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SURVEY PAPER

A Review of Task Allocation Methods for UAVs

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Abstract
Unmanned aerial vehicles, can offer solutions to a lot of problems, making it crucial to research more and improve the task allocation methods used. In this survey, the main approaches used for task allocation in applications involving UAVs are presented as well as the most common applications of UAVs that require the application of task allocation methods. They are followed by the categories of the task allocation algorithms used, with the main focus being on more recent works. Our analysis of these methods focuses primarily on their complexity, optimality, and scalability. Additionally, the communication schemes commonly utilized are presented, as well as the impact of uncertainty on task allocation of UAVs. Finally, these methods are compared based on the aforementioned criteria, suggesting the most promising approaches.

Keywords Task allocation · UAVs · Auction based algorithms · Optimisation · Reinforcement learning · Game theory · Metaheuristics

1 Introduction

In this review we focus on the task allocation techniques used in UAVs applications. With the increase in computational power over the last years as well as the production of more efficient electrical motors and composite materials the usage of UAVs has increased dramatically for both domestic and military applications. These applications, that require the use of task allocation techniques in multiple UAVs systems, include mobile edge computing (MEC), military applications, like attack of ground or aerial targets, intelligence surveillance and reconnaissance (ISR), Suppression of Enemy Air Defenses (SEAD) and Destruction of Enemy Air Defenses (DEAD), Search and Rescue missions (SAR) for both military and civilian operations as well as other civilian operations.

A lot of tasks need to be allocated in UAVs applications and specifically the distributed ones, are highly complex and may need more than one agent in order to be successfully completed. Also, having multiple agents competing or cooperating in an environment can lead to more efficient task allocation, since usually multiple agents can allocate tasks faster and also improve the robustness of the system, being more tolerant to agent's losses or malfunctions. Moreover, the usage of multiple agents can help reduce cost, since rather than using a costly agent, it may be feasible to employ inexpensive and disposable ones. All these reasons highlight, why the scientific community has increased the research efforts in task allocation of UAVs, showing an ever increasing interest in this research direction [1].

One crucial problem that task allocation techniques aim to solve, is the problem of division of labour, that basically entails the choice of the tasks that should be allocated to specific agents and also the choice of the communication type that will be used between the agents. Generally, division of labour has to do with the procedure that determines each agent's performance in order for the system to achieve optimal overall performance [1, 2]. Moreover, the procedure of finding an optimal or near optimal solution to task allocation is not easy, since it has been proven to be NP hard in the general case [2, 3].

Task allocation can serve various objectives, including minimizing task execution time, reducing agent idle time, maximizing task completion time, increasing the number of completed tasks within a specified time frame, enhancing the

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reliability of the task allocation process (i.e., successfully completing the assigned tasks), among others. Generally, the primary goal is always to achieve overall optimal performance of the system [4], but the notion of optimal performance can be difficult to define, since it is a notion difficult to quantify and also can depend on each agent's own perception of the environment. Therefore, the concept of utility is used instead, that is mainly an estimate of the value or cost of the task allocation process in relation to the system's performance [2].

Task allocation can be either static or dynamic, depending on the problems it aims to solve. Static task allocation can be easier to implement, therefore most of the initial algorithms were static. But, since most real life problems are complex dynamic environments, these types of algorithms are getting more and more attention from the research community, since they exhibit greater resilience in handling online alterations to tasks or the environment, thereby resulting in a more robust performance [5]. Also, the task allocation methods can be divided into decentralised and centralised methods, depending on the method of communication between the agents and also to homogeneous and heterogeneous methods, depending on the type of agents used. Working with homogeneous agents is easier, since they have the same communication requirements and action and observation spaces and can also have less computational cost. But, again, in real applications heterogeneous agents are frequently needed. For example, UAVs, that are the focus of this review, can have different types of sensors on board, depending on the task they have to fulfill and different types of UAVs might be needed for the successful completion of a mission. Although heterogeneity might augment both computational and purchasing costs, it can be required in many cases of more complex or closer to reality scenarios [6, 7].

Auction (or market) based approaches, game theory based approaches, optimization based approaches (including deterministic optimization, heuristic algorithms, metaheuristic algorithms, etc.), and reinforcement learning techniques are among the primary task allocation techniques employed in UAVs. There are also hybrid approaches involving two or more techniques and also some other approaches that do not belong to the above categories. Depending on the task allocation method used, the solution found is almost always a suboptimal, approximate one and depending on the task allocation method used, can have various degrees of efficiency, complexity and scalability.

