous team with resource constraint	ST-SR-IA	Distributed	Y	N	5	3	–	–	S
Luo *et al.* (2012)	Generic	Repeated greedy auction algorithm	Maximize total payoff	Task group	ST-SR-TA	Distributed	N	N	60	20	–	–	S
Liu and Shell (2012)	Generic	Optimal auctioning with strategic pricing	Minimize distance travelled	–	ST-SR-IA	Distributed	Y	N	500	500	0.5	–	S
Tolmidis and Petrou (2013)	Generic	Hybrid genetic algorithm (GA) distributed auction	Maximize robot battery energy and relevance degree, minimize time	Remaining energy has to be above a predefined level	ST-SR-IA	Distributed	Y	N	10	6	5.62	–	S
Liekna *et al.* (2012)	Multiple vacuum cleaning robots	Contract Net protocol	Minimize the effort required for cleaning an area	–	SR-MT-IA	Centralized	Y	N	2	2	–	–	S
Liu and Shell (2013)	Generic	Linear integer programming with partitioning of tasks	Maximize profit	–	ST-SR-IA	Distributed	N	N	100	100	–	–	S
Luo *et al.* (2015)	Generic	Iterative auctioning	Maximize remaining battery power	Task deadline	ST-SR-TA	Distributed	N	N	100	20	–	–	S
Wei *et al.* (2016)	Search and retrieval	SSI. Extend SSI	Minimize the completion time and fuel consumption	Temporal constraint	ST-SR-IA	Centralized/ distributed	N	N	30	10	–	150.57 (s)	S
Farinelli *et al.* (2017)	Multi-robot patrolling	SSI auctions	Maximize the number of visits	–	ST-SR-IA	Distributed	N	Y	8	3	–	–	R
Hooshangi and Alesheikh (2017)	Search and rescue	Contract Net protocol	Maximize the number of rescued victims	Heterogeneous team	ST-SR-IA	Distributed	Y	Y	2000	200	–	738 (min)	S
Otte *et al.* (2020)	Lossy communication environment	Comparison of six auction algorithms	Minimize the maximum path length	Communication limited environments	ST-SR-IA	Distributed	N	N	1000	300	–	–	S

Table 3 Analysis of optimization-based task allocation

Source	Application	Method	Objective function	Additional constraint	Problem type	Coordination	Reallocation	Uncertainty	Maximum no.: tasks	Maximum no.: robots	Average task allocation time (s)	Average task completion time (s)	Real time/ simulation
Wawerla and Vaughan (2010)	Puck transportation	Centralized planner and heuristic rules	Minimize robot energy consumption	–	ST-SR-IA	Centralized/ distributed	Y	N	2	18	–	–	S
Jevtic *et al.* (2011)	Generic	Distributed bee colony optimization	Maximize task distribution	–	ST-SR-IA	Distributed	N	N	4	100	–	–	S
Liu and Kroll (2012)	Industrial plant inspection	A* and GAs	Maximize task completion	–	ST-SR-IA	Centralized	N	N	90	3	170.48	–	S
Wang *et al.* (2012)	Generic	ACO	Minimize travel distance	Resource constraints	ST-SR-IA	Distributed	N	N	–	–	–	–	S
Giordani *et al.* (2013)	Industry production	Iterative auction-based negotiation	Minimize production cost	–	ST-SR-IA	Distributed	Y	N	50	250	–	–	S
Zhao *et al.* (2015)	Search and rescue	Heuristic based	Minimize sum of path cost	Limited resources	MT-MR-IA	Distributed	Y	N	32	16	–	238.49	S
Kartal *et al.* (2016)	Generic	Monte Carlo tree search	Minimize travel distance		ST-SR-TA	Centralized	N	N			–		S
Arif and Haider (2017)	Generic	GA	Minimize travel distance	–	ST-SR-IA	Centralized	N	N	30	3	–	41.54	S
Alshawi and Shalan (2017)	Foraging	PSO	Minimize time	–	ST-SR-IA	Distributed	N	N	10	7	14.6	–	S
Z. Zhu *et al.* (2017)	Generic	Improved PSO	Maximize benefit with minimum travelling distance and paid cost	Payload constraint	ST-SR-IA	Distributed	N	N	40	6	5208	–	S
Li and Li (2017)	Warehouse automation	Integer programming and GA	Minimize the sum of the fixed cost of robot and the cost of robot operation	–	ST-SR-IA	Centralized	Y	N	10	10		–	S
Li *et al.* (2017b)	Generic	ACO	Minimize travel distance	–	ST-SR-IA	Distributed	N	N	10	–	–	–	S
Tsang *et al.* (2018)	Warehouse automation	GA	Minimize travel distance	–	MT-MR-IA	Centralized	N	N	100	100	0.340	–	S
Turner *et al.* (2017)	Search and Rescue	PI-MaxAss	Maximize the number of task allocations	Time and fuel limit	ST-SR-TA	Distributed	Y	N	–	–	–	–	S
Chen *et al.* (2018a)	Generic	PSO multi-objective	Maximize time utility and energy utility	–	ST-SR-IA	Distributed	N	N	16	16	–	–	S
Mitiche *et al.* (2019)	Generic	Iterated local search	Maximize the number of tasks	Spatio-temporal and capacity	ST-SR-TA	Distributed	N	N	––	–	–	–	S
Zhou *et al.* (2019)	Generic	Integer programming and approximation tree-based GA	Minimize task completion time	–	ST-SR-IA	Centralized	N	N	–	–	–	–	S

