Multi-robot Task Allocation: A Review of the State-of-the-Art

Alaa Khamis, Ahmed Hussein and Ahmed Elmogy

Abstract Multi-robot systems (MRS) are a group of robots that are designed aiming to perform some collective behavior. By this collective behavior, some goals that are impossible for a single robot to achieve become feasible and attainable. There are several foreseen benefits of MRS compared to single robot systems such as the increased ability to resolve task complexity, increasing performance, reliability and simplicity in design. These benefits have attracted many researchers from academia and industry to investigate how to design and develop robust versatile MRS by solving a number of challenging problems such as complex task allocation, group formation, cooperative object detection and tracking, communication relaying and self-organization to name just a few. One of the most challenging problems of MRS is how to optimally assign a set of robots to a set of tasks in such a way that optimizes the overall system performance subject to a set of constraints. This problem is known as Multi-robot Task Allocation (MRTA) problem. MRTA is a complex problem especially when it comes to heterogeneous unreliable robots equipped with different capabilities that are required to perform various tasks with different requirements and constraints in an optimal way. This chapter provides a comprehensive review on challenging aspects of MRTA problem, recent approaches to tackle this problem and the future directions.

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1 Introduction

Multi-robot systems (MRS) are a group of robots that are designed aiming to perform some collective behavior. By this collective behavior, some goals that are impossible for a single robot to achieve become feasible and attainable. MRS have been on the agenda of the robotics community for several years. It is only in the last decade, however, that the topic has really taken off, as seen from the growing number of publications appearing in the journals and conferences. One of the reasons that the topic has become more popular is the various foreseen benefits of MRS compared to single robot systems. These benefits include, but are not limited to the following:

- **Resolving task complexity**: some tasks may be quite complex for a single robot to do or even it might be impossible. This complexity may be also due to the distributed nature of the tasks and/or the diversity of the tasks in terms of different requirements.
- **Increasing the performance**: task completion time can be dramatically decreased if many robots cooperate to do the tasks in parallel.
- **Increasing reliability**: increasing the system reliability through redundancy because having only one robot may work as a bottleneck for the whole system especially in critical times. But when having multiple robots doing a task and one fails, others could still do the job.
- **Simplicity in design**: having small, simple robots will be easier and cheaper to implement than having only single powerful robot.

These benefits have attracted many researchers from academia and industry to investigate the applicability of MRS in many pertinent areas of industrial and commercial importance such as intelligent security [1], search and rescue [2], surveillance [3], humanitarian demining [4], environment monitoring [5, 6] and health care [7].

In order to develop and deploy robust MRS in real-world applications, a number of challenging problems needs to be solved. These problems include, but are not limited to, task allocation, group formation, cooperative object detection and tracking, communication relaying and self-organization to name just a few. The following section discuses in details the task allocation problem as one of the challenging problems of MRS.

MRTA problem is one of the most challenging problems of MRS especially when it comes to heterogeneous unreliable robots equipped with different types of sensors and actuators and are required to perform various tasks with different requirements and constraints in an optimal way. This problem can be seen as an optimal assignment problem where the objective is to optimally assign a set of robots to a set of tasks in such a way that optimizes the overall system performance subject to a set of constraints.

In spite of the great number of MRTA algorithms reported in the literature, important aspects have, to date been given little attention. These aspects include but are not restricted to allocation of complex tasks, dynamic task allocation, heavily constrained task allocation and heterogeneous allocation.

The main objective of this chapter is to provide a comprehensive review on challenging aspects of MRTA problem, recent approaches to tackle this problem and the future directions. The remainder of the chapter is organized as follows: Sect. 2 describes MRTA problem as one of challenging problems of MRS. Section 3 highlights different MRTA schemes and planning followed by discussing different organizational paradigms that can be used in Sect. 4. Section 5 reviews two well-known MRTA approaches, namely, metaheuristic-based and market-based approaches. Finally conclusion and future directions are summarized in Sect. 6.

2 Multi-robot Task Allocation (MRTA) Problem

MRTA problem addresses the question of finding the task-to-robot assignments in order to achieve the overall system goals [8, 9]. This can be divided into two subproblems. First, how a set of tasks is assigned to a set of robots. Second, how the behavior of the robot team is coordinated in order to achieve the cooperative tasks efficiently and reliably. Because the problem of task allocation is a dynamic decision problem that varies in time with phenomena including environmental changes, the problem should be solved iteratively over time [10]. Thus, the problem of task allocation becomes more complex to tackle. The requirements of the particular domain under consideration affect the features and complexity of multi-robot task allocation problems [11].

2.1 Problem Formulation

As illustrated in Fig. 1, MRTA can be formulated as an optimal assignment problem where the objective is to optimally assign a set of robots to a set of tasks in such a way that optimizes the overall system performance subject to a set of constraints.

