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Optimization techniques for Multi-Robot Task Allocation problems: Review on the state-of-the-art

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A B S T R A C T

In the last years, Multi-Robot Systems (MRS) have experienced considerable recognition due to various possible real-world applications. Multi-Robot Task Allocation (MRTA) is among the most interesting MRS problems. This problem concerns the situation when a set of given tasks must be performed by a team of mobile robots with the intention of optimizing an objective function (e.g., minimizing the mission time). This paper aims to present MRTA applications and categorizes methods into market-based, behavior-based, and optimization-based approaches. The paper focus on the latter and review several works in order to point out their advantages and limitations and to identify possible future research opportunities. Furthermore, a statistical analysis is provided to identify the most used methods and the evolution of the topic over the years.

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1. Introduction

The main thrust in the improvement of robotic systems is their capacity for replacing humans in monotonous work and reducing their presence in risky environments. In addition, in order to perform complex tasks, robots need to cooperate, and thus Multi-Robot Systems (MRS) are preferred rather than single-robot systems. Over the last few years, MRS have been employed in different fields for a variety of applications including agriculture [1], surveillance [2–4], search and rescue [5–7], target detection [8,9], product pick-up and delivery in distribution centers [10,11], and health care [12]. Mainly, there are two approaches for multi-robot collaboration: intentional cooperation, and emergent cooperation [13]. In regards to emergent approaches, collective behavior is based on robots that interchange with each other and with the environment (e.g., swarm robotics which is inspired by bee's behavior). It deals generally with a fleet of homogeneous robots aiming to perform numerous repetitions of the same activity over a wide region, such as monitoring a large area. In the case of intentional coordination approaches, the problem becomes more difficult since a set of heterogeneous robots must perform several distinct tasks where each co-worker is only qualified for some given tasks. So, robots cooperate explicitly intending to maximize the overall performance of the team.

The problem of deciding which robot should execute a given task is called Multi-Robot Task Allocation (MRTA) (Fig. 1) and is the main focus of this paper. MRTA aims to coordinate a large number of robots in order to complete a set of tasks with specific constraints. Intentional cooperation approaches are more appropriate for MRTA problems [14]. It can be viewed as a supervisory level in the robot's control architecture by giving intelligence to the system from a high-level perspective in order to perform concurrent tasks through their collective behavior. There are three main types of mobile robots. The first type is land-based robots that can be wheeled, tracked, or legged such as Automated Guided Vehicle (AGV) or Unmanned Ground Vehicle (UGV). Then, there are air-based robots such as planes, blimps, or drones that we refer to as Unmanned Aerial Vehicles (UAVs). Finally, water-based robots that operate on the surface of the water such as Autonomous Underwater Vehicle (AUV), and Unmanned Surface Vehicle (USV) represent the third type. Mobile robots can deliver items, perform measurements, distribute survival kits to potential victims, remove debris to reach them, etc.

MRTA assigns tasks to robots in order to maximize or minimize a given objective function. It operates in an imperfect environment where the information may be inaccurate and incomplete. Moreover, the failure of robots, dynamic tasks, moving obstacles, unknown environments, or other unexpected events can bring the problem to a higher level of difficulty. So, task allocation in dynamic environments [15,16] is one of the most challenging aspects of this problem since it requires handling several constraints that may appear during task execution. In the last few years, the interest in dynamic task allocation research has increased significantly. Therefore, robust and scalable algorithms must be developed in terms of communication and learning between robots to handle unpredicted events.

This paper aims to survey optimization-based strategies to solve MRTA problems to provide a global view of the problem

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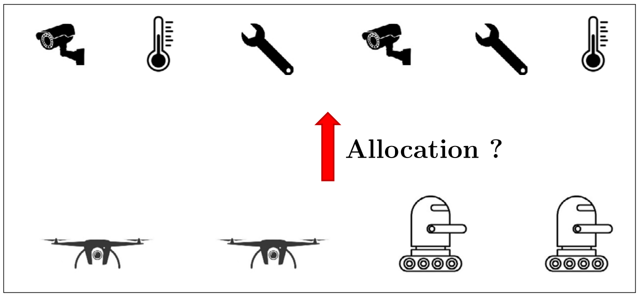

Fig. 1. MRTA problem presentation.

and give some future work directions. This study analyzes significant recent contributions from the perspectives of application, problem taxonomy, and optimization method. It provides a new perspective compared to some papers that have been presented in the past [17–20] and focuses on the possible strategies that can be adopted. In [14], Gerkey and Matarić present a taxonomy that classifies MRTA problems according to the robot's abilities, task requirements, and time. Further, Korash, Dias, and Stentz [21] extend the last taxonomy by adding a classification layer according to dependencies between tasks. Moreover, authors in [22] present a new taxonomy that classifies MRTA problems according to temporal constraints (deadlines of tasks, priority, and so on). Other surveys focus on MRTA aspects from a robotic point of view [23], and strategies for dynamic environments [24]. In this study, conferences and journal papers published from 2006 to 2022 are considered. Contributions have been selected based on their relevance to the MRTA subject, combinatorial optimization, and scheduling methods.

This paper is organized as follows: Section 2 introduces the main approaches used in combinatorial optimization. Then, it presents MRTA problem taxonomies, categorizations, and connected optimization problems from the literature. Section 3 presents the different possible techniques to solve MRTA problems. Sections 4 and 5 provide successively a technical view of the most relevant works from the literature and a detailed discussion about these researches. In Section 6, we conclude with the main results of this study.

2. MRTA problem

2.1. Combinatorial optimization

MRTA is a combinatorial optimization problem. It is generally modeled using methods from operations research, that makes use of mathematical models to improve complex systems. It is a wide field that incorporates techniques from artificial intelligence, machine learning, software engineering, applied mathematics, and computer sciences. Using machine learning and artificial intelligence approaches can autonomously assign tasks to robots while learning from mistakes and adapting to changing conditions. Software engineering concepts are also important. For this purpose, applied mathematics and computer science are required to design effective algorithms and implement the robot control software.

MRTA can be viewed as a branch of discrete optimization where problems are dealing with graph structures. Most of the approaches are based on a mathematical model. A given combinatorial optimization problem consists in finding the best solution among a finite number of feasible ones according to an objective function whose domain is discrete and has a large search space. Moreover, a set of conditions or properties called constraints must be satisfied by all the feasible solutions. To solve this type of problem, resolution methods have been classified into two main categories: exact approaches and approximate approaches [25].