Table 4 Analysis of behaviour-based task allocation

Source	Application	Method	Behaviour	Objective function	Additional constraint	Problem type	Coordination	Reallocation	Uncertainty	Maximum no.: tasks	Maximum no.: robots	Average task allocation time (s)	Average task completion time (s)	Real time/ simulation
Chen and Sun (2012)	Generic	Sequential coalition method	Coalition	Maximize coalition utility	Resource constraint	MR-ST-IA	Distributed	N	–	6	10	–	–	R
Lee *et al.* (2014)	Foraging	Iterative search on *ad hoc* network	Resource aware cost generation	Minimize resource consumption	Limited resources	ST-SR-IA	Distributed	Y	–	100	16	–	64.9	S
Kanakia *et al.* (2016)	Generic	Game theory Bayesian Nash equilibrium	Continuous response threshold	Maximize task completion	No communication	ST-SR-IA	Distributed	N	Communication	–	–	–	–	S
Riccio *et al.* (2016)	Soccer game/foraging	Distributed world modelling and task allocation	Context knowledge based	Minimize time	–	ST-SR-IA	Distributed	N	–	1	3	–	–	R
Abukhalil *et al.* (2016)	Search and Rescue	Robot utility-based task assignment	Robot utility-based allocation	Maximize utility	Heterogeneous team	ST-MR-IA	Centralized/ distributed	Y	–	5	1	–	110.3	R
Lee and Kim (2017)	Foraging	Task selection probability model	Response threshold behaviour	Maximize task distribution	No communication	ST-SR-IA	Distributed	Y	–	50	20	–	–	S
Wu *et al.* (2017)	Generic	Gini coefficient and auction-based allocation	Gini coefficient-based allocation	Minimize resource consumption	Limited energy resources	ST-SR-IA	Centralized	N	Resource constraint	50	5	–	–	S
Lee (2018)	Goods delivery mission	Probabilistic bid auctioning	Resource-based task allocation	Minimize the maximum cost and time	Fuel refill station	ST-SR-IA	Distributed	Y	Resource-level uncertainty	72	11	–	–	S
Talebpour and Martinoli (2018)	Pedestrian walking	Adaptive risk-based re-planning strategy	Risk-based allocation	Minimize travel distance	Social constraints	ST-SR-IA	Distributed	Y	Human walking	5	4	–	–	R
Dai *et al.* (2019)	Soccer game	Incomplete information game modelling	Ball velocity-based allocation	Minimize the payoff	No communication	ST-SR-IA	Distributed	N	–	–	3	–	–	R
Jin *et al.* (2019)	Target tracking	Competition-based task allocation	Besieging behaviour-based allocation	Maximize task completion	Limited communication	ST-MR-IA	Distributed	N	–	–	–	–	–	S

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coordination requires local communication rather than global communication between robots for task allocation. Therefore, this strategy is suitable for weak communication applications. Task switching or swapping behaviour is incorporated with the task allocation model. Thus, this strategy could handle a robot's failure that occurred during the task execution phase (Zhao *et al.*, 2015). The resource-based task allocation behaviour provides an improved task distribution rate (Lee and Kim, 2019). Therefore, behaviour-based task allocation is recommended for task allocation in uncertain and dynamic real-world multiple mobile robot (MMR) applications.

3.4 Clustered task allocation

Clustered task allocation strategies group the similar or nearby tasks into clusters, and then the clusters are allocated to robots rather than single task allocation. This strategy decreases the average travel distance of the robot team (Chen *et al.*, 2018b). For search and rescue applications, nearby tasks are clustered. Similarly, for warehouse operations, nearby tasks clustering is implemented. According to Sarkar *et al.* (2018b), as the robots execute the nearby tasks, the overall travel distance and the resource utilization are less. Similar types of tasks are clustered for heterogeneous robots' teams, and the consent task type is allocated to the corresponding type of robots. For the clustering of tasks, methods such as Euclidean distance clustering, K means clustering, fuzzy clustering (Ghassemi and Chowdhury, 2018) are reported to be used in the literature.

The critical challenge in clustering-based task allocation is the identification of the optimal number of tasks per cluster (Nam and Shell, 2016). The determination of optimal number of tasks for a cluster is empirically studied in Mitiche *et al.* (2019). The performance analysis of clustering-based task allocation approaches is given in Table 5. A task clustering strategy minimizes the travel distance; thus, it is recommended for foraging applications. Clustered task allocation reduces the number of individual tasks to be allocated. Therefore, computational complexity is drastically reduced in this approach. This strategy is adaptable with centralized coordination. Thus, it is not relevant for weak communication applications. As a group of tasks is assigned to a robot, the occurrence of a robot's failure will decrease the task completion rate drastically. This downside is solved by task switching/swapping with the next available robots in case of robot failure conditions.