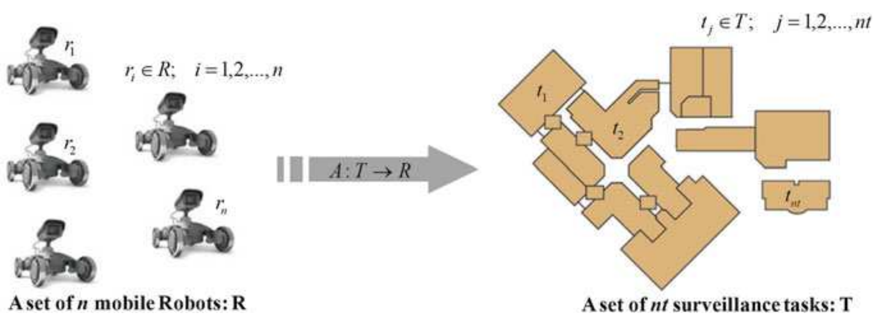

Fig. 1 MRTA problem

In this problem, it is given:

1. R: a team of mobile robots r_i; $\{i = 1, 2, \ldots n\}$.
2. T: a set of tasks t_{ij}; $\{j = 1, 2, \ldots nt\}$.
3. U: a set of robots' utilities, u_{ij} is the utility of robot i to execute task j.

For a single sensor task, the problem is to find the optimal allocation of robots to tasks, which will be a set of robot and task pairs [12]:

$$(r_1, t_1), (r_2, t_2), \ldots (r_k, t_k)\ for\ 1 \leq k \leq m \tag{1}$$

For the general case, the problem is to find the optimal allocation of a set of tasks to a subset of robots, which will be responsible for accomplishing it [13]:

$$A : T \rightarrow R \tag{2}$$

In some MRTA approaches such as market-based approaches (Sect. 5.1), each robot $r \in R$ can express its ability to execute a task $t \in T$, or a bundle of tasks $G \subseteq T$ through bids b_r(t) or b_r(G). The cost of a bundle of tasks can be simply computed as the sum of costs of the individual tasks:

$$b_r(G) = \sum_{k=1}^{f} b_r(t_k)\ \{t_k \in G\} \tag{3}$$

where f is the number of tasks of the bundle G. The group's assignment determines the bundle $G \subseteq T$ of tasks that each robot $r \in R$ receives.

2.2 Problem Modeling

Many methods have been proposed in the literature to model the MRTA problem as described in the following sections.

2.2.1 Discrete Fair Division

The MRTA problem can be seen as an example of a Fair Division Problem [14]. Given a set of N robots $(r_1, r_2, \ldots r_N)$ and a set of tasks S. It is required to divide S into N shares $(s_1, s_2, \ldots s_N)$ so that each robot gets a fair share of S. A fair share is a share that, in the opinion of the robot receiving it, is worth *1/N* of the total value of S.

Fair division problems can be classified depending on the nature of the set of shares S into two kinds:

- Indivisible tasks, such that each item should be given entirely to a single robot.
- Divisible tasks, which are often modeled as a subset of a real space. Additionally, the set to be divided may be homogeneous, or heterogeneous. Thus the set of the dividable tasks should be given to homogeneous or heterogeneous robot team.

Two different schemes have been reported in the literature to deal with discrete fair division problems. The first scheme is called the method of sealed bids [15] at which each bidder submits a secret sealed bid. The bids are kept private until the closing of the bidding period. After the auction closes, the bids are opened by the auctioneer and the auction winner is determined. The winner will be the one with the highest bid price. The second scheme for discrete fair division is the method of markers [16]. In this method, the tasks could be arranged in a linear fashion. This may be the case when a large number of small tasks need to be shared. The N available robots indicate their opinion as regard a fair division by placing $N-1$ markers and agree to accept any segment of the tasks that lies between any pair of their consecutive markers. The next step is to find the leftmost among the consecutive markers. The owner of this marker receives the first segment (the one from the left end and up to the marker itself) and all the remaining markers of that robot are removed from further consideration. This step is repeated until all robots received what they think a fair share in their opinion. Fair division-based MRTA approach is described in [17]. This approach only addresses the allocation of a single global task between a group of heterogeneous robots.

2.2.2 Optimal Assignment Problem (OAP)

As mentioned previously, MRTA can be seen as an example of optimal assignment problem. In this type of problems [18], given a set of robots *R*, a set of tasks *T* the goal is to maximize the profit W(*rt*) made by assigning robot *r* to task *t*. By adding virtual tasks or robots with zero profitability, it can be assumed that *R* and *T* have the same size *n* which can be written as $R = r_1, r_2, \ldots r_N$ and $T = t_1, t_2, \ldots t_N$.

Mathematically, the problem can be stated: given an $n \times n$ matrix *W*, find permutation π of $1, 2, 3, \ldots n$ for which:

$$\sum_{i=1}^{n} w(r_i \; t_{\pi(i)}) \;\; is \; maximized \tag{4}$$

Such matching from *R* to *T* is called an optimal assignment. Related to multi-robot task allocation, the goal is to assign the set of robots *R* to the set of tasks *T* such that the profit is maximized [19].