An exact approach is defined as a method that provides one or several optimal solutions for an optimization problem. It consists generally in listing implicitly all the solutions in the search space to find the optimal one that will be assessed according to the performance criteria set by the controller. Among these methods, the simplex algorithm can obtain the optimal solution of a problem by traversing the convex closure of the search set by passing from vertex to vertex [26]. However, it can only be applied to problems having the property of convexity, and problems with continuous or integer variables. Further, dynamic programming is a practical technique for solving MRTA problems. It is particularly well-suited for problems that can be decomposed into smaller sub-problems. The recursive nature of this method enables solving these sub-problems by separating them into smaller and more manageable sub-problems and then combining their solutions to obtain the optimal solution for the original problem. Dynamic programming has been applied to a wide range of MRTA problems including MRTA with uncertainty and communication constraints [27]. Observe that there is also the Branch and Bound (BnB) that may identify the best solution to a given optimization. It generates dynamically sub-problems during the execution of the algorithm and iteratively solves their real-valued linear programming (LP) relaxations. The algorithm then branches on the resulting solutions based on the integrality of the LP's solution [28].

For example, considering a set of n tasks $\mathcal{T} = \{T_1, \ldots, T_j, \ldots, T_n\}$ that must be executed by a set of n mobile robots $\mathcal{R} = \{R_1, \ldots, R_i, \ldots, R_n\}$ and a matrix that defines each robot-task cost C_{ij}. The goal is to assign suitable robots to the tasks in a way that minimizes the total cost of the mission under the constraints that impose exactly one robot per task and each robot will be assigned to one task. This specific MRTA problem can be formulated by an Integer Linear Program (ILP) model as follows (the variable of decision $x_{ij} = 1$ if the robot i is assigned to accomplish the task j, otherwise $x_{ij} = 0$).

$$\min \sum_i \sum_j C_{ij} x_{ij} \tag{1}$$

$$\text{s.t.} \sum_j x_{ij} = 1 \qquad \forall i \in \mathcal{R} \tag{2}$$

$$\sum_i x_{ij} = 1 \qquad \forall j \in \mathcal{T} \tag{3}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i \in \mathcal{R}\ ,\ \forall j \in \mathcal{T} \tag{4}$$

Approximate methods represent an alternative to deal with large-size optimization problems in which an optimal solution cannot be obtained in a reasonable time. This type of method is also useful for problems requiring a real-time solution on large numerical instances. They can also be used to initialize an exact method. Approximate methods can be divided into two categories: heuristics-based methods and metaheuristics-based methods. On the one hand, heuristics are mental shortcuts for quickly solving problems based on experience. On the other hand, the majority of metaheuristics solve a problem from a population of feasible solutions or from a randomly generated initial population of candidates with an iterative process that improves progressively the population [29]. The list below presents the main approximate methods.

- Constructive method (Greedy Algorithm) [30].
- Local search algorithms (Simulated Annealing (SA), Tabu Search) [31].
- Evolutionary algorithms (Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Bee Colony Optimization (BCO)) [32].

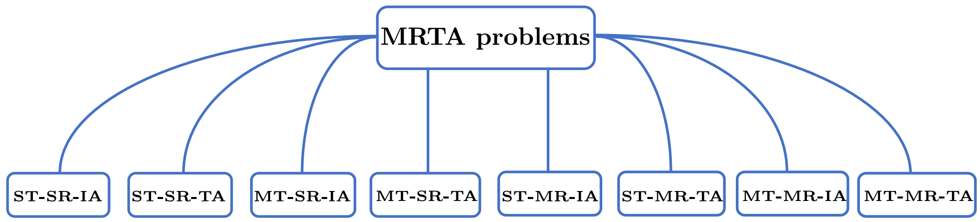

Fig. 2. Classification of MRTA problems.

2.2. MRTA taxonomies

Defining the type of tasks is a key mechanism for modeling a MRTA problem. In general, there are two main types of tasks [33]. A task in the first type is performed by one robot, whereas a task in the second type is decomposed into sub-tasks being performed by different robots. **Elemental** or **Atomic** task cannot be decomposed to sub-tasks. Further, a **simple** task is either an elemental task or a task that can be decomposed into sub-tasks that must be allocated to the same robot. Besides, **compound** tasks are decomposed into sub-tasks, and each one is performed by a different robot. A compound task has a single decomposition. Finally, a **complex** task is a task with several possible decompositions and at least, one of these decompositions can be allocated to robots. Moreover, each of its sub-tasks can be simple, compound, or complex.

In order to categorize a MRTA problem, Gerkey and Matarić [14] suggest a taxonomy based on robots' capabilities, task requirements, and time.

- **Single-task robots (ST)/Multi-task robots (MT):** Robots can execute only one task at a time/Robots are capable of executing multiple tasks at a time.
- **Single-robot tasks (SR)/Multi-robot tasks (MR):** Tasks require exactly one robot to be accomplished/Tasks require multiple robots to be accomplished.
- **Instantaneous assignment (IA)/Time-extended assignment (TA):** Each robot performs one task, there is no future planning/A sequence of tasks can be assigned to a robot over a planning horizon.

Consequently, a given MRTA problem can be characterized according to the three previous features. For example, MT-SR-IA is a problem where robots can execute multiple tasks at a time, tasks require exactly one robot, and the allocation is instantaneous. Therefore, there are eight types of MRTA problems as shown in Fig. 2.

Korash, Dias, and Stentz [21] propose another taxonomy based on interrelated utilities (costs) and task constraints. It is called iTax and can be considered as an extension of Gerkey and Matarić's taxonomy by adding a new feature corresponding to the interdependence of the robots-tasks costs. There are four types of dependencies.

- **No Dependencies (ND):** The cost of a given pair robot-task is independent of all others.
- **In-Schedule Dependencies (ID):** The cost of a given pair robot-task depends on the other tasks assigned to this robot. It is intra-schedule dependencies.
- **Cross-Schedule Dependencies (XD):** The cost of a given pair robot-task depends not only on the other tasks assigned to this robot but also on other robots' schedules. It is inter-schedule dependencies.
- **Complex Dependencies (CD):** The cost of a given pair robot-task depends on other robots' schedules, which have dependencies for complex tasks. It is a combination of task decomposition and task allocation.

Nunes et al. [22] suggest a taxonomy that develops Time Extended assignment (TA) into two sub-problems with temporal and ordering constraints as shown in Fig. 3. It is called MRTA-TOC taxonomy. It expresses temporal constraints as Time Windows (TW), and ordering constraints as Synchronisation and Precedence constraints (SP).