4. Discussion

This paper presents a detailed review of the state-of-the-art MMR dynamic task allocation strategies. Even though every task allocation technique in the literature has been analyzed and validated by simulations, it lacks validation through real-time experimentation. Identification of the gaps between simulation and experimental results is still open research in the field of dynamic task allocation (Jang *et al.*, 2018). In market-based task allocation, robots have the provision to opt for profitable tasks. This method results in the optimal selection of subsequent tasks. Conventionally, sequential single-item (SSI) and parallel auctioning require a prior list of tasks. Repeated auctioning is preferred for dynamic task allocation problems because it updates tasks in a dynamic manner, in turn eliminating the requirement for the prior tasks list. Under uncertain conditions, it is plausible to lose communication within the robot's team. From survey, it is found that a robust and reliable communication network is mandatory for the market-based task allocation leading to an open challenge that is not yet been solved. Relying on a single-point auctioneer for task allocation is the major downside of this strategy. Development of a systematic strategy to handle this single-point failure is a further potential research direction in market-based task allocation. Various optimization algorithms based on dynamic task allocation strategies are reported in the literature. Task allocation quality relies on the fitness function used in the optimization algorithms. Overall, the optimization-based task allocations provide less robustness. Thus, determination of self-adaptive fitness function to successfully handle uncertainties is yet to be considered by the researchers. The analysis of the literature states that multi-objective optimization techniques outperform single-objective dynamic task allocation. However, there exists a huge research gap in deriving multi-objective cost function with the trading-off objective factors. Several heuristic algorithms are available; thus, further research is recommended for identification and validation of optimal heuristic technique for specific multi-robot problems. Implementation and performance comparison of various optimization algorithms is another research direction that could be performed.

The uniqueness of behaviour-based task allocation strategy makes it flexible to incorporate reactive behaviours of robots for various problem constraints and uncertainties. This feature increases the robustness and scalability of task allocation. Arbitration among multiple behaviours is the challenging aspect of this strategy. This strategy consumes more computation resources, which is another drawback. However, this strategy is recommended for applications with various uncertainties.

Task clustering-based allocation strategy consumes minimal travel distance for the robots. This strategy is suitable for autonomous multi-robot surveillance applications. Identification of an optimal number of tasks in a cluster is the research problem open for further study. Simultaneous task allocation and path planning strategy increase the task completion rate (Sung *et al.*, 2018). Development of effective switching strategies between clusters to handle uncertainty like robot failures is the further research direction in this strategy. Similarly, integrating the different task allocation strategies like behaviour-based allocation with task clustering-based task allocation strategy is also a significant research direction for the future. Table 6 illustrates the performance factors for MRTA problems. The ways of adapting to these factors by the four task allocation strategies are presented in detail.

5. Gaps and future research scope

From the literature review analysis, it is identified that a multiple-robot system with different depot points for each robot decreases the total travel distance and inter-robot collisions (Lu *et al.*, 2018). Task allocation for complex constraint problems, including time window tasks (Liu *et al.*, 2017), hierarchical tasks (Blankenburg *et al.*, 2017), robot dependent tasks, task unknown problems, is still open for

Table 5 Analysis of clustered task allocation

Source	Application	Method	Objective function	Additional constraint	Problem type	Coordination	Reallocation	Uncertainty	Maximum no.: tasks	Maximum no.: robots	Average task allocation time (s)	Average task completion time (s)	Real time/ simulation
Zhang *et al.* (2012)	Generic	Stochastic clustering auction, constrained Prim's algorithm	Minimize time	–	MT-SR-IA	Centralized/ distributed	N	N	–	6	–	–	S
Faigl *et al.* (2012)	Exploration	Multiple travelling salesmen-based assignment; K-means clustering	Minimize travel distance	–	MT-SR-IA	Distributed	N	N	–	10	–	–	S
Biswas *et al.* (2017)	Generic	PSO with k-means clustering	Minimize travel distance	–	MT-SR-TA	Distributed	N	N	10	3	–	–	S
Chen *et al.* (2018b)	Search and rescue	Cluster first consensus-based strategy	Maximize the no.: of rescued survivors, minimize the waiting time of survivors, the total travelling distance of robots	–	MT-SR-IA	Distributed	N	N	2	14	–	–	S
Lu *et al.* (2018)	Foraging	Central place foraging algorithm, k-means clustering	Minimize travel distance	–	MT-MR-IA	Distributed	N	N	384	24	–	–	S
Sarkar *et al.* (2018b)	Warehouse	Nearest neighbour-based clustering and routing	Minimize travel distance	Robot capacity constraint	MT-SR-IA	Distributed	N	N	–	–	–	–	S
Ghassemi and Chowdhury (2018)	Generic	Fuzzy clustering, bipartite graph matching	Minimize travel distance	–	MT-SR-IA	Distributed	N	N	100	50	4.63		S
Whitbrook *et al.* (2019)	Generic	Robust performance impact algorithm	Minimize mean individual task cost	–	MT-SR-IA	Distributed	N	Y	32	16			S
Dutta *et al.* (2019)	Generic	Linear programming-based graph partitioning	Maximize coalition structure, after minimizing the cost of forming it	–	MT-MR-IA	Centralized	N	N	10	100	230	–	S

Table 6 Factors for MRTA problems

Performance factors	Market-based allocation	Optimization-based allocation	Behaviour-based allocation	Task clustering-based allocation
No communication/lossy communication	Multiple times broadcasting of winner robot details after bidding	Local communication among neighbour robots	Local communication among neighbour robots	Local communication among neighbour robots
Objective function	Single/multiple objective	Single/multiple objective	Single/multiple objective	Single/multiple objective
Coordination type	Centralized/distributed	Centralized/distributed	Centralized/distributed	Centralized/distributed
Method for task reallocation	Iterative auctioning methods	Iterative searching and allocation	Heuristics rules searching/ Bayesian Nash equilibrium	Difficult reallocate within different task clusters
Uncertainty handling techniques	Iterative auctioning methods	Difficult to handle uncertainties	Game theory/probabilistic predictive modelling	Difficult to handle uncertainty
Complex problem constraints	Difficult to conduct auctions	Complex and difficult to solve due to multiple decision variables	Can be handled in a collective manner	Can be handled in a collective manner
Computational cost	Lower than optimization strategy	Higher than market-based strategy	Higher than optimization-based strategy	Lower than other methods

research (Khamis *et al.*, 2015). Development of soft agents for robust task allocation is also a further research direction that can be explored (Ismail and Sariff, 2018). Development of the game theoretical approach for distributed task allocation for communication loss problems is recommended for further research analysis (Dai *et al.*, 2019). A very few researchers identified dynamic task allocation strategies by applying some modern approaches such as learning automata (Khani *et al.*, 2019), deep learning, machine vision (Li and Yang, 2018), self-organizing map neural networks (Zhu *et al.*, 2017).