2.2.3 ALLIANCE Efficiency Problem (AEP)

The alliance algorithm is a mono-objective optimization algorithm that was first used to solve *NP* problems [20]. It has been generalized to tackle any mono-objective optimization problem [8], and has been used to solve artificial life problems and robotics problems [9]. In this algorithm, several tribes, with certain skills try to conquer an environment that offers resources needed for their survival [20]. Two features characterize each tribe: the skills and the resources necessary for survival.

A tribe t is a tuple (x_t, s_t, r_t, a_t) composed of:

- a point of solution space x_t
- a set of skills $s_t = [s_{t,1}, s_{t,2}, \ldots s_{t,N_s}]$ that depends on the values of N_s objective function $S = [S_1, S_2, \ldots S_{N_s}]$ evaluated at x_t:

$$s_{t,i} = S_i(X_t)\forall i = 1, 2, \ldots N_s \tag{5}$$

- a set of resource demands $r_t = [r_{t,1}, r_{t,2}, \ldots r_{t,N_s}]$ that depends on the values of the N_R. Generally there is only one constraint function:

$$r_t = R(x_t) \tag{6}$$

- An alliance a_t that records the IDs of the tribes allied to tribe t.

2.2.4 Multiple Traveling Salesman Problem

The Multiple Traveling Salesman Problem (mTSP) is a generalization of the Traveling Salesman Problem (TSP) in which more than one salesman is allowed [21, 22]. Given a set of cities, and m salesmen, the objective of is to determine a tour for each salesman such that, starting from the same base city, each salesman visits at least one city and returns to the base city so as to minimize the total cost. The cost could be distance or time. A comprehensive study of 32 formulations for the multiple traveling salesman problem is investigated in [22] considering their relative performances. The presented formulations differ by the way the sub-tour elimination constraints are modeled. Thus, the models can be accordingly classified as follows: *(i)* those that are based on the ranking of the cities; *(ii)* those that are based on explicit time-indexed variables for ranking the cities, and *(iii)* those that are based on multi commodity flow constructs.

The main difference in the mTSP is that instead of a single salesman, a number of salesmen m are given. The salesmen are required to cover all the available nodes and return back to their starting node such that each salesman make a round trip. The mTSP can be formally defined on a graph $G = (V, A)$ where V is the set of n nodes and A is the set of arcs. Let $C = (c_{ij})$ be the distance matrix associated with A. Assuming the more general case which is an asymmetric mTSP, thus $c_{ij} \neq c_{ji}$ $\forall$ $(i, j) \in A$. The mTSP can be formulated as follows [23]:

$$x_{ij} = \begin{cases} 1 & \text{if arc (i, j) is used in the tour} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$\text{minimize } \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij} \times x_{ij} \tag{8}$$

$$\sum_{j=2}^{n} x_{1j} = m \tag{9}$$

$$\sum_{j=2}^{n} x_{j1} = m \tag{10}$$

$$\sum_{i=1}^{n} x_{ij} = 1, j = 2, \ldots, n \tag{11}$$

$$\sum_{j=1}^{n} x_{ij} = 1, i = 2, \ldots, n \tag{12}$$

$$x_{ij} \in \{0, 1\}, \forall (i, j) \in A \tag{13}$$

$$\sum_{i \in S}\sum_{j \in S} x_{ij} \leq |\text{subTour}| - 1, \quad \forall S \subseteq V \backslash \{1\}, \text{subTour} \neq \phi \tag{14}$$

where (8) represents the objective function which is the summation of the total distance traveled, (9) and (10) ensures that exactly m salesmen departed their starting node and returned back. Equations (11)–(13) are the usual assignment constraints. Finally, (14) is the sub-tour elimination constraint.

A number of variations of the original mTSP were introduced by different researchers to accommodate the mTSP to their problems. These variations included the following [23]:

- **Salesmen starting node**: all the salesmen may start from a single depot node and then all of them must return back to the same node or every salesman can start from a certain node, and thus each salesman must return back to his starting node.
- **Number of salesmen**: the number of salesmen used in different applications varies according to the type and requirements of the application itself. In some applications, the number of salesmen is dynamic such that after each iteration the number of salesman may or may not change.
- **City time frame**: in some applications the task of the salesman is not only to visit the city, but also to stay in the city for a certain time in order to move to the next city.
- **Fair division of salesmen**: another variation of the general mTSP is the addition of constraints that specify the maximum number of cities or the maximum distance that can be traveled by a single salesman. This variation can be used in applications that are concerned with the fair division of the available resources (salesmen).

In [24], the MRTA problem is modeled as a multi-traveling salesman problem considering that robots play the roles of the salesmen and the tasks are the same as cities.

3 MRTA Schemes and Planning

As illustrated in Fig. 2, existing task allocation schemes can be categorized according to several dimensions [25]:

- Single task (ST) versus multi-task (MT), related to the parallel task performing capabilities of robots,
- Single robot (SR) versus multi-robot (MR), related to the number of robots required to perform a task, and
- Instantaneous assignment (IA) versus time extended assignment (TA), related to the planning performed by robots to allocate tasks.