A TW is a time interval expressing the start and end time of a task. Both times can have lower and upper bound values considering the earliest start/finish time and the latest start/finish time. For example, deadline constraints can be modeled using the latest time robots can perform a given task. On the other side, precedence constraints impose an order in which tasks must be accomplished. Therefore, it creates cross-schedule dependencies between robots.

2.3. MRTA related problems

MRTA problems have been studied since the 90's [22]. Such problems concern several research areas such as computer science, mathematics, operations research, robotics, and artificial intelligence. The authors of [22] summarize the related problems:

2.3.1. Multiple traveling salesman problem (mTSP)

mTSP is an extension of the popular Traveling Salesman Problem (TSP) which consists of solving allocation and optimizing a set of routes for m salesmen aiming to visit n cities by starting and ending at the same city (depot) [34–36]. Since the appearance of mTSP, several variations have appeared in the literature, such as allowing multi-depots and adding specific constraints including scheduling and the maximum number of cities each salesman can visit [19]. If we replace the salesmen with robots and the cities by tasks, the multiple traveling salesman problem becomes a MRTA problem (ST-SR-TA problem specifically) [37,38].

2.3.2. Vehicle Routing Problem (VRP)

VRP is a problem that aims to solve allocation and find a set of optimal trajectories for a fleet of homogeneous vehicles to deliver items to clients [39]. To deal with this problem, a cost function subjected to several constraints must be minimized. Many variations of the VRP have been introduced including the Capacitated Vehicle Routing Problem (CVRP) which does not impose a maximum number of deliveries per vehicle and the Vehicle Routing Problem with Time Windows (VRPTW) where temporal constraints are considered. In VRP, robots may be heterogeneous with different capabilities and capacities [40,41], they may start at different depots, and they may need to communicate with each other. Moreover, VRP considers that an infinite number of homogeneous vehicles is available [42]. The only MRTA problem that can be modeled as a VRP is ST-SR-TA.

2.3.3. Location routing problem (LRP)

LRP consists of the location of facilities (depots) and the determination of an optimal set of vehicle trajectories in order to deliver items to customers [43]. The LRP extends the VRP by including decisions regarding the location of facilities, such as

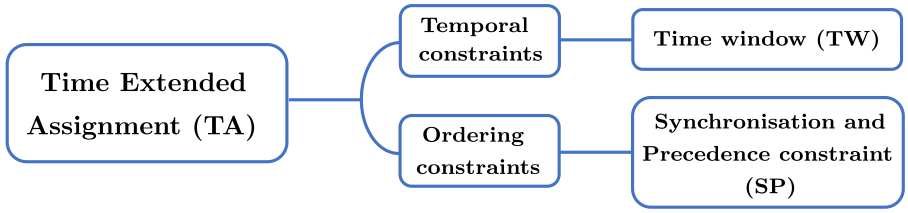

Fig. 3. MRTA-TOC Taxonomy.

warehouses or distribution centers, as well as the routing of vehicles. The goal is to find the facilities' ideal locations and the vehicles' matching routes while minimizing the overall cost. The main variation of LRP is the Capacitated Location Routing Problem (CLRP) where it is assumed that an infinite number of locations is accessible [44].

2.3.4. Job scheduling problem (JSP)

JSP consists of allocating a group of jobs to a set of machines to minimize the cost function of accomplishing all the jobs [45]. Classical JSP models may not be able to fully capture the difficulties of MRTA problems, especially those that involve location-dependent travel times. JSP models frequently make the assumption that the processing times for each job remain constant, the machine locations are fixed, and the processing power is fixed. MRTA problems, on the other hand, entail dynamic, spatially distributed agents with a range of abilities and travel times. However, some JSP model extensions, like those that take into account sequence-dependent setup times [46], can be used to model particular aspects of MRTA problems, like the amount of time needed for a robot to switch between tasks or travel between locations. These additions make scheduling more flexible and can more accurately reflect the difficulty of MRTA scenarios.

2.3.5. Linear assignment problem (LAP)

LAP consists of optimally assigning n jobs to n workers with at most one worker to each job and at most one job to each worker. It can be described as a bipartite graph $G = (V, W, E)$ where the vertex set V corresponds to workers and the vertex set W corresponds to jobs [47,48]. In MRTA, the ST-SR-IA problem can be modeled as LAP. In this case, the workers correspond to the robots and the jobs correspond to the tasks that need to be performed.

2.4. MRTA topologies

MRS algorithms can be classified into two categories [13]: centralized and decentralized approaches (Fig. 4).

- **Centralized methods:** The coordination between robots is controlled through a leader (a server) based on the information of the system. There are two types of centralized approaches [49]: weakly centralized and strongly centralized. When it comes to weakly centralized approaches, the system can change the leader during the mission according to specific criteria such as environment, robot battery, etc. In the case of strongly centralized methods, a unique leader is in charge of the whole mission. In terms of robustness, weakly centralized methods are more robust since the leader can be replaced in case of trouble.
- **Decentralized methods:** There are two types of decentralized approaches: hierarchical and distributed [49]. The system is locally centralized in hierarchical approaches which means it has several leaders, and that robots are divided into groups, each group performs a set of tasks. In the case of distributed techniques, robots decide which tasks to do autonomously without the need for a leader. The robots can enter and leave the plant during operation. Thus, the number of robots in the team may change during the mission. In terms of robustness, distributed methods are more robust since the system does not have a single decision-maker (if a robot fails, other robots will perform its tasks) [12]. However, hierarchical approaches can be performed with less numerical complexity and communication cost.

In MRTA algorithms, Gerkey and Matarić [14] identified three types of assignments: offline, iterated, and online assignments.

- **Offline assignment** deals with the allocation of tasks that are known in advance and can be assigned before the beginning of the robots' mission. Hence, when the environment is stable and the mission can be scheduled in advance, this type of assignment is ideal. It is important to note that offline methods are unsuitable for dynamic environments as they cannot handle the inclusion of new tasks during the mission.
- **Iterated assignment** deals with the allocation of new coming tasks. Once a new task is added, the algorithm discharges the robots from their previous tasks without checking if the task has been already performed and then assigns them to perform the remaining tasks.
- **Online assignment** also deals with the allocation of new coming tasks. But, robots do not cancel their earlier assigned tasks, they receive new tasks after the completion of the previous ones.

3. MRTA related works

MRTA problems can be formulated in many ways and various domains in order to achieve a given optimization objective. It can be solved using one of the three strategies represented in Fig. 5 [50].