Consider the following examples of MRTA problems, dynamic task allocation for search and rescue of victims by autonomous heterogeneous MMR in disaster field problem is a highly challenging problem for the researchers (Abukhalil *et al.*, 2016). The list of search and rescue tasks to be performed is unknown in prior. Thus, the task allocation strategy for this problem must be scalable for tasks as well as robots during runtime. Rescue tasks must be given higher priority than the search tasks (Sung *et al.*, 2018). Priority of the behaviour-based task allocation strategy ensures the execution of rescue tasks prior to the search tasks. Integration of task clustering-based allocation reduces the robot travel distance. This problem contains an uncertain environment and obstacles. Thus, it is recommended to develop a task allocation strategy that is reactive for the uncertain behaviours of obstacles (ElGibreen and Youcef-Toumi, 2019). The distributive task allocation strategy is applicable to this problem because strong communication may not exist in all the disaster fields. Incorporating task switching and reallocation mechanisms in case of robot failures and other uncertainties improves the robustness of task allocation (Chen *et al.*, 2016; Woosley and Dasgupta, 2018). Another challenge in this problem is the proper dynamic task allocation and coordination between heterogeneous mobile robots. Modelling the dynamic task allocation problem in a three-dimensional environment is efficacious to manipulate real-time application environment (Yi *et al.*, 2016). In multi-robots gaming applications, the unpredictable changes in the game environment are the challenging aspect for task allocation. Similar to these scenarios, every real-world multiple robot application places itself with distinct challenges and uncertainties for task allocation. The performance comparison of different task allocation strategies in real-time is a significant research direction (Ismail and Sariff, 2018). In Table 7, various future research scopes in MRTA problems are summarized for the reader's clarity.

6. Conclusion

This paper analyzed in detail several dynamic task allocation strategies developed and reported for multiple-robot systems. Even though many of the proposed strategies are

Table 7 Future research avenues in MRTA problems

- **Development of task allocation strategies for tightly coupled tasks**
- **Development of efficient failure handling mechanisms for all types of task allocation**
- **Development of hybrid task allocation strategies**
- **Development of energy-aware task allocation strategies for recharging robots to perform long-running tasks**
- **Evaluation of task priorities in task allocation**
- **Unifying the performance evaluation metrics of task allocation strategies**
- **Development of task allocation for strict time-constraint problems**
- Development of effective task rescheduling/reallocation mechanism
- Development of task allocation within a heterogeneous team
- Development of task allocation for unknown environment exploration problems
- Development of adaptive heuristic parameters for task allocation
- Identification of ideal cluster size and procedure for task switching among task clusters
- Development of task allocation in no communication problem environment
- Development of uncertainty handling task allocation techniques
- Real-time experimentation of task allocation problems

validated using simulations study, very few strategies are tested in real time. There exists a large gap between the simulated and real-time multi-robot applications. Further research needs to be conducted exclusively to overcome the experimental challenges of real-world applications. The multi-robot systems are prone to communication uncertainty; thus, the current dynamic task allocation techniques intend to be improved for achieving robustness in weak or no communication scenarios. Robust task allocation with efficient task switching and swapping techniques to manipulate the uncertainties is a needful research direction in multi-robot systems. Multiple behaviour-based dynamic task allocation techniques improve the scalability and robustness. Another major challenge is the development of dynamic task allocation strategies for exploration problems because an inadequate number of studies have been reported on this problem. The major challenge exists in the obscure knowledge of tasks to be allocated in the unperceived application environment. The exploration problem entails task allocation in parallel with the path planning of an unknown application environment. Hence, a successful exploration task allocation strategy is required to be scalable for tasks and to be robust for environment uncertainties. Researchers can also develop integrated and robust behaviour-based dynamic task allocation strategies for search and rescue applications as future work.

References

Abukhalil, T., Patil, S. Patel, M. and Sobh, T. (2016), "Coordinating a heterogeneous robot swarm using robot utility-based task assignment (RUTA)", *in: 2016 IEEE 14th International Workshop on Advanced Motion Control (AMC), IEEE.*

Alshawi, M.A. and Shalan, M.B. (2017), "Minimal time dynamic task allocation for a swarm of robots", *International Journal of Mechanical Engineering and Robotics Research*, Vol. 6 No. 6.

Arif, M.U. and Haider, S. (2017), "An evolutionary traveling salesman approach for Multi-Robot task allocation", in: *Icaart (2)*.

Arif, M.U. and Haider, S. (2018), "A flexible evolutionary algorithm for task allocation in multi-robot team", *in: International Conference on Computational Collective Intelligence, Springer.*

Badreldin, M., Hussein, A. and Khamis, A. (2013), "A comparative study between optimization and Market-Based approaches to Multi-Robot task allocation", *Advances in Artificial Intelligence*, Vol. 2013(16877470).