ST means that each robot is capable of executing as most one task at a time, while MT means that some robots can execute multiple tasks simultaneously. Very similarly, SR means that each task requires exactly one robot to achieve it, while MR means that some tasks can require multiple robots. In IA approaches the available information concerning the robots, the tasks, and the environment permits only an instantaneous allocation of tasks to robots (i.e. tasks independence is a strong assumption). These approaches are sometimes used in order to avoid the need for highly computationally scheduling algorithms. At the other extreme, there are continuous task allocation or time extended assignment approaches where more information is available, such as the set of all tasks that will need to be assigned. Because robots have to reason about the dependencies between tasks, TA is more demanding from a planning perspective [26].

From the perspective of planning, there are two common approaches to the task allocation problem: decompose-then-allocate and allocate-then-decompose. In the first technique, the complex mission is decomposed to simple sub-tasks and then these sub-tasks are allocated to the team members based on their capability and availability to complete the sub-tasks as required [27, 28]. In this type of techniques, the cost of the final plan cannot be fully considered, because the task decomposition

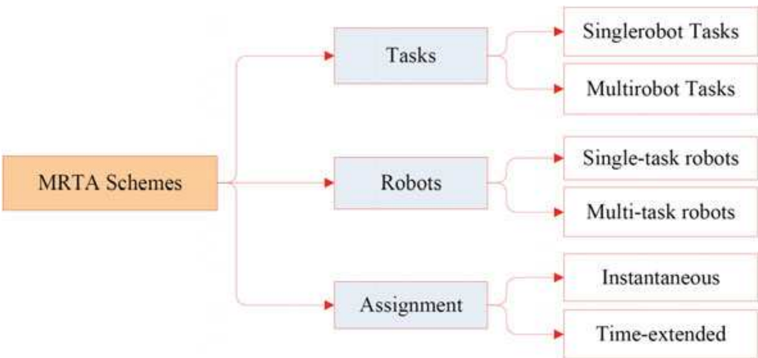

Fig. 2 MRTA schemes

is done without knowing to whom tasks will be allocated. Another disadvantage of this type is inflexibility to changes in the designed plan. So, the plan designed by the central agent cannot be rectified even if it is found costly. On the other side, in the allocate-then-decompose approach [28], the complex tasks are allocated to mobile sensors, and then each mobile sensor decomposes the awarded tasks locally. The main disadvantage of this approach is the allocation of all tasks to only one mobile sensor and thus, the preferred task decomposition is purely dependent on the plan of that mobile sensor, which increases the possibility of reaching a sub-optimal solution. It may be more beneficial to allocate tasks to more than one mobile sensor in order to consider different plans for the required task. While the decompose-then-allocate and the allocate-then-decompose methods may be capable of finding feasible plans, there are drawbacks to both approaches.

4 Organizational Paradigms

MRTA approaches can be classified according to team organizational paradigm. This paradigm shows how the multiple robots/agents of the system are organized by specifying the relationships and interactions among the agents and the specific roles of each agent within the system. The following subsections describe centralized and decentralized organizational paradigms.

4.1 Centralized Approaches

In this type of systems, each agent maintains a connection to one central agent that allocates the tasks to the other agents. Thus, the separate agents send all the information they have to this central agent, which in turn processes this information and sends the appropriate commands to these agents to execute the assigned tasks. The advantages of this type include the reduction of duplication of effort, resources, and increased savings of cost and time [29]. Although the centralized systems are widely implemented in the literature [30], there are many disadvantages that restrict the use of this paradigm in multi-robot task allocation. The lack of robustness is one of the most important disadvantages of the centralized system. In other words, if the central agent fails, the whole system will fail. Also, the system scalability is restricted because all the agents are connected to the central agent that is considered as a bottleneck. Practically, fully centralized approaches can be computationally intractable, brittle, and unresponsive to changes. Thus, for multi-robot task allocation problems where number of robots and tasks are small and the environment is static or global state information is easily available, centralized approaches are the best-suited solution. The centralized approach is one of the most widely reported approaches in the literature for solving the task allocation problems [31]. In [32], a centralized algorithm is proposed to solve the MRTA problem in order to assign tasks to mobile

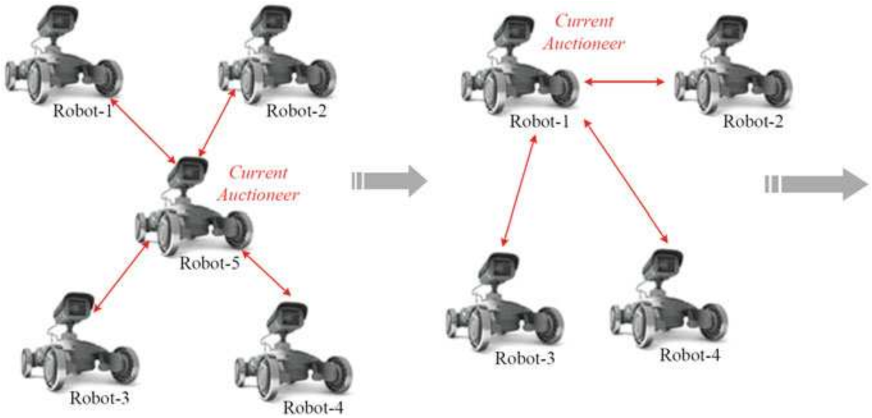

Fig. 3 Hierarchical organizational paradigm

robots to extend the life time of the sensor network. Also in [33], a centralized approach is introduced to solve the MRTA for the inspection problem in an industrial plant. Fair division-based MRTA approach described in [17] is another centralized algorithm that allocates a single global task between a group of heterogeneous robots.