Market-based approaches are inspired by market trading and thus provide functional solutions for MRTA problems. It has been proposed for several resource allocation and optimization problems because of the similarities between economic systems and distributed computer systems [51]. It is based on a process where goods are sold to the highest bidder. In MRTA, robots bid for tasks according to some specific criteria. A central agent (server or robot) is responsible for receiving bids and allocating tasks to robots. Robots can also communicate with each other in order to solve conflicts and allocate tasks. Thus, these methods rely on a robust communication network.

The auction algorithm is a market-based approach and has been widely adopted in MRTA literature [52,53]. In [54,55], the multi-robot task allocation problem with task deadline constraints has been solved optimally using a distributed auction algorithm. The objective function is to maximize the total payoff of assigning tasks to robots while respecting the deadlines and the limited number of tasks each robot can perform. The authors of [56] have introduced a distributed market-based algorithm with a polynomial time complexity that surpasses the classic

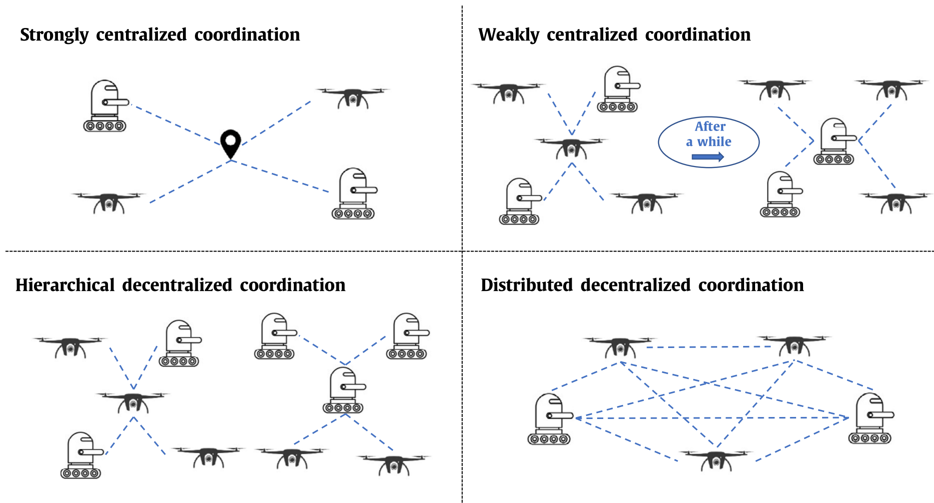

Fig. 4. Centralized vs. Decentralized coordination.

auction algorithm. Based on the latter, Choi et al. have developed a Consensus-Based Bundle Algorithm (CBBA) which associates auction properties and a consensus routine to establish a conflict-free allocation [57]. CBBA can provide optimal or sub-optimal solutions near some optimization-based approaches. This work has motivated researchers in [58–62], to propose other algorithms that can outperform CBBA. Moreover, authors in [63] have extended CBBA to deal with communication issues. Among other primary market-based algorithms for MRTA, we find MURDOCH algorithm [64] which deals with tasks randomly injected into the system over time, Traderbots [65], M+ [66], which are distributed multi-robot coordination-approach in dynamic environments, and S+T [67] which deals with robots coalition formation to execute tasks.

When it comes to Behavior-based approaches [68,69], tasks are divided into behaviors. A behavior must motivate a robot to perform a given task according to some specific criteria. Moreover, behaviors must have a rule of prioritization or combination. ALLIANCE [70,71] and BLE [72] are the pioneering algorithms in this category. The first one aims to allocate a schedule of tasks to robots to minimize the time taken by a robot to perform its assigned activities, and the second algorithm considers the allocation when tasks are dynamically appearing in the environment. Furthermore, Markov decision processes can also be used to solve some specific class of MRTA where tasks have dependencies and temporal window validity [73].

Optimization-based approaches are the third possible strategy to solve MRTA problems. It was found in [74,75] that optimization-based strategies outperform other strategies in terms of performance and numerical complexity. In this study,

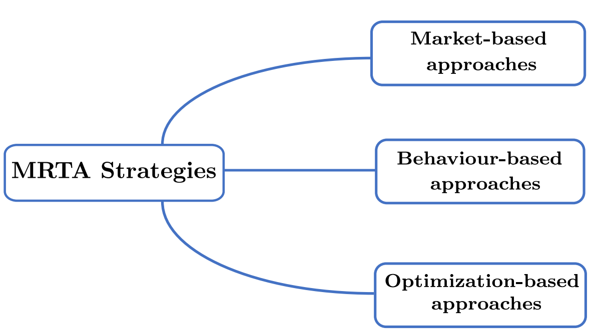

Fig. 5. Classification of MRTA strategies.

we focus on this category by reviewing and discussing most of the solutions detailed in the literature.

4. Optimization methods for MRTA problems

MRTA can be solved by various optimization approaches such as ILP, heuristics, and metaheuristics algorithms. This section provides an overview of recent research works that are summarized in Table 1. A detailed explanation of the papers with the largest number of citations is provided.

The Hungarian Algorithm (HA) is among the most used algorithms to solve MRTA problems. H. W. Kuhn [132] proposed this computational method to solve LAP optimally with $\mathcal{O}(n^3)$ complexity. Further, this algorithm has been improved by Munkres to deal with the case where the number of workers is not the same as the number of jobs [133,134]. In the MRTA context, Cai et al. [89–92] has demonstrated the steps of modeling and controlling a warehouse using mobile robots by combining a discrete-event system model with the HA. The authors have applied the assignment algorithm iteratively to deal with new coming tasks during the mission. In [76], the authors have developed a decentralized version of the HA where a centralized controller is not available. Therefore, robots execute independently different steps of the algorithm according to the data received from each other (each robot knows its distance to the targets in the environment). Ismail et al. [75] have proposed another decentralized version of the HA for assignment problems. It was demonstrated that it outperforms the CBAA in terms of numerical complexity and optimality. Furthermore, the authors of [77,78] have proposed a distributed HA-based approach for unmanned aerial systems that can be implemented for search and rescue, mobile-target tracking, and surveillance applications. Later, they extended this algorithm to deal with uncertainty in the robot states [79]. Chopra et al. [94] have solved a class of "spatiotemporal" multi-robot routing problems where a distributed version of the HA computes a sequence of assignments iteratively to obtain sub-optimal routes for the robots aiming to perform different musical pieces. However, this method has several limitations, in particular, it cannot efficiently handle situations where the number of tasks exceeds the number of robots. So, the algorithm will solve the assignment iteratively in order to allocate the remaining tasks. In this case, we lose the optimality of the solution [91,92,94]. Consequently, the HA is more suitable for problems that fall within the scope of ST-SR-IA.

Another notable approach in addressing the problem is the use of **ILP or Mixed Integer Linear Programming (MILP)** models.