Bänziger, T., Kunz, A. and Wegener, K. (2018), "Optimizing human–robot task allocation using a simulation tool based on standardized work descriptions", *Journal of Intelligent Manufacturing*, Vol. 31 No. 7.

Biswas, S., Anavatti, S.G. and Garratt, M.A. (2017), "Nearest neighbour based task allocation with multi-agent path planning in dynamic environments", *in: 2017 International Conference on Advanced Mechatronics, Intelligent Manufacture, and Industrial Automation (ICAMIMIA), IEEE.*

Blankenburg, J., Banisetty, S.B., Alinodehi, S.P.H., Fraser, L., Feil-Seifer, D., Nicolescu, M. and Nicolescu, M. (2017), "A distributed control architecture for collaborative multi-robot task allocation", *in: 2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids), IEEE.*

Cano, J., White, D.R., Bordallo, A., McCreesh, C., Michala, A.L., Singer, J. and Nagarajan, V. (2018), "Solving the task variant allocation problem in distributed robotics", *Autonomous Robots*, Vol. 42 No. 7, pp. 1477-1495.

Chen, J. and Sun, D. (2011), "Resource constrained multirobot task allocation based on leader–follower coalition methodology", *The International Journal of Robotics Research*, Vol. 30 No. 12, pp. 1423-1434.

Chen, J. and Sun, D. (2012), "Coalition-based approach to task allocation of multiple robots with resource constraints", *IEEE Transactions on Automation Science and Engineering*, Vol. 9 No. 3, pp. 516-528.

Chen, J., Wang, J., Xiao, Q. and Chen, C. (2018a), "A Multi-Robot task allocation method based on Multi-Objective optimization", in: *2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV), IEEE.*

Chen, X., Zhang, P., Li, F. and Du, G. (2018b), "A cluster first strategy for distributed multi-robot task allocation problem with time constraints", in: *2018 WRC Symposium on Advanced Robotics and Automation (WRC SARA), IEEE.*

Chen, Y., Mao, X., Hou, F., Wang, Q. and Yang, S. (2016), "Combining re-allocating and re-scheduling for dynamic multi-robot task allocation", *in: 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE.*

Chetty, R.K., Singaperumal, M. and Nagarajan, T. (2010), "Behaviour based planning and control of leader follower formations in wheeled mobile robots", *International Journal of Advanced Mechatronic Systems*, Vol. 2 No. 4, pp. 281-296.

Chetty, R.K., Singaperumal, M., Nagarajan, T. and Tetsunari, I. (2011), "Coordination control of wheeled mobile robots? A hybrid approach", *International Journal of Computer Applications in Technology*, Vol. 41 Nos 3/4, pp. 195-204.

Dai, W., Lu, H., Xiao, J. and Zheng, Z. (2019), "Task allocation without communication based on incomplete information game theory for multi-robot systems", *Journal of Intelligent & Robotic Systems*, Vol. 94 Nos 3/4, pp. 841-856.

Darmanin, R.N. and Bugeja, M.K. (2017), "A review on multi-robot systems categorised by application domain", *in: 2017 25th Mediterranean Conference on Control and Automation (MED), IEEE.*

D'Emidio, M. and Khan, I. (2017), "Multi-robot task allocation problem: current trends and new ideas", *in: Joint Proceedings of the 18th Italian Conference on Theoretical Computer Science and the 32nd Italian Conference on Computational Logic (ICTCS/CILC)*.

dos Reis, W.P.N. and Bastos, G.S. (2017), "An arrovian view on the multi-robot task allocation problem", *in: 2017 18th International Conference on Advanced Robotics (ICAR), IEEE.*

Dutta, A., Ufimtsev, V. and Asaithambi, A. (2019), "Correlation clustering based coalition formation for multi-robot task allocation", *in: Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing*.

ElGibreen, H. and Youcef-Toumi, K. (2019), "Dynamic task allocation in an uncertain environment with heterogeneous multi-agents", *Autonomous Robots*, Vol. 43 No. 7, pp. 1639-1664.

Faigl, J., Kulich, M. and Přeučil, L. (2012), "Goal assignment using distance cost in multi-robot exploration", *in: 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, *IEEE*.

Fang, B., Zhang, Q., Wang, H. and Yuan, X. (2018), "Personality driven task allocation for emotional robot team", *International Journal of Machine Learning and Cybernetics*, Vol. 9 No. 12, pp. 1955-1962.

Farinelli, A., Iocchi, L. and Nardi, D. (2017), "Distributed on-line dynamic task assignment for multi-robot patrolling", *Autonomous Robots*, Vol. 41 No. 6, pp. 1321-1345.

Gerkey, B.P. and Matarić, M.J. (2004), "A formal analysis and taxonomy of task allocation in multi-robot systems", *The International Journal of Robotics Research*, Vol. 23 No. 9, pp. 939-954.

Ghassemi, P. and Chowdhury, S. (2018), "Decentralized task allocation in multi-robot systems via bipartite graph matching augmented with fuzzy clustering", *in: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *American Society of Mechanical Engineers*.

Giordani, S., Lujak, M. and Martinelli, F. (2010), "A distributed algorithm for the multi-robot task allocation problem", *in: International conference on industrial, engineering and other applications of applied intelligent systems*, *Springer*.