4.2 Decentralized Approaches

Decentralization is the process of dispersing the administrative tasks and authorities between the agents of the multi-agent system [29]. In this type of configuration, there is no centralized agent that allocates the tasks to the other agents. Each agent is communicating its information with the other agents. Each agent can work on its own without major consideration of the other agents. Also, sometimes an agent of the decentralized system needs to exchange information with other agents in order to achieve its mission efficiently in harmony with other agents.

Many decentralized approaches are proposed to solve MRTA problem. In [34], the authors proposed a decentralized implementation of the Hungarian method proposed in order to solve the MRTA problem. In [35], two decentralized auction-based approaches, namely, the consensus-based auction algorithm and the consensus-based bundle algorithm are proposed for solving the MRTA problem of a fleet of autonomous mobile robots. Also an evolutionary computation decentralized approach is proposed for solving the MRTA problem using genetic algorithm in [36]. Hierarchical market-based approach has been proposed in [26] as a decentralized approach for MRTA problem. As shown in Fig. 3, the tasks are allocated initially to the robots 1; 2; 3; and 4 via a central auctioneer 5. Each robot can hold auctions in rounds for the tasks it won in the initial auction.

The main advantage of the decentralized system is its robustness. For example, in distributed systems, if one of the agents fails, the other agents are still working on their own and/or cooperatively with others [37]. As there is no centralized agent as a bottleneck, new agents can be added in case of failure for example. This means that scalability is no longer an issue in decentralized systems. In general, decentralized approaches have many advantages over centralized approaches such a flexibility, robustness, and low communication demands. However, because a good local solution may not sum to a good global solution, decentralized approaches can produce highly sub-optimal solutions.

5 MRTA Approaches

The following subsections describe two of most commonly used MRTA approaches, namely market-based approaches and optimization-based approaches.

5.1 Market-Based Approaches

Market-based approach gained a considerable attention within the robotics research community because of several desirable features, such as the efficiency in satisfying the objective function, robustness and scalability [9]. The market-based approach is an economically inspired approach that provides a way to coordinate the activities between robots/agents. It is mainly based on the concept of auctions. In economic theory, an auction is defined by any mechanism of trading rules for exchange [38]. An auction is a process of assigning a set of goods or services to a set of bidders according to their bids and the auction criteria. Auctions are common and simple ways of performing resource allocation in a multi-agent system.

Market-based approaches for MRTA problem involve explicit communications between robots about the required tasks. Robots bid for tasks based on their capabilities. The negotiation process is based on market theory, in which the team seeks to optimize an objective function based upon robots utilities for performing particular tasks [13]. The following subsections provide more details about auctions, and winner determination strategies.

5.1.1 Auctions

Auctions, in one form or another, have been used in societies throughout history to allocate scarce resources among individuals and groups. Generally, any protocol that allows agents to indicate their interest in one or more resources or tasks is considered an auction. This makes auctions very important to consider when tackling many applications. Moreover, auctions provide a general theoretical structure for understanding resource allocation among self-interested agents. Since auctions are simply mechanisms for allocating goods, there are various types of auction that can achieve this goal. These auctions can be divided into two main categories, simple-good auctions and combinatorial auctions. Figure 4 shows taxonomy for different auctions types.

5.1.2 Auction Design

The auction has several designs that can be used to solve multi-robot task allocation problem. In this section some of these designs are defined and discussed.

- **Contract Net Protocol (CNP)**: CNP is a task-sharing protocol in multi-agent systems. It specifies the interaction between agents for autonomous competitive negotiation through the use of contracts. Thus, CNP allows tasks to be distributed among multi-agents. Smith in 1980 was the first one to apply CNP to a simulated distributed acoustic sensor network [39]. The contract net protocol enables dynamic distribution of information via three methods:
  - Nodes can transmit a request directly to another node for the transfer of the required information.
  - Nodes can broadcast a task announcement in which the task is a transfer of information.
  - Nodes can note, in its bid on a task, that it requires particular information in order to execute the task.

  The details of CNP algorithm as shown in Fig. 5 and it works as follows:

- **Announcement stage**: an agent takes up the role of the coordinator/auctioneer and announces the tasks or a set of tasks to be available for bidding.
- **Submission stage**: after calculating the individual utility values based on the objective function, individual agents/bidders communicate this value to the coordinator agent.