Federated Learning

Table 1
Overview of research works on optimization techniques for MRTA.

References	Application	Problem type	Method	Optimization objective	Topology	Architecture
[32]	Non-specific	ST-SR-IA	GA + ACO	Minimize travel distance	Centralized	Offline
[75–79]	Non-specific	ST-SR-IA	HA	Minimize travel distance	Decentralized	Offline
[80]	Houseworks	ST-SR-IA	MILP + GA	Minimize mission time	Centralized	Offline
[81–83]	Non-specific	ST-SR-IA	ACO	Minimize travel distance	Decentralized	Offline
[84,85]	Non-specific	ST-SR-IA	BCO	Maximize task completion	Decentralized	Offline
[86]	Non-specific	ST-SR-IA	PSO	Minimize mission time and energy consumption	Decentralized	Online
[87]	Non-specific	ST-SR-IA	Iterative search	Minimize travel distance	Decentralized	Online
[88]	Non-specific	ST-SR-IA	Game theory	Maximize task completion	Decentralized	Offline
[89–92]	Warehouse automation	ST-SR-TA	HA	Minimize travel distance	Centralized	Iterated
[93,94]	Orchestral floor	ST-SR-TA	HA	Minimize travel distance	Decentralized	Iterated
[95–99]	Monitoring	ST-SR-TA	GA	Minimize travel distance	Centralized	Offline
[100]	Warehouse automation	ST-SR-TA	GA	Minimize mission time and energy consumption	Centralized	Offline
[101]	Assembly of airplanes	ST-SR-TA	MILP	Minimize mission time	Centralized	Offline
[28]	Non-specific	ST-SR-TA	GA + BnB	Minimize travel distance	Centralized	Offline
[30]	Non-specific	ST-SR-TA	PSO + Greedy Algorithm	Minimize travel distance	Centralized	Offline
[31]	Non-specific	ST-SR-TA	SA	Minimize travel distance	Centralized	Offline
[102]	Search and rescue	ST-SR-TA	Clustering + GA	Maximize task completion	Centralized	Offline
[103]	Exploration	ST-SR-TA	GA + Q-learning	Minimize travel distance	Centralized	Offline
[104,105]	Disaster response	ST-SR-TA	ILP	Maximize task completion	Decentralized	Online
[106]	Targets detection	ST-SR-TA	MILP	Maximize task completion	Decentralized	Offline
[107]	Non-specific	ST-SR-TA	Clustering + GA	Minimize travel distance	Centralized	Offline
[108]	Targets detection	ST-SR-TA	Clustering + SA	Minimize travel distance	Centralized	Offline
[109]	Monitoring	ST-SR-TA	Nearest neighbor-based clustering	Minimize travel distance	Centralized	Offline
[110]	Disaster response	ST-SR-TA	Reinforcement learning	Maximize task completion	Decentralized	Offline
[111]	Non-specific	ST-SR-TA	Monte carlo tree search	Minimize travel distance	Centralized	Offline
[112]	Non-specific	ST-SR-TA	Iterative search	Maximize task completion	Decentralized	Offline
[113]	Monitoring	ST-SR-TA	GA	Minimize travel distance	Decentralized	On-line
[114,115]	Inspection	ST-SR-TA	ILP	Minimize mission time	Centralized	Offline
[116]	Non-specific	ST-SR-TA	Clustering + Game theory	Maximize task completion	Centralized	Offline
[117]	Non-specific	ST-SR-TA	Clustering + Auction	Minimize travel distance + Balancing the work loads among robots	Centralized	Offline
[118]	Warehouse automation	MT-SR-IA	Clustering	Minimize travel distance	Decentralized	Offline
[119]	Non-specific	MT-SR-IA	Clustering	Minimize travel distance	Decentralized	Offline
[120]	Inspection	MT-SR-TA	Beam search	Minimize travel distance	Centralized	Offline
[121]	Non-specific	MT-SR-TA	PSO + Clustering	Minimize travel distance	Decentralized	Offline
[122]	Disaster response	ST-MR-IA	PSO	Maximize task completion	Centralized	Offline
[123]	Non-specific	ST-MR-IA	Clustering	Minimize travel distance	Centralized	Offline
[124]	Non-specific	ST-MR-TA	MinStepSum + Local search	Minimize travel time + task execution time + waiting time	Centralized	Offline
[125,126]	Non-specific	ST-MR-TA	Game theory	Maximize task completion	Centralized	Offline
[127]	Search and rescue	ST-MR-TA	MILP	Minimize travel distance	Centralized	Offline
[128,129]	Non-specific	ST-MR-TA	GA	Minimize travel time + task execution time + waiting time	Centralized	Offline
[130]	Non-specific	ST-MR-TA	Q-learning	Maximize task completion	Centralized	Offline
[131]	Non-specific	MT-MR-IA	Invariant theory	Maximize task completion	Decentralized	Offline

These frameworks all include mathematical formulations that enable the optimization of the objective function while taking both discrete and continuous variables into account. The authors of [104,105] have considered task allocation for disaster response where the tasks are modeled as the distribution of survival kits to potential victims. The algorithm aims to maximize the number of delivered kits (maximizing the number of performed tasks) with respect to several constraints such as task deadlines, and robots' limited payload. The authors have developed an ILP formulation of the problem and implemented an online method based on the weighted matching of bipartite graphs. The Karp maximum matching algorithm was used to solve the assignment as a weighted matching problem (this algorithm outperforms the HA in terms of computational complexity). Mathematical models such as linear or dynamic programming can be implemented to find the optimal solution according to a given objective function. In [106], a MILP solution was proposed to coordinate robots for covering areas of interest in an unknown environment. Likewise, the study in [127] develops a MILP algorithm in order to solve task allocation, scheduling, and path planning for search and rescue in disaster areas. However, the big complication of these approaches is the computation time for large-scale problems. The determination of the optimal solution for a scenario where a large fleet of heterogeneous robots must perform a lot of tasks may have a large numerical complexity.