Giordani, S., Lujak, M. and Martinelli, F. (2013), "A distributed multi-agent production planning and scheduling framework for mobile robots", *Computers & Industrial Engineering*, Vol. 64 No. 1, pp. 19-30.

Hooshangi, N. and Alesheikh, A.A. (2017), "Agent-based task allocation under uncertainties in disaster environments: an approach to interval uncertainty", *International Journal of Disaster Risk Reduction*, Vol. 24, pp. 160-171.

Huang, L., Ding, Y., Zhou, M., Jin, Y. and Hao, K. (2018), "Multiple-solution optimization strategy for multirobot task allocation", *IEEE Transactions on Systems, Man, and Cybernetics: Systems*.

Irfan, M. and Farooq, A. (2016), "Auction-based task allocation scheme for dynamic coalition formations in limited robotic swarms with heterogeneous capabilities", *in: 2016 International Conference on Intelligent Systems Engineering (ICISE)*, *IEEE*.

Ismail, Z.H. and Sariff, N. (2018), *A Survey and Analysis of Cooperative Multi-Agent Robot Systems: challenges and Directions*, Applications of Mobile Robots, IntechOpen.

Jang, I., Shin, H.-S. and Tsourdos, A. (2018), "Anonymous hedonic game for task allocation in a large-scale multiple agent system", *IEEE Transactions on Robotics*, Vol. 34 No. 6, pp. 1534-1548.

Jevtic, A., Gutiérrez, A., Andina, D. and Jamshidi, M. (2011), "Distributed bees algorithm for task allocation in swarm of robots", *IEEE Systems Journal*, Vol. 6 No. 2, pp. 296-304.

Jha, S.S. and Nair, S.B. (2017), "TANSA: task allocation using nomadic soft agents for multirobot systems", *IEEE Transactions on Emerging Topics in Computational Intelligence*, Vol. 2 No. 4, pp. 308-318.

Jia, X. and Meng, M.Q.-H. (2013), "A survey and analysis of task allocation algorithms in multi-robot systems", *in: 2013 IEEE International Conference on Robotics and biomimetics (ROBIO)*, *IEEE*.

Jin, L., Li, S., La, H.M., Zhang, X. and Hu, B. (2019), "Dynamic task allocation in multi-robot coordination for moving target tracking: a distributed approach", *Automatica*, Vol. 100, pp. 75-81.

Johnson, L.B., Choi, H.-L. and How, J.P. (2016), "The role of information assumptions in decentralized task allocation: a tutorial", *IEEE Control Systems Magazine*, Vol. 36 No. 4, pp. 45-58.

Kanakia, A., Touri, B. and Correll, N. (2016), "Modeling multi-robot task allocation with limited information as global game", *Swarm Intelligence*, Vol. 10 No. 2, pp. 147-160.

Kartal, B., Nunes, J. Godoy, E. and Gini, M. (2016), "Monte Carlo tree search with branch and bound for multi-robot task allocation", in: *The IJCAI-16 Workshop on Autonomous Mobile Service Robots*.

Khamis, A., Hussein, A. and Elmogy, A. (2015), *Multi-Robot Task Allocation: A Review of the State-of-the-Art. Cooperative Robots and Sensor Networks*, 2015, Springer, pp.31-51.

Khani, M., Ahmadi, A. and Hajary, H. (2019), "Distributed task allocation in multi-agent environments using cellular learning automata", *Soft Computing*, Vol. 23 No. 4, pp. 1199-1218.

Korsah, G.A., Stentz, A. and Dias, M.B. (2013), "A comprehensive taxonomy for multi-robot task allocation", *The International Journal of Robotics Research*, Vol. 32 No. 12, pp. 1495-1512.

Lee, D.-H. (2018), "Resource-based task allocation for multi-robot systems", *Robotics and Autonomous Systems*, Vol. 103, pp. 151-161.

Lee, W. and Kim, D. (2017), "History-based response threshold model for division of labor in multi-agent systems", *Sensors*, Vol. 17 No. 6, p. 1232.

Lee, W. and Kim, D. (2019), "Adaptive approach to regulate task distribution in swarm robotic systems", *Swarm and Evolutionary Computation*, Vol. 44, pp. 1108-1118.

Lee, D.-H., Zaheer, S.A. and Kim, J.-H. (2014), "Ad hoc network-based task allocation with resource-aware cost generation for multirobot systems", *IEEE Transactions on Industrial Electronics*, Vol. 61 No. 12, pp. 6871-6881.

Lerman, K., Jones, C., Galstyan, A. and Matarić, M.J. (2006), "Analysis of dynamic task allocation in multi-robot systems", *The International Journal of Robotics Research*, Vol. 25 No. 3, pp. 225-241.

Li, Z. and Li, X. (2017), "Research on model and algorithm of task allocation and path planning for multi-robot", *Open Journal of Applied Sciences*, Vol. 7 No. 10, pp. 511.

Li, J. and Yang, F. (2018), "Research on multi-robot scheduling algorithms based on machine vision", *EURASIP Journal on Image and Video Processing*, Vol. 2018 No. 1, pp. 1-11.

Li, D., Fan, Q. and Dai, X. (2017a), "Research status of multi-robot systems task allocation and uncertainty treatment", in: *J. Phys. Conf. Ser.*

Li, X., Liu, Z. and Tan, F. (2017b), "Multi-robot task allocation based on cloud ant colony algorithm", *in: International Conference on Neural Information Processing*, *Springer*.