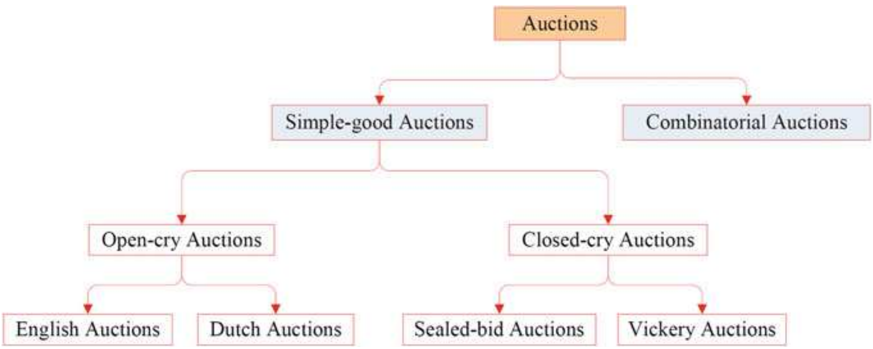

Fig. 4 Auctions types

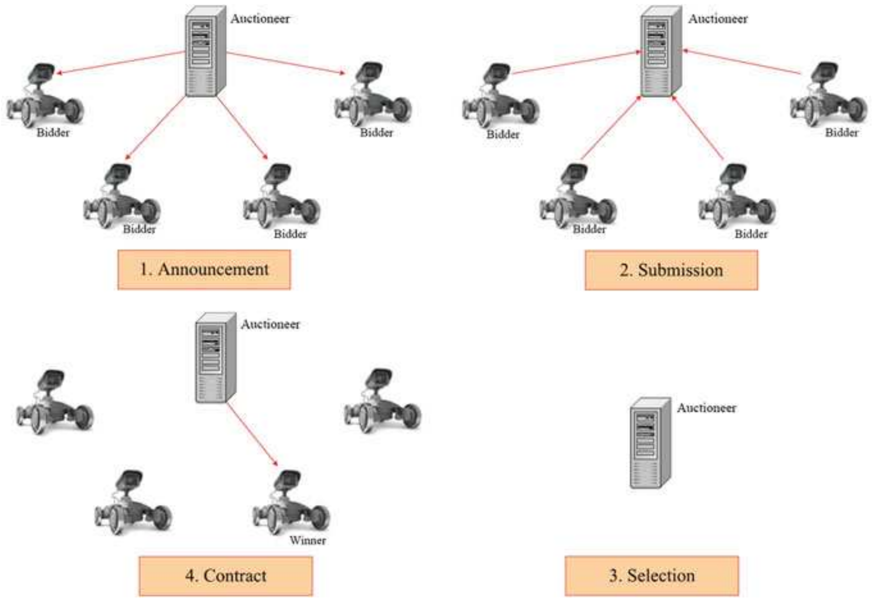

Fig. 5 Contract net protocol algorithm

- **Selection stage**: after receiving all the bids from the bidders, the job of the auctioneer is to evaluate the received bids based on an optimization strategy to determine the winning agent.
- **Contract stage**: the winning agent get assigned by a contract to execute the task and the process loops all over again.

The main contribution of the contract net protocol is that it offers structuring high-level interactions between nodes for cooperative task execution. Wherever, the main drawback is that each agent is a self-interested agent; meaning that the final solution may be the best for the agents involved, but not for the group as whole [40].

- **Trader-Bots**: Trader-Bots approach applies market economy techniques for generating efficient and robust multi-robot coordination in dynamic environments. The top level of Trader-Bots architecture consists of multiple traders; one trading agent for each robot, plus other trading agents representing operators or other resources such as computers and sensors. Each trader has the ability to reason about tasks and resources in order to make rational decisions when negotiating contracts [12]. The objective functions for this approach are designed to reflect the nature of the application domain. These functions reflect the domain characteristics in terms of priorities for task completion, hard deadlines for relevant tasks, and acceptable margins of error for different tasks. The goal in this algorithm is to have a team of robots which can complete the tasks efficiently maximizing overall profits, while maximizing the individual profits for each robot as well. The main advantages of this algorithm are self-organization, learning and adaptation, and robustness [12]. The trader representing a robot is called a RoboTrader, and the trader representing an operator is called an OpTrader. For single-task contracts, Trader-Bots uses first-price sealed-bid auctions in generating the efficient coordination [13]. Trader-Bots makes use of two modes of contracts; subcontracts and transfers.

– **Subcontract**: the bidder is agreeing to perform a task for the seller at a given price, and must report back to the seller upon completion to receive payment.
– **Transfer**: the right to perform a task is sold for a price and the payment goes from the seller to the buyer upon the awarding of the contract.