Bio-inspired methods have emerged as a promising approach to tackle the MRTA problem. Drawing inspiration from biological systems and natural processes, these techniques aim to simulate the efficiency and adaptability found in nature. The study of [95–98] has considered heuristic methods to solve allocation and routing for 3 robots that must inspect multiple fixed locations in a known environment. The authors used a GA for assignment and A* algorithm to find the shortest trajectories in a centralized manner. Besides, Li et al. [98] have solved allocation and path-planning for multiple robots using GA with collision detection (a collision penalty term was included). Saeedvand et al. [102] have discussed the MRTA problem as Multi-Humanoid Robots Task Allocation (MHTA) problem where humanoids robots replace humans to rescue, explore, and defend in dangerous environments. They use in the first phase constraint k-medoids algorithms to cluster tasks according to the available robots and then perform GA in the second phase to solve allocation and routing with respect to robots' energy consumptions. In [103], tasks over a set of points were distributed into sub-regions in order to explore the environment (each robot is responsible for the tasks inside its region). In this work, the Generalized Voronoi Diagram was used for partitioning, then GA and Q-learning approaches were implemented for routing. Likewise, the authors in [107] have implemented k-means clustering to divide the environment according to the number of robots, then assign robots to clusters and finally execute a GA for each cluster to optimize the robots' routing. Partitioning the environment leads to reducing the size of the state space, then solving reasonable-size sub-problems instead of solving a large-size one. Choi et al. [113] have presented a decentralized task assignment based on GA and communication between multiple UAVs. It aims to compute for each UAV a solution set that follows a specified order of tasks that minimizes the cumulative flight time of all UAVs. The GA was also used in robots' coalition formation where a task needs the cooperation of multiple robots to be accomplished (multi-robot tasks) [128,129]. In [128], multi-robot coalition formation was solved using GA. Further, the work in [129] can be viewed as an extension of [128] since a set of homogeneous robots must perform several tasks with precedence constraints. The objective function is considered as the sum of the total traveled time taken by the robots to complete the tasks, the time taken for each task, the waiting time for other robots to arrive in order to perform a task that requires cooperation, and the waiting time when a robot remains unassigned for a while because of precedence constraints. Other Bio-inspired algorithms such as ACO, BSO, and PSO are also used to solve MRTA problems [81,84]. The study of [32] shows that GA outperforms ACO in terms of performance. However, GA needs more time to converge to the solution. In these approaches, each robot starts from a random or a given location and constructs its solution by moving to the unvisited vertices in the graph according to pheromone and heuristic information. Once a solution is computed, the pheromone information is updated according to the quality of the result. This process is iteratively applied until a termination criterion is met. The study in [30] provides a MRTA method that combines the greedy algorithm and PSO. The suggested approach tries to maximize the work distribution over several robots while reducing the mission time and improving the system's overall effectiveness. The PSO method is used to find the best allocation, while the greedy algorithm is used to refine it.

Clustering methods are also among the strategies used to solve MRTA problems. This technique is based on grouping the tasks into clusters according to some specific criteria and then allocating them to robots. K-means clustering is the most used for task allocation problems [107,117]. The authors in [117] have tackled the issue of balancing the workload among robots along with minimizing the traveled distance. The tasks are grouped using k-means clustering and the assignment is done using an auction mechanism. In [107], a k-means clustering approach is proposed to solve a large-scale problem by partitioning the state space. Once the tasks are divided into clusters, the HA allocates robots to clusters optimally, and then GA is applied in each cluster. Moreover, nearest neighbor algorithms can be used to improve the results of clustering [109,118]. The authors of [109] have considered border patrolling as a LRP of multiple drones. So, the optimization problem concerns drone base stations and flying paths for surveying each target. The clustering will allocate every target to its nearest station and then the nearest-neighbor algorithm will improve the solution. Besides, the work in [119] has combined a fuzzy clustering approach with a bipartite graph to solve robots assignment. The Fuzzy C-Means clustering algorithm is a soft clustering, in which each task can be part of more than one cluster. It aims to reduce the state space of the problem and then compute the optimal task sequence for each agent.

5. Discussion

This section presents a detailed discussion of the state-of-the-art of optimization approaches in the context of MRTA. Some preliminary general comments can be found in Table 1.

- Several variables, including the number of robots, the number of tasks, and the size of the environment in which the robots operate, can be used to quantify the size of a MRTA problem. It is significantly influenced by the number of robots in the system. The size of the problem grows exponentially as the number of robots rises. This adds more possible robot-task assignments since each additional robot expands the problem's dimensions. Likewise, the number of tasks in the system can have an impact on the size of the problem. Finding an optimal or sub-optimal solution may get increasingly challenging since the number of possible task assignments grows exponentially as the number of tasks increases. For instance, the problem becomes more challenging if task execution timing must be considered with temporal limits on the tasks, such as deadlines or time slots. Finally, the size of the environment has also an impact on the problem's size. For example, some algorithms may require the calculation of distances or travel times between robots and tasks, which can be computationally expensive if the navigation environment is large. The combination of these factors generally determines the size of a MRTA problem, and solving larger problems might need extensive computational resources.
- The performance of optimization strategies is assessed based on many criteria, including optimality, scalability, consistency, and appropriateness. The approach should first be able to determine the optimal solution. However, in some cases, finding the exact optimal solution might be computationally expensive or even infeasible. In such situations, sub-optimal solutions that are sufficiently close to the optimal solution are sought. Additionally, consistency is also crucial, which means that the method should produce consistent results when applied repeatedly to solve the same problem scenario. Finally, the method's appropriateness is related to the fair distribution of tasks among robots while taking their workloads and capacities into account.
- The numerical complexity is a crucial factor in MRTA problems. The quantity of potential robot-task assignments can be utilized to evaluate how complex an MRTA scenario is. So, it becomes more challenging as the size of the problem

Table 2
Pros and cons of the reviewed articles.