Liekna, A., Lavendelis, E. and Grabovskis, A. (2012), "Experimental analysis of contract net protocol in multi-robot task allocation", *Applied Computer Systems*, Vol. 13 No. 1, pp. 6-14.

Liu, C. and Kroll, A. (2012), "A centralized multi-robot task allocation for industrial plant inspection by using a* and genetic algorithms", *in: International Conference on Artificial Intelligence and Soft Computing*, *Springer*.

Liu, L. and Shell, D.A. (2012), "Large-scale multi-robot task allocation via dynamic partitioning and distribution", *Autonomous Robots*, Vol. 33 No. 3, pp. 291-307.

Liu, L. and Shell, D.A. (2013), *Optimal Market-Based Multi-Robot Task Allocation via Strategic Pricing. in: Robotics*, Science and Systems.

Liu, S., Kurniawan, E., Tan, P.H., Zhang, P., Sun, S. and Ye, S. (2017), "Dynamic scheduling for heterogeneous resources with time windows and precedence relation", *in: TENCON 2017-2017 IEEE Region 10 Conference*, *IEEE*.

Lu, Q., Hecker, J.P. and Moses, M.E. (2018), "Multiple-place swarm foraging with dynamic depots", *Autonomous Robots*, Vol. 42 No. 4, pp. 909-926.

Luo, L., Chakraborty, N. and Sycara, K. (2012), "Competitive analysis of repeated greedy auction algorithm for online multi-robot task assignment", *in: 2012 IEEE International Conference on Robotics and Automation*, *IEEE*.

Luo, L., Chakraborty, N. and Sycara, K. (2014), "Provably-good distributed algorithm for constrained multi-robot task assignment for grouped tasks", *IEEE Transactions on Robotics*, Vol. 31 No. 1, pp. 19-30.

Luo, L., Chakraborty, N. and Sycara, K. (2015), "Distributed algorithms for multirobot task assignment with task deadline constraints", *IEEE Transactions on Automation Science and Engineering*, Vol. 12 No. 3, pp. 876-888.

Mitiche, H., Boughaci, D. and Gini, M. (2019), "Iterated local search for time-extended multi-robot task allocation with spatio-temporal and capacity constraints", *Journal of Intelligent Systems*, Vol. 28 No. 2, pp. 347-360.

Muhuri, P.K. and Rauniyar, A. (2017), "Immigrants based adaptive genetic algorithms for task allocation in multi-robot systems", *International Journal of Computational Intelligence and Applications*, Vol. 16 No. 4, p. 1750025.

Nam, C. and Shell, D. (2016), *An Empirical Study of Task Bundling for Sequential Stochastic Tasks in Multi-Robot Task Allocation, Technical Report TAMU-CSE-16-7-1*, CSE Department, TX A&M University.

Notomista, G., Mayya, S., Hutchinson, S. and Egerstedt, M. (2019), "An optimal task allocation strategy for heterogeneous multi-robot systems", in: *2019 18th European Control Conference (ECC)*, *IEEE*.

Nunes, E., Manner, M., Mitiche, H. and Gini, M. (2017), "A taxonomy for task allocation problems with temporal and ordering constraints", *Robotics and Autonomous Systems*, Vol. 90, pp. 55-70.

Otte, M., Kuhlman, M.J. and Sofge, D. (2020), "Auctions for multi-robot task allocation in communication limited environments", *Autonomous Robots*, Vol. 44 Nos 3/4, pp. 547-584.

Padmanabhan Panchu, K., Rajmohan, M., Sundar, R. and Baskaran, R. (2018), "Multi-objective optimisation of multi-robot task allocation with precedence constraints", *Defence Science Journal*, Vol. 68 No. 2.

Palmer, A.W., Hill, A.J. and Scheding, S.J. (2018), "Modelling resource contention in multi-robot task allocation problems with uncertain timing", *in: 2018 IEEE International Conference on Robotics and Automation (ICRA)*, *IEEE*.

Riccio, F., Borzi, E., Gemignani, G. and Nardi, D. (2016), "Multi-robot search for a moving target: integrating world modeling, task assignment and context", *in: 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, *IEEE*.

Rishwaraj, G. and Ponnambalam, S. (2017), "Integrated trust based control system for multirobot systems: development and experimentation in real environment", *Expert Systems with Applications*, Vol. 86, pp. 177-189.

Sarkar, C., Dey, S. and Agarwal, M. (2018a), "Semantic knowledge driven utility calculation towards efficient multi-robot task allocation", *in: 2018 IEEE 14th International Conference on Automation Science and Engineering (CASE)*, *IEEE*.

Sarkar, C., Paul, H.S. and Pal, A. (2018b), "A scalable multi-robot task allocation algorithm", *in: 2018 IEEE International Conference on Robotics and Automation (ICRA)*, IEEE.

Schillinger, P., Bürger, M. and Dimarogonas, D.V. (2018), "Simultaneous task allocation and planning for temporal logic goals in heterogeneous multi-robot systems", *The International Journal of Robotics Research*, Vol. 37 No. 7, pp. 818-838.

Schillinger, P., Bürger, M. and Dimarogonas, D.V. (2019), "Hierarchical LTL-Task MDPs for Multi-Agent coordination through auctioning and learning", *The International Journal of Robotics Research*,

Schneider, E., Sklar, E.I. and Parsons, S. (2017), "Mechanism selection for multi-robot task allocation", *in: Annual Conference Towards Autonomous Robotic Systems*, *Springer*.