5.1.3 Pros and Cons of Market-Based Approaches

Market-based approaches have several advantages such as [12, 38]:

- **Efficiency**: one of the greatest strengths of market-based approaches is their ability to utilize the local information and preferences of their participants to arrive at an efficient solution given limited resources [32]. Market-based approaches have elements that are centralized and other elements that are distributed [32]. Thus they can produce efficient solutions by capturing the respective strengths of both distributed and centralized approaches. It has been shown in [26, 32, 41, 42] that efficient solutions can be produced by market approaches with respect to a variety of team objective functions.
- **Robustness**: as mentioned previously, fully centralized approaches employ a single agent to coordinate the entire team in a multi-agent system. They may suffer from a single point of failure, and have high communication demands. Market-based approaches implemented based on decentralized paradigm do not require a permanent central coordinator agent and therefore there is no common-mode failure point or vulnerability in the system. These approaches can be made robust to several types of malfunctions, including complete or partial failures of agents [32, 38, 43].
- **Scalability**: as mentioned before, the computational and communication requirements of market-based approaches are usually manageable, and do not prohibit these systems from providing efficient solutions because they are not fully centralized systems. Thus, as the size of the inputs in the system increases, these approaches can still provide an efficient solution [32]. Market-based approaches can scale well in applications where the team mission can be decomposed into tasks that can be independently carried out by small sub-teams [38]. However and as concluded in [42], optimization-based approach outperforms market-based approach in handling large-scale MRTA scenario (fifty tasks and fifteen robots).
- **Online input**: market-based approaches are able to seamlessly incorporate the introduction of new tasks [41]. Market-based approaches can often incorporate online tasks by auctioning new tasks as they are introduced to the system or generated by the agents themselves [38].

- **Uncertainty**: market-based systems are able to operate in unknown and dynamic environments by allowing team members to adapt cost estimates over time, and reallocate tasks when appropriate [44].

Although market-based approaches have many advantages, they are not without their disadvantages. Perhaps the biggest drawback of market-based approaches is the lack of formalization in designing appropriate cost and revenue functions to capture design requirements [45]. Also, negotiation protocols, developing appropriate cost functions, and introducing relevant penalty schemes can complicate the design of the market approach [12]. In domains where fully centralized approaches are feasible, market-based approaches can be more complex to implement, and can produce poorer solutions [45]. Also, when fully distributed approaches suffice, market-approaches can be unnecessarily complex in design and can require excessive communication and computation [45].

5.2 *Optimization-Based Approaches*

Optimization is the branch of applied mathematics focusing on solving a certain problem in the aim of finding the optimum solution for this problem out of a set of available solutions. This set of available solutions is restricted by a set of constraints, and the optimum solution is chosen within these constrained solutions according to a certain criteria. This criteria defines the objective function of the problem that quantitatively describes the goal of the system [46]. There is a wide variety of optimization approaches available, and the use of these approaches depends on the nature and the degree of complexity of the problem to be optimized. Moreover the optimization-based approaches algorithms have higher potential for exploring new search areas in the search space because the randomness of the algorithm variables which also enable an enhanced performance when dealing with noisy input data [47–49]. Figure 6 shows a general classification of optimization techniques [50].

Deterministic techniques follow a rigorous procedure and its path and values of both design variables and the functions are repeatable. For the same starting point, they will follow the same path whether you run the program today or tomorrow. Deterministic techniques include numerical and classical methods such as graphical methods, gradient and hessian based methods, derivative-free approaches, quadratic programming, sequential quadratic programming, penalty methods, etc. They also include graph-based methods such as blind/uninformed search and informed search methods.

Stochastic techniques always have some randomness. These techniques can be classified into trajectory-based and population-based algorithms. A trajectory-based metaheuristic algorithm such as simulated annealing uses a single agent or solution which moves through the design space or search space in a piece-wise style. A better move or solution is always accepted, while a not-so-good move can be accepted with certain probability. The steps or moves trace a trajectory in the search space,

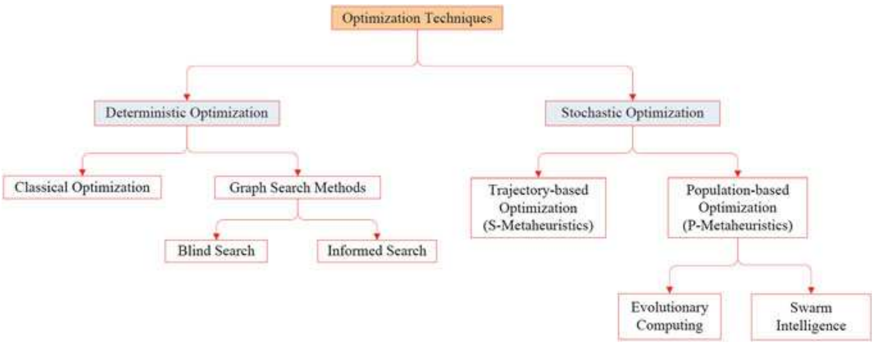

Fig. 6 Optimization techniques

with a non-zero probability so that this trajectory can reach the global optimum. On the other hand, population-based algorithms such as genetic algorithms, ant colony optimization and particle swarm optimization use multiple agents to search for an optimal or near-optimal solution.