References	Advantages	Disadvantages
[75–79]	Fast and scalable allocation.	Limited to a certain class of MRTA problems.
[30–32,80,81,84,85]	Applicable to dynamic environments Simple and easy to implement	No guarantee on optimality May exhibit slow convergence
[82,83]	Efficiently handles large-scale cooperative tasks Simple and easy to implement	No guarantee on optimality Performance may be affected by complex precedence constraints
[87,111,112]	Fast and scalable allocation Simple and easy to implement	Does not take into account delays in communication
[88,116,125,126]	Considers strategic interactions among robots	Limited robustness
[89–92]	Ability to adjust to dynamic environments	Necessitates a model depicting the dynamics of the system Computationally expensive
[93,94]	Suitable for handling large-scale systems	Computationally expensive
[95–99]	Effective for multiple objectives optimization Effective for systems of small to medium sizes Robust to communication errors	Require a fine-tuning of parameters May not handle large-scale systems
[28,100,128,129]	Effective for multiple objectives optimization Effective for systems of small to medium sizes Considers precedence constraints and cooperation	Require a fine-tuning of parameters May exhibit slow convergence
[103]	Efficient exploration of unknown environments	Computationally expensive
[101]	Ensures optimal solutions Addresses real-world constraints and large-scale coordination	Computationally expensive
[104,105]	Considers dynamic tasks Minimizes communication workload	No guarantee on optimality Computationally expensive
[106]	Provides optimal solution	Computationally expensive
[102,107,108,123]	Suitable for dynamic environment Suitable for handling large-scale systems	Limited clustering accuracy
[109]	Real-world implementation in border surveillance	Not applicable for dynamic environments or uncertainties
[110,130]	Incorporates machine learning techniques into task allocation Offers adaptability and learning capabilities	Performance may depend on the availability and quality of training data
[113]	Handles dynamic environments	Does not take into account delays in communication or failures in sensors
[114,115]	Real-world implementation in power transmission line inspection Considers fault-tolerance and robots' failures	Not applicable for dynamic environments or uncertainties
[117]	Simple and effective approach	No guarantee on optimality
[118]	Suitable for handling large-scale systems	Not applicable for dynamic environments or uncertainties
[119]	Suitable for handling large-scale systems Provides robustness to incomplete or inaccurate data	No guarantee on optimality
[120]	Addressing the problem of performing multiple measurement tasks based on robots capabilities	Require a fine-tuning of parameters
[86,121,122]	Utilizes swarm intelligence and social learning	May require additional optimization for large-scale problems
[124]	Considers precedence constraints	Lack of comparison with other methods
[127]	Uses coordination architecture that facilitates collaboration among robots	Limited scalability
[131]	Achievement of multitasking in multi-robot tasks	Lack of specific details on the approach

increases. In this manner, researchers should develop novel optimization approaches while reducing computational requirements and making them more scalable for real-world applications. However, in most reviewed papers in this survey, the numerical complexity of the algorithms is insufficiently addressed. So, it is difficult to determine whether it is justified by the quality of the solutions or whether it is reduced.

- Observe that the performance of the result may not always be correlated with the algorithm's numerical complexity. In some circumstances, more complicated algorithms could be needed to address this issue and produce effective solutions. Acceptable solutions are the ones that lead to a trade-off between performance and computational complexity.
- Finding a suitable method to solve a certain MRTA problem is challenging. In this manner, Table 2 provides a summary of the advantages and disadvantages of the papers cited in Chapter 4. While certain approaches are fast and scalable for some specific problems, others can be used in dynamic contexts with uncertainties. However, certain algorithms might not offer the best results, have limited scalability, or necessitate parameter fine-tuning. So, it is important to keep in mind that no single algorithm is ideal for all applications and researchers have to carefully consider the trade-offs

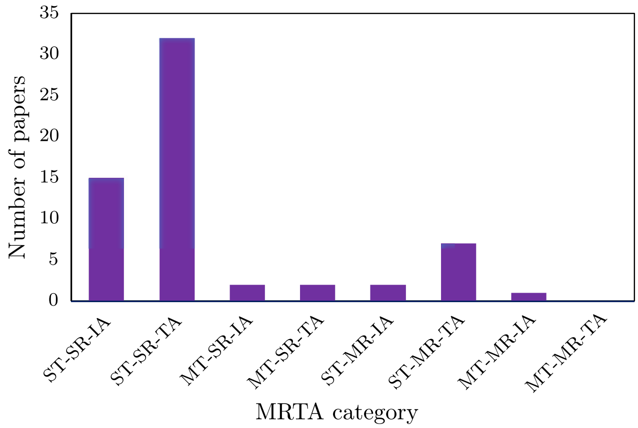

Fig. 6. Number of papers in terms of problem configuration.

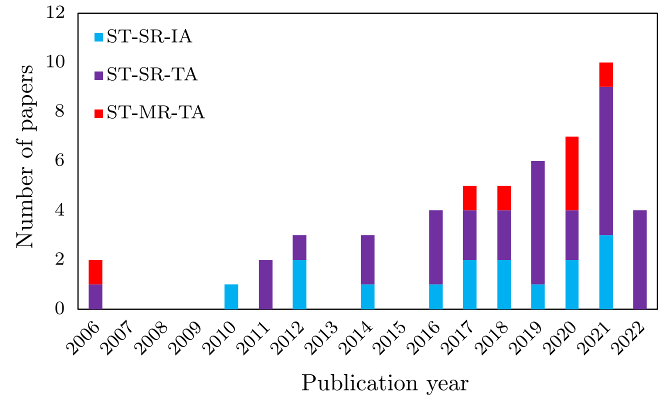

Fig. 7. Number of papers in terms of publication years.

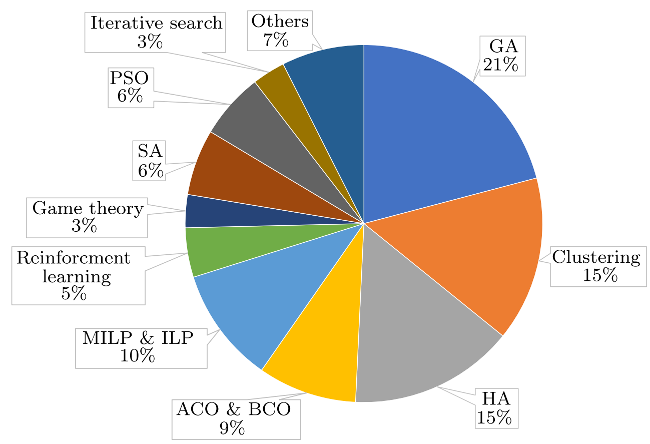

Fig. 8. Portion of each method.

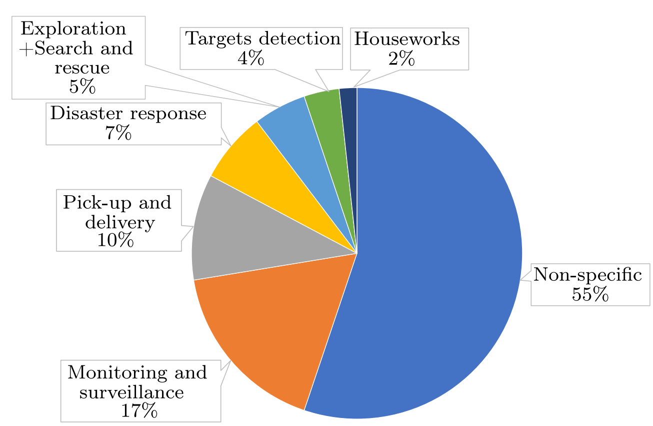

Fig. 9. Portion of each real-world application.

between advantages and disadvantages when choosing a MRTA algorithm.