1.1 Common Task Allocation Applications of UAVs

1.1.1 MEC Applications

In the last few years, UAVs have been researched a lot in the field of Mobile Edge Computing (MEC). UAVs can play the role of mobile base stations in areas with low coverage of base stations, they can be used in computation offloading to MEC servers or to the cloud and in spectrum resource allocation, among others. MEC covers a very broad spectrum of applications [8–12]. Most of the papers researching MEC focus on minimising the energy consumption, sometimes together with computation delays, of the UAVs used, like in [13–23]. There are, also, other applications of MEC involving task allocation, like space-air-ground networks [24, 25], security in MEC [26, 27] and mobile cloud computing [28].

1.1.2 Military Applications

The greater portion of applications in UAVs task allocation covers military applications. Many researchers are occupied with intelligence, surveillance and reconnaissance (ISR) missions for multiple UAVs. ISR applications include general reconnaissance [29], reconnaissance for heterogeneous UAVs and targets [30], cooperative reconnaissance and mission strategy [15] and surveillance and reconnaissance [31, 32]. Also, other applications include surveillance with intercept probability [33] and surveillance with task uncertainties [11].

Other military applications include Suppression of Enemy Air Defense (SEAD) [34, 35], target attacking [36–38] and air combat [39].

A very broad category is the combination of ISR missions with attack. In most of the approaches, there are UAVs that have both ISR and attack capabilities, like in [40–42] and heterogeneous UAVs that have both ISR and attack capabilities, but with different performance values in some of these capabilities, like in [43]. Also, there are approaches having different UAVs for each role [44, 45] and a mixture of all the previous approaches [46].

1.1.3 Search and Rescue (SAR)

Search and Rescue (SAR) missions are a very common field of usage of UAVs, having mostly as goals the maximisation of the number of survivors, the minimization of the time needed for the termination of the SAR mission and the minimisation of the distance travelled from the UAVs. The UAVs taking part in SAR missions can have both search and rescue capabilities [47, 48] or two different types of UAVs could exist, with one type being focused on searching for survivors and the other types focused on the rescue mission [49–51]. Other schemes used include the usage of two different types of UAVs, where one type is used for providing food to survivors and the other one for providing medicines like in [52, 53] and the cooperation of UAVs and UGVs for SAR missions in mountain difficult terrain areas [54].

1.1.4 Civilian Applications

There are also other civilian applications where task allocation techniques for multiple UAVs are needed. One field with potential for future deployment of UAVs is the agricultural sector where UAVs can be used for crops protection, spraying with pesticides and fertilizers and humidity monitoring, among others, like in [25, 55]. Other applications like areas monitoring and target tracking might need a high degree of cooperation between UAVs, especially when they navigate in complex urban environments, including high densely built buildings or factories [56, 57].

Other applications include electric grid inspection [58], product transfers and logistics [59], structure assembly by cooperative aerial robots [60], crowdsensing [61], and wildfires (see [62] for a comprehensive review).

2 Communication Schemes of Task Allocation Methods

Based on whether or not a central agent exists, the task allocation methods are divided into the following two categories (Figs. 1 and 2).

2.1 Centralised Task Allocation

In centralised methods a central agent exists, that can combine information and observations from other agents and also manage any existing negotiations, if required by the algorithm used, allocating the tasks to the other agents. Usually, in that case, a global utility function of the system exists too [1, 63–65].

This type of task allocation algorithms might be recommended in cases where reduced system resources or reduced implementation cost is the goal, since most of the computational power is needed on the central agent only, unlike the decentralised case. They usually can't be efficiently applied to systems with large numbers of agents, since they have increased computational cost. Also, another reason for the lower degree of scalability is that all the agents have to communicate with the central one making the communication burden very high on large numbers of agents. But, the central allocation of the tasks helps avoid conflicting task assignments, sometimes making unnecessary the existence of a consensus phase and also in some cases an optimal solution can be found. Also, these algorithms are frequently used in static task allocation methods, since they cannot easily adjust to highly dynamic environments, lacking in robustness, especially in cases of malfunction of the central agent, impairing the overall performance [46, 66].