By reviewing the literature, it was found that different optimization approaches have been used in order to solve the general task allocation problems and MRTA problem. In [51], a mixed integer linear programming optimization approach was used in order to allocate heterogeneous robots for maximizing the coverage area of the regions of interest. Also in [52], a mixed integer linear programming approach was used for solving the task allocation problem in the context of UAV cooperation. In [53, 54], a simulated annealing approach was used to solve the allocation of multi-robot system through formulating the MRTA problem as mTSP. In [55, 56], simulated annealing incorporated with other heuristic approaches was used to allocate a set of tasks to a number of processors in computer system problems.

Different optimization approaches were also used for solving the task allocation problem. For example, population-based approaches such as the genetic algorithm was used in [57] for providing a feasible solution for a group tracking system which is capable of tracking several targets rather than individual targets. Genetic algorithm was also used in [58] to provide a solution for the time extended task allocation of multi-robots in a simulated disaster scenario. Ant colony optimization, another technique of the population-based optimization approaches, was used in [59] to solve the task allocation problem of MRS. In [60], ant algorithm was used in the context of multi-robot cooperation for the aim of solving the task allocation problem.

The task allocation problem was also solved using hybrid optimization approaches such as tabu search with random search method in [56] and tabu search with noising method in [61]. In [62], a simultaneous approach for solving the path planning and task allocation problems for a MRS is proposed, where simulated annealing and ant colony optimization approaches were investigated and applied for solving the problem.

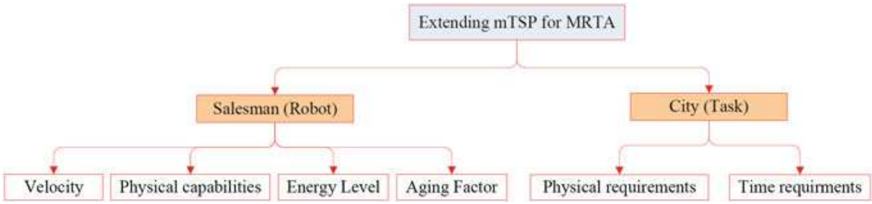

Fig. 7 Extending mTSP formulation for MRTA

Trajectory-based metaheuristics and population-based metaheuristics have been proposed in [42]. These two optimization-based approaches were extensively tested over a number of test scenarios showing the efficacy of the proposed algorithms in handling complex heavily constrained MRS applications that include extended number of heterogeneous tasks and robots. Figure 7 illustrates the extension of the mTSP formulation to accommodate the requirements of the MRTA problem. Since most real MRS applications require heterogeneous robots of different capabilities, it was a must to consider the heterogeneity of the robots in the proposed approach. Four main features of the robot were considered and thus were added to the traveling salesman in the implementation phase. The four features are velocity of the robot; robot capabilities; energy level of the robot and aging factor (efficiency). In the same manner, the mTSP formulation for solving the MRTA problem needed to be adapted to handle the heterogeneity of the tasks and therefore it was a must to add extra features to the cities. The added features to the cities are task requirements and minimum time required to finish the task.

A comparative study between metaheuristics-based and market-based approaches is reported in [42]. This study quantitatively evaluates the performance of these two approaches in terms of their ability to produce feasible solutions that maximize overall system performance and decrease the costs and the ability to handle real-world constraints such as time constraints and robot capabilities-task requirements matching constraints. Scalability is also considered as an evaluation metric in this study. The experimental results using different scenarios show that metaheuristics approaches outperform market-based approach in the scalability scenario while both approaches provide nearly similar results in the constraints handling scenarios. The results of this compartive study is presented in Table 1. The suitability of the algorithms depends on the required application domain of the MRTA problem. The stars evaluate the algorithm's efficiency in handling the application scenario, i.e. more stars means better algorithm [42].

6 Conclusion

This chapter reviewed the different challenging aspects of multi-robot task allocation problem, the recent approaches to tackle this problem and the future directions. The

Table 1 MRTA approaches applicability results

Scenario/algorithm	Market-based	Simulated annealing	Genetic algorithm
Small-scale	⋆	⋆	⋆
Medium-scale	⋆	⋆ ⋆ ⋆	⋆ ⋆
Large-scale	⋆	⋆ ⋆ ⋆	⋆ ⋆
Capabilities matching	⋆ ⋆	⋆	⋆
Time matching	⋆	⋆	⋆
Heavily constraints	⋆	⋆	NA

chapter also discussed two well-known approaches, metaheuristic-based and market-based approaches that are used extensively to solve the MRTA problem. Many of the reviewed approaches are capable of handling complex task allocation with different forms of constraints such as time constraints and robot capabilities-task requirements matching constraints.

Multi-robot task allocation with ability to handle more complex constraints is still open and needs to be tackled by researchers. These complex constraints can be categorized into environment-related constraints, robot-related constraints and task-related constraints. Environment-related constraints include, but are not limited to, the dynamic and unpredictable nature of the environment and its partial observability and complexity. Robot-related constraints can include limited sensing/acting range, limited radio coverage and partial malfunctions. Task-related constraints may include time extended tasks and tight tasks that cannot be decomposed into single robot tasks or tasks with precedence constraints.

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