- It is found that there is a lack of work in dynamic task allocation i.e. online and iterated approaches that deal with new coming tasks, unexpected events, and environmental uncertainties. This can be explained by the difficulty of determining a real-time adaptable cost function to handle such dynamic situations. Thus, researchers have orientated the works of dynamic task allocation towards multi-objective optimization that requires more than one objective function to be optimized simultaneously [129].
- Multi-robot communication networks may be affected by external factors such as interference, signal attenuation, and network congestion and thus they may face errors. Subsequently, to ensure reliable and effective communication among the robots, novel approaches in the field must take into account potential communication problems.
- Furthermore, despite a large number of research works in this field, there is a huge gap between simulation and experimentation. The developed algorithms need validation through a real-time robotic experiment. In this study, only 7 papers from all the reviewed ones have presented results from an experimental validation involving real robots.

We provide quantitative analysis for a selection of 61 articles reviewed in this survey (Table 1). This analysis is realized from the perspectives of (i) Gerkey and Matarić MRTA taxonomy; (ii) optimization approaches; (iii) applications. Fig. 6 presents the number of research works among the selection for each MRTA problem category. The MRTA problem configurations are reported on the x-axis from the less complex one to the most complex one.

It is worth noting that most researchers focus their works on problems that fall within the scope of ST-SR. This can be explained by the fact that most real-world applications belong to this category. Moreover, there is a lack of research that belongs to other configurations. Further, Fig. 7 shows the variation in function of the time for the works that belong to the three dominant configurations seen in Fig. 6: ST-SR-IA, ST-SR-TA, and ST-MR-TA. The number of research works has increased significantly over the years for ST-SR problems. Besides, ST-MR-TA configuration began to attract the research community since in the past few years there has been a tendency to study coalition formation problems i.e. situations for which tasks require the coordination between robots.

In regards to the optimization approaches used for MRTA, GA is the most used by researchers as shown in Fig. 8 (21% of papers). Then, clustering and the HA are in the same position (15% of papers). Exact approaches like BnB and HA can give the optimal solution for a few cases. The first method cannot deal with large instances problems, and the second one is only suitable for ST-SR-IA problems when there are no dependencies between tasks (the only MRTA configuration that is not NP-hard [14]). Consequently, Meta-heuristic and heuristic techniques have been widely used to propose efficient solutions in a reasonable time. Although GA is the most used, other approaches such as ACO, BCO, PSO, and SA began to attract the research community since they offer results in a reasonable execution time. However, these methods become unsuitable for large-size problems and real-time applications since the execution time becomes too long. Therefore,

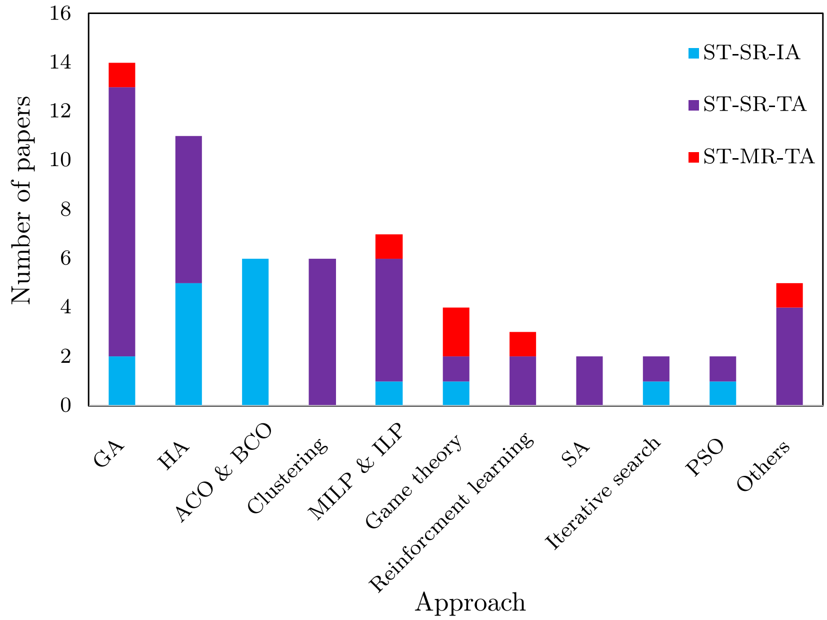

Fig. 10. Distribution of methods for the most used configurations.

researchers have proposed to combine a clustering algorithm with a meta-heuristic technique to solve a MRTA problem [107]. The problem is then divided into two parts such that the first part concerns task assignment and the second part concerns task planning and scheduling. So, the clustering partitions the environment according to the number of robots then assigns each robot to a cluster, and then the meta-heuristic solves the routing in each cluster. Although this approach might not give the optimal solution, it reduces the computational complexity. Moreover, the scheduling part can be solved by using a local search or a TSP algorithm (e.g., 2-opt algorithm [109]) instead of a meta-heuristic.

Fig. 9 evaluates the proportions of real-world applications considered in the reviewed papers. It is found that 55% of contributions do not mention a specified application and present general contributions suitable for various real-world employments.

Fig. 10 refines the previous analysis by detailing how often each class of optimization method is used for the three MRTA configurations previously mentioned. It is seen that GA is the most used technique, especially for ST-SR-TA and ST-MR-TA problems. The HA is the most used for ST-SR-IA problems since it is an exact approach. Then, it comes to clustering that is coupled with a meta-heuristic to complete the routing procedure for ST-SR-TA problems.

6. Conclusion

This paper analyzes MRTA optimization-based approaches by giving a global view of the possible optimization strategies, for various classes of problems and real-world applications. In particular, we examine a selection of papers to provide a quantitative analysis of the relevant literature. It was found that a significant amount of MRTA works focus on ST-SR-TA problems. GA approach is the most used in this context and the majority of the papers do not consider a specified application. In addition, the numerical complexity of the algorithms is not sufficiently studied in the literature and few methods consider an online assignment to deal with dynamic environments. It was also found that the performances can be improved by the combination of different approaches either by refining an approximate solution or by dividing the problem into two parts: task assignment and task planning.

Collision avoidance between robots, uncertainty such as sensor malfunction, and robots' kinematic constraints are other important issues that should be considered as future directions of research since most of the existing works do not consider such issues for simplification. Moreover, communication issues such as latency and throughput limitations may prevent the achievement of the multi-robot mission. Therefore, the fifth-generation technology standard for broadband cellular networks (5G) can handle such issues by offering higher speed and greatly reducing latency [135]. In summary, all the specifications mentioned previously must be satisfied to be able to experimentally validate the developed algorithms and to face down progress in mobile robotics.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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