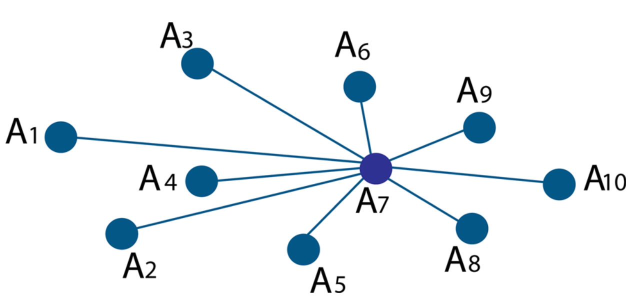

Fig. 1 A centralised system, with agent A_7 being the central coordinator

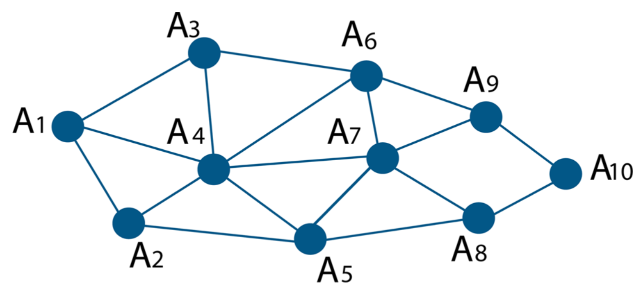

Fig. 2 A decentralised system

2.2 Decentralised Task Allocation

Recently, researchers are more and more interested in decentralised algorithms due to their ability to address some of the limitations of centralised algorithms. Decentralised algorithms operate without a central agent responsible for assigning the tasks, but with agents using their local observations and a local perception of the environment as well as having the ability to communicate and negotiate with one another, if it is required by the algorithm in use. This allows for the task allocation decision to be made locally, by each agent, in a distributed manner. Each agent may also have its own utility function, with the overall utility function being estimated [1, 63–65].

These methods offer several benefits, including robustness in terms of agent malfunctions with little impact on overall performance. Additionally, they are highly scalable, since the communication requirements are usually less than in the centralised methods, since no frequent communication with a central coordinator is necessary and in some cases, the other agents can even be perceived as part of the environment. Another advantage is their relatively low computational cost, compared with the centralised methods, making them well-suited for use in large-scale systems. However, the downside is that these methods may only provide suboptimal or approximate solutions to the task allocation problem. Furthermore, because of the lack of the central coordinator, a consensus algorithm may be necessary, in some task allocation methods, to resolve conflicts that can arise from local task assignments [46, 66].

3 Types of Methods used in Task Allocation of UAVs

Numerous methods are employed for task allocation in UAVs. Presented below, is a classification and comprehensive explanation of these techniques, emphasizing their key features. (see Fig. 3). Also, in every category, a table summarizes the key information from every algorithm, like the application on which the UAVs could be used, the name of the algorithm used, the metric and the key characteristics of the algorithm. The metric used is usually the baseline algorithm with which the performance of the proposed algorithm was compared or the method that was used to prove the key advantages of the algorithm, like simulation or experiments. The characteristics of the proposed algorithm are proved by comparing it to the metric, usually being the baseline as mentioned before.

3.1 Auction Based Algorithms

A commonly utilized group of algorithms used in task allocation of UAVs are the auction-based algorithms. These methods rely on economic principles, with agents utilizing a negotiation protocol to bid on tasks in an auction, based on their local perception of the environment. As a result, these approaches are often referred to as market-based. The agents bid based on the calculated utility or cost of the task, aiming to achieve the highest utility or lowest cost for the allocated task. Taking into consideration the local utility functions of the agents, a global objective function can be optimised. Depending on whether the algorithm is centralised or not, the auctioneer can either be either the central coordinator agent or the auction can be conducted in a decentralised way by the other agents. The auctions, which can involve one or several tasks, may require multiple rounds [7, 63, 67, 68].

Auction-based algorithms have numerous benefits, including high solution efficiency, despite the fact that they may only provide suboptimal solutions, as well as a good degree of robustness. This is because they incorporate elements of both centralized and decentralized methods. Additionally, they are scalable, as they have a moderate computational and communication cost. They are particularly well-suited for dynamic task allocation, as new tasks can be added or removed from the auction procedure [1].