Semwal, T., Jha, S.S. and Nair, S.B. (2017), "On ordering multi-robot task executions within a cyber physical system", *ACM Transactions on Autonomous and Adaptive Systems (Systems)*, Vol. 12 No. 4, pp. 1-27.

Shenoy, M.V. and Anupama, K. (2017), "DTTA-Distributed, time-division multiple access based task allocation framework for swarm robots", *Defence Science Journal*, Vol. 67 No. 3, p. 316.

Su, X., Wang, Y., Jia, X., Guo, L. and Ding, Z. (2018), "Two innovative coalition formation models for dynamic task allocation in disaster rescues", *Journal of Systems Science and Systems Engineering*, Vol. 27 No. 2, pp. 215-230.

Sung, Y., Budhiraja, A.K., Williams, R.K. and Tokekar, P. (2018), "Distributed simultaneous action and target assignment for multi-robot multi-target tracking", *in: 2018 IEEE International conference on robotics and automation (ICRA)*, *IEEE*.

Talebpour, Z. and Martinoli, A. (2018), "Risk-based human-aware multi-robot coordination in dynamic environments shared with humans", *in: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, *IEEE*.

Tolmidis, A.T. and Petrou, L. (2013), "Multi-objective optimization for dynamic task allocation in a multi-robot system", *Engineering Applications of Artificial Intelligence*, Vol. 26 Nos 5/6, pp. 1458-1468.

Tsang, K.F.E., Ni, Y., Wong, C.F.R. and Shi, L. (2018), "A novel warehouse multi-robot automation system with semi-complete and computationally efficient path planning and adaptive genetic task allocation algorithms", *in: 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, *IEEE*.

Turner, J. (2018), "Distributed task allocation optimisation techniques", *in: Proceedings of the 17th international conference on autonomous agents and multiagent systems*.

Turner, J., Meng, Q., Schaefer, G., Whitbrook, A. and Soltoggio, A. (2017), "Distributed task rescheduling with time constraints for the optimization of total task allocations in a multirobot system", *IEEE Transactions on Cybernetics*, Vol. 48 No. 9, pp. 2583-2597.

Wang, J., Gu, Y. and Li, X. (2012), "Multi-robot task allocation based on ant colony algorithm", *Journal of Computers*, Vol. 7 No. 9, pp. 2160-2167.

Wang, X., Rui, F. and Hu, H. (2018), "Task allocation policy for UGV systems using colored petri nets", *in: 2018 Annual American Control Conference (ACC)*, *IEEE*.

Wawerla, J. and Vaughan, R.T. (2010), "A fast and frugal method for team-task allocation in a multi-robot transportation system", *in: 2010 IEEE International Conference on Robotics and Automation*, *IEEE*.

Wei, C., Hindriks, K.V. and Jonker, C.M. (2016), "Dynamic task allocation for multi-robot search and retrieval tasks", *Applied Intelligence*, Vol. 45 No. 2, pp. 383-401.

Whitbrook, A., Meng, Q. and Chung, P.W. (2019), "Addressing robustness in time-critical, distributed, task allocation algorithms", *Applied Intelligence*, Vol. 49 No. 1, pp. 1-15.

Woosley, B. and Dasgupta, P. (2018), "Integrated real-time task and motion planning for multiple robots under path and communication uncertainties", *Robotica*, Vol. 36 No. 3, pp. 353-373.

Wu, D., Zeng, G., Meng, L., Zhou, W. and Li, L. (2017), "Gini coefficient-based task allocation for multi-robot systems with limited energy resources", *IEEE/CAA Journal of Automatica Sinica*, Vol. 5 No. 1, pp. 155-168.

Xie, B., Gu, X., Chen, J. and Shen, L. (2018), "A multi-responsibility–oriented coalition formation framework for dynamic task allocation in mobile–distributed multi-agent systems", *International Journal of Advanced Robotic Systems*, Vol. 15 No. 6, pp. 1729881418813037.

Yi, X., Zhu, A., Yang, S.X. and Luo, C. (2016), "A bio-inspired approach to task assignment of swarm robots in 3-D dynamic environments", *IEEE Transactions on Cybernetics*, Vol. 47 No. 4, pp. 974-983.

Zhang, K., Collins, E.G., Jr. and Shi, D. (2012), "Centralized and distributed task allocation in multi-robot teams via a stochastic clustering auction", *ACM Transactions on Autonomous and Adaptive Systems (Systems)*, Vol. 7 No. 2, pp. 1-22.

Zhao, W., Meng, Q. and Chung, P.W. (2015), "A heuristic distributed task allocation method for multivehicle multitask problems and its application to search and rescue scenario", *IEEE Transactions on Cybernetics*, Vol. 46 No. 4, pp. 902-915.

Zhou, X., Wang, H., Ding, B., Hu, T. and Shang, S. (2019), "Balanced connected task allocations for multi-robot systems: an exact flow-based integer program and an approximate tree-based genetic algorithm", *Expert Systems with Applications*, Vol. 116, pp. 10-20.

Zhu, Z., Tang, B. and Yuan, J. (2017), "Multirobot task allocation based on an improved particle swarm optimization approach", *International Journal of Advanced Robotic Systems*, Vol. 14 No. 3, p. 1729881417710312.

Zhu, D., Cao, X., Sun, B. and Luo, C. (2017), "Biologically inspired self-organizing map applied to task assignment and path planning of an AUV system", *IEEE Transactions on Cognitive and Developmental Systems*, Vol. 10 No. 2, pp. 304-313.

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