3.1.1 CBBA Based Methods

The consensus based bundle algorithm (CBBA) [69] is a decentralised technique for solving multi-objective optimization problems in UAVs. It enables agents to obtain solutions regardless of inconsistencies in their situational awareness. The utility perceived by each agent for performing bundles of tasks serves as the cost function and the algorithm employs auctions with greedy heuristics in the first stage to select tasks and uses a consensus-based procedure in the second stage to resolve any overlapping tasks. Although CBBA provides suboptimal solutions for the single robot single task allocation problem [2], the algorithm is highly scalable and well-suited for dynamic task allocation applications due to its polynomial time bidding. [69, 70].

The approaches presented below can be classified into two primary categories, being either enhancements to the CBBA algorithm or the performance impact (PI) algorithm. The PI algorithm is a distributed approach that runs on all agents

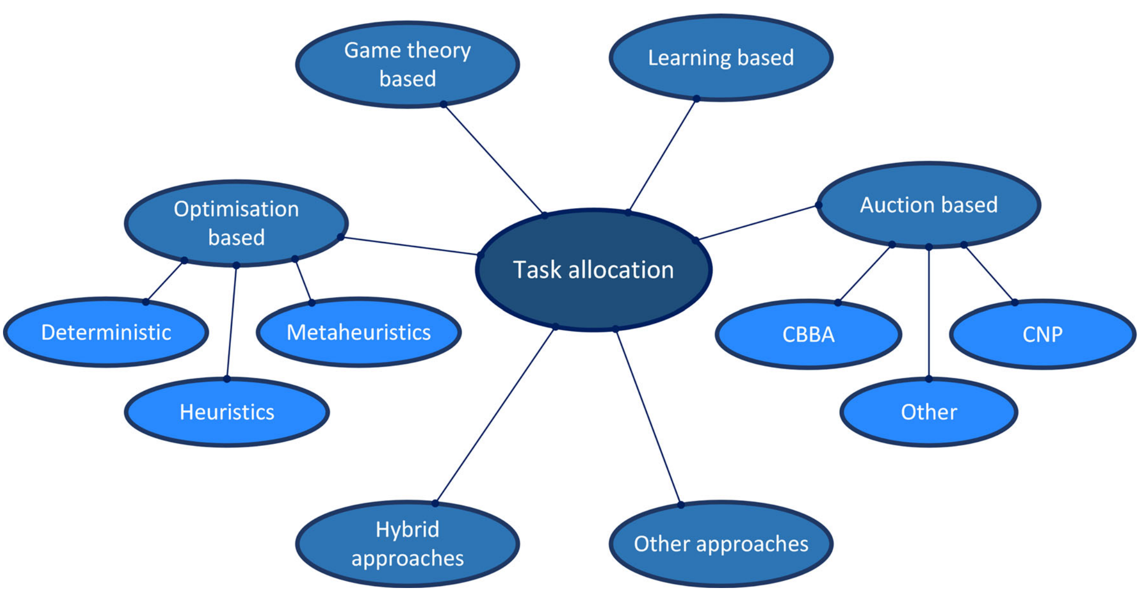

Fig. 3 Task allocation techniques categories

concurrently. However, unlike CBBA, it employs the performance impact metric to assess and arrange task bundles. [53]

CBBA Improvement Approaches

A very common UAV application using CBBA based task allocation methods is SAR missions. In [52] the authors focus on giving priority to tasks closer to each agent, proposing a cluster first strategy combined with a CBBA based algorithm, for improving the CBBA based task allocation. In [50] the authors propose the consensus-based bundle algorithm with task coupling constraints (CBBA-TCC). This is a two stage approach where initially the heterogeneous agents define on a list the tasks they can do. This method compared with baseline CBBA, a negotiation-based algorithm and a hybrid auction algorithm has better efficiency and is more reliable, but also has higher computational cost. Focusing on task replanning for dynamic tasks in [49] an algorithm, called CBBA with local replanning (CBBA-LR) is proposed, that has better performance than other baseline replanning methods. When we state "better performance", it implies that the method outperforms the other methods compared with respect to performance criteria, e.g., total utility value, used in the paper. The proposed algorithm chooses the tasks for reallocation considering the time window available resetting fewer tasks and leading to lower computational cost.

Also, CBBA based methods are used in ISR applications like, [32], where a CBBA based method for task allocation together with a behaviour based system called subsumption architecture (SA) for task execution is proposed, leading to the bound consensus based bundled algorithm (BCBBA) that has faster convergence than baseline CBBA. An approach taking into consideration task uncertainties is [71], where an MDP-based robust CBBA scheme is proposed and is compared with baseline CBBA, robust CBBA [72] and cost benefit greedy algorithm. The MDP-based approach has more robust allocation and better task assignment than all the baselines and less computational cost than baseline robust CBBA, but still, it is unsuitable for large scale problems, having more computational cost than baseline CBBA and CB greedy algorithm. Also, in [34] an improved variant of CBBA is proposed for SEAD applications. It uses a dynamic task generation mechanism, decomposing complex tasks into simpler subtasks that are appointed to single UAVs. In [73] they study the problem of task allocation with multiple UAVs in collaborative tasks, proposing an improved Consensus-Based Grouping Algorithm (CBGA), that permits task bundle revision, selecting better candidate UAVs. The proposed method, even though it has similar performance with baseline CBGA with small number of tasks, succeeds better task allocation with greater number of tasks, having higher quality of solutions.

PI Improvement Approaches

Also, there are a lot of PI based methods for SAR applications, like in [53], where a robustness module for distributed multi-agent task allocation algorithms is studied. This module is developed using the performance index (PI) algorithm. In most of the cases faster mean task time than conventional PI is achieved, but with lower scalability and bigger run time. In [66] they study the problem of task allocation in ST-SR-TA problems (single task single robot time extended) and propose an improved version of the PI algorithm, that can deal with dynamic task allocation (online replanning) and has a broader solution area, since it can escape local minima. The proposed approach is suitable for dynamic task allocation, because classical PI is usually used in static task allocation. It also has improved solution fitness, by enlarging search space and escaping local minima, compared to baseline PI and CBBA, but higher computational time, especially for large scale systems. In [44] the authors focus on critical tasks for ISR and attack applications, proposing an algorithm that prioritizes the task allocation of the critical tasks. They propose the extended PI algorithm with critical tasks (EPIAC), which is a PI variant. The proposed approach has better performance while increasing UAVs number, capacity and critical tasks number, compared to baseline PI and CBBA. Nevertheless, this approach has more computational cost and requires more iterations to converge.

3.1.2 CNP Based Methods

The Contract Net Protocol (CNP) [74] was the initial negotiation platform applied in task allocation problems and forms the basis for various task allocation algorithms. It is a standardized protocol that assigns tasks to the most suitable agents and allows for task reassignment when necessary [75]. However, CNP is susceptible to message congestion, which can disrupt the negotiation procedure between agents. In contrast to other approaches, like pheromone-based techniques, CNP relies heavily on message-based communication between agents, increasing the computational cost of the algorithm and leading to reduced communication efficiency and system performance [76].

In [29] the authors study the problem of real-time task allocation in reconnaissance missions of multiple UAVs in the battlefield, proposing an improved contract network algorithm. The proposed method has higher efficiency and needs less auction rounds than baseline contract network.

3.1.3 Other Auction Based Methods

Also, there are other auction based approaches except for the CBBA and CNP based ones, like in [54], where the problem of task allocation in Wilderness Search and Rescue missions

Table 1 Characteristics of auction based approaches

Ref.	Application	Algorithm	Metric	Characteristics
[52]	SAR	improved CBBA	baseline without clustering	higher efficiency, faster convergence
[34]	SEAD	improved CBBA	simulation	efficiency under time constraints
[49]	SAR	CBBA-LR	baseline replanning methods	better performance, lower computational cost
[32]	ISR	BCBBA	baseline CBBA	faster convergence
[50]	SAR	CBBA-TCC	baseline CBBA, negotiation based, hybrid auction	better efficiency and reliability, higher computational cost
[71]	ISR	MDP-based robust CBBA	baseline robust CBBA, CBBA, CB-Greedy	better performance, unsuitable for large scale
[53]	SAR	improved PI	PI	faster task time, worse scalability, computational time
[44]	ISR and attack	EPIAC	PI, CBBA	better performance, more computational time and iterations
[66]	urban SAR	improved PI	PI, CBBA	dynamic task allocation, improved solution fitness, higher computational time
[73]	collaborative tasks	improved CBGA	CBGA	higher efficiency for large number of UAVs

(WiSAR) for heterogeneous UAVs and UGVs is studied, using a market based approach together with a coordinated decentralized perspective. The algorithm proved its computational efficiency in simulation results. In [77] the authors study the problem of task allocation with tasks having different requirements in UAVs swarms. They propose an auction mechanism based task allocation (AMTA) algorithm, which they compared with the closed - loop CBBA. The proposed algorithm has better performance compared to the baseline in total reward, total path length, completion time, and energy consumption.

Table 1 summarizes the main characteristics of some typical auction based approaches.

3.2 Game Theory Based Methods

Game theory-based methods assume that agents are players who choose their actions according to a specific strategy, that is basically the task allocation concept that will be applied. The payoff, which is the reward they receive, depending on their chosen actions, after the game has finished, determines their strategy. The objective of these approaches is to reach a Nash equilibrium, where players have selected the optimal strategy and will not want to change it since it is the best outcome achievable [78].

Games can be divided into two basic categories, the cooperative and non-cooperative ones. In cooperative games, agents collaborate or form coalitions before taking actions, which can impact their overall strategy and utilities. One example is the coalition formation game. In non-cooperative games, agents act individually and choose their own strategies based on self-interest, aiming to achieve the highest payoff. Examples of non-cooperative games include Bayesian games, non-cooperative differential games, and sub-modular games, among others [79].

Some game theory approaches are used for MEC applications like [28], where the problem of continuous offloading in UAV assisted mobile edge computing is studied, where drones can decide the percentage of a task computed locally and the one to offload in cloud. They propose a potential game theory based approach leading to a decentralised offloading algorithm. Compared to a global optimal decentralised Particle Swarm Optimization with Simulated Annealing (PSO-SA), the proposed method has the same performance, but with lower computational cost. Furthermore, in [81], the uncertain task allocation problem in UAVs MEC systems is examined using a Bayesian coalition game approach. The approach is based on possible environments that incorporate a belief update scheme for acquiring the probability of environments associated with the uncertainty of tasks. Maximum utility of the coalition structure is achieved, while maintaining stability. Also, the increase in the detail of the division of the environment, leads to better coalition structure, but with higher computational cost, because of the higher algorithm complexity and the scale of the environment segmentation. In [82] the problem of task allocation of swarm of UAVs, with limited communications and partial information for city mapping applications is studied. They propose one cooperative and another one competitive game theoretic algorithm. Even though the competitive algorithm has higher social utility, meaning it spends less resources, the cooperative approach has higher task completion rate and therefore has better overall performance. The competitive algorithm has smaller communication burden and because of the higher utility is suitable for applications with limited resources. In [80] the authors study a pursuit - evasion problem which they simplify

Table 2 Characteristics of game theory based approaches

Ref.	Application	Algorithm	Metric	Characteristics
[80]	NA	AAPC	simulation	good scalability, suitable for large scale systems
[28]	MEC	potential game theory based	PSO-SA	lower computational cost
[81]	MEC	Bayesian coalition game	simulation	better performance, high computational cost
[82]	area mapping	cooperative and competitive derivative	simulation	cooperative has better overall performance

with a dynamic divide and conquer strategy. The task allocation algorithm uses the Apollonius circle to help the pursuers allocate their resources and capture the evaders in minimum time, proposing the Apollonius circle-based Active Pursuer Check (AAPC) algorithm. The algorithm demonstrates good scalability therefore is appropriate for large scale systems.

Table 2 summarizes the main characteristics of some typical game theory based approaches.

3.3 Optimisation Based Methods

Optimisation refers to the application of mathematical principles to find the most suitable solution for a given problem, by selecting the best option from a group of potential solutions, either by minimizing the cost or maximizing the profit of an objective function while adhering to certain constraints. The selection of the objective function determines the system's aim [1, 83]. Optimisation techniques can be deterministic or stochastic based on the specific algorithm used. Deterministic methods do not involve randomness and generate the same solution for a problem, provided the same starting point is used. Examples of deterministic techniques are graphical methods, graph-based methods, sequential programming, linear programming, and mixed-integer linear programming (MILP). On the other hand, stochastic techniques, or metaheuristics, involve randomness in the calculations and include evolutionary algorithms, swarm intelligence, and simulated annealing. Another category of methods is heuristic algorithms that are employed for obtaining fast and quality solutions to challenging optimization problems, where using deterministic optimisation methods would lead to disproportional computational cost. Nevertheless, the drawback of these methods is that they provide approximate, suboptimal solutions [84].

3.3.1 Deterministic Optimisation Based

The Hungarian algorithm [85], is a frequently used optimisation algorithm that sometimes serves as the foundation for developing new task allocation algorithms. It views the task allocation problem as a combinatorial optimisation problem, using graph theory to solve it in polynomial time. By estimating each agent's utility, the algorithm maximises the overall utility. However, this approach can be computationally expensive and of lower value when significant uncertainties are present in the system. As a result, numerous enhancements to the algorithm have been proposed [86].

Some Hungarian based approaches include [56], where the problem of multi-UAV collaboration and target allocation is studied in area monitoring applications, focusing on minimising the battery consumption of UAVs. They propose a Hungarian method based algorithm called Multi-UAV Collaborative Target Allocation algorithm (MCTA). The proposed method demonstrates better performance than random and greedy baseline derivatives. In [14] they study the problem of task allocation of UAV-aided IoT network, taking into consideration balanced tasks, limited channel resources and signal interference and aiming to minimise the total transmission power. They decompose this MINLP into three sub-problems and solve them using a modified K means clustering algorithm to balance tasks, matching theory based modified-Hungarian-based dynamic many-many matching (HD4M) for channel allocation and an alternative iterating method for power control of UAVs. The proposed approach has better efficiency than a benchmark with random allocation and fixed altitudes.

A very big portion of the deterministic optimisation based task allocation techniques found, regard MEC applications, focusing mainly on the energy consumption minimization, like in [17]. Here the problem of energy consumption minimization in UAV-enabled MEC networks is studied by addressing jointly the problems of service placement, UAV trajectory, task scheduling, and computation resource allocation, having task latency and network resources constraints. An alternating optimisation algorithm with BnB and SCA techniques is used, as well as another one algorithm of the same category, but with lower complexity. Both algorithms have lower overall energy consumption compared to random and greedy baselines, but with the higher complexity algorithm achieving lower overall energy consumption than the lower complexity one. In [22] the authors study the problem of device association, task assignment and computing resource allocation in multi-UAV-assisted MEC systems, focusing again on decreasing energy consumption of UAVs, having as constraints the task completion deadlines, the maximum energy consumption of the UAVs, as well as the available computational resources. They solve this MINLP problem by decomposing it in convex sub-problems using an iterative block coordinate descent (BCD) algorithm. The proposed methods have better performance than random association and offloading baselines. Also, in [19] they study the problem of dynamic task allocation in multi-UAV-enabled MEC systems, following a layered approach dealing with task scheduling and bit allocation and UAVs trajectory planning. The goal is the minimisation of total energy consumption, while the UAVs trajectory satisfies specific safety constraints aiding to UAVs conflicts resolution. The algorithm proposed is a dynamic programming bidding method together with alternating direction method of multipliers (ADMM). Compared with greedy and random strategies the proposed method demonstrates lower energy consumption and satisfactory conflict resolution. In [27] the challenge of task offloading, resource allocation, and security assurance in UAV-assisted MEC networks is investigated. The authors introduce an iterative algorithm based on the relax-and-rounding method and the Lagrangian method, referred to as the LBTO algorithm. In terms of task processing ratio and delay, the LBTO algorithm outperforms other algorithms significantly, according to the study. In [18] they study the problem of joint resource allocation and trajectory optimization for multi-UAV-assisted multi-access MEC systems by simultaneously optimising bit allocation, transmit power, CPU frequency, bandwidth allocation, and UAV trajectories, with a primary focus on minimizing the weighted energy consumption of both UAVs and users. The proposed algorithm, which is based on sequential convex approximation (SCA) technique and alternative optimization demonstrated better efficiency compared to fixed trajectory, fixed bandwidth allocation and the single access schemes. In [87] the authors study the problem of task assignment in collaborative UAVs with sequence-dependent tasks. They propose a spatial brunch limiting algorithm (SBLA) to solve this MINLP problem that has task assignment constraints, bandwidth and energy consumption of the UAVs constraints, as well as, time constraints for the time dependent tasks. The proposed method has higher quality of solution and less energy consumption than ant colony algorithm (ACA) and simulated annealing algorithm (SAA). An another approach focusing on maximising the number of IoT devices served and following certain time deadlines is [8], where the problem of resource allocation and computation offloading in multi-UAV-enabled MEC is studied. They solve this MINLP problem by decomposing it to the sub-problems of resource allocation and trajectory optimisation and using jointly alternating optimization and successive convex approximation (SCA), leading to the multiple traveling salesman problem with time windows (m-TSPTW) based method. The proposed method has better performance than greedy, static and local computing baselines.

Other optimisation based approaches include [88], studying the problem of UAV-priority-based resource coordination, with focus on reliable communication in a base station controlled UAV network. In order to control channel assignment they propose a mixed integer programming approach using smoothing and alternating optimisation. This method is more efficient than a baseline random channel assignment method. In [59] they study the problem of using UAVs for logistics, especially for product transfer from the warehouse to the customers. They use a dynamic allocation algorithm assuming this problem as a type of vehicle routing problem, taking into consideration load, endurance and airspace constraints. In [89] the authors study the problem of energy efficiency and profit maximising in multiple UAVs assisted MEC networks. They use a Lyapunov optimisation method proposing the joint optimization algorithm of the deployment and resource allocation of UAVs (JOAoDR). Compared with a greedy algorithm the proposed method has better long-term performance.

Table 3 summarizes the main characteristics of some typical deterministic optimisation based approaches.

3.3.2 Metaheuristic Based

Metaheuristics comprise various methods, such as genetic algorithms, simulated annealing, and swarm intelligence. Swarm intelligence is a biologically inspired algorithm that has found extensive use in the task allocation of multi-agent systems. It draws inspiration from animals with social behaviour, including insect colonies, schools of fish, and flocks of birds, among others [90]. These animals exhibit efficient division of labor, with specialized members contributing to the overall efficiency of the colony [91]. Although individual agents may not be complex, they can perform complex tasks collectively through cooperation, resulting in robust, efficient, and not computationally expensive solutions [92]. However, these algorithms may sometimes allocate not required tasks to agents, resulting in conflicts and also exhibit slow global responses to environmental changes [90]. The two main categories of metaheuristic methods are threshold-based and probabilistic methods.

Threshold-based methods, like the response threshold method [93], determine agent actions based on some monitored values and a fixed or variable threshold. Agents may have only local or global information about these values. In probabilistic methods, the tasks are changed randomly utilising probability distributions exported from environmental observations or historical data. Moreover, in this type of methods an environmental stimulus can be used, with the stimulus value being the criterion of selection of a specific task [94].

Table 3 Characteristics of deterministic optimisation based approaches

Ref.	Application	Algorithm	Metric	Characteristics
[56]	Monitoring	MCTA	random and greedy baseline	better performance
[14]	MEC	HD4M	random allocation	better efficiency
[17]	MEC	Alternating optimisation	random, greedy, local	lower energy consumption
[22]	MEC	BCD based	random	better performance
[8]	MEC	Alternating optimization, successive convex approximation (SCA)	greedy, static, local	better performance
[19]	MEC	Dynamic programming bidding, ADMM	random, greedy	lower energy consumption
[27]	MEC	Relax-and-rounding, Lagrangian method	vehicle local computing, average task offloading, RSU LBTO	better task processing ratio and processing delay
[18]	MEC	Sequential convex approximation (SCA), alternative optimization	fixed trajectory, fixed bandwidth allocation, single access scheme	better efficiency
[87]	MEC	SBLA	ACA,SAA	better solutions, less energy consumption
[88]	channel allocation	Smoothing, alternating optimisation	random	higher efficiency
[59]	logistics	Dynamic allocation	simulation	effectiveness in dynamic environments
[89]	MEC	Lyapunov optimisation (JOAoDR)	greedy	better long-term performance

Most of the metaheuristics based techniques are focused on ISR combined with target attacking applications like, [95] where they study the problem of task allocation between cooperative UAVs in attack and reconnaissance applications. They use the beetle antennae search (BAS) together with a genetic algorithm, thus enhancing the diversity and search ability of the genetic algorithm. The new algorithm is proved to have faster convergence and better performance than the baseline genetic algorithm and a PSO based baseline variant. Also, in [43] the problem of task allocation in reconnaissance and attack applications of multiple UAVs is studied, proposing an improved simulated annealing fusion genetic algorithm (ISAFGA), that has improved solution acceptance criteria compared to simulated annealing. The algorithm has lower solving time than baseline simulated annealing and improved efficiency. In [42] the authors study the problem of cooperative search-attack joint mission planning of multiple UAVs, proposing a dynamic discrete Pigeon-inspired Optimization (D2PIO) algorithm. The effectiveness of the algorithm is shown by simulation results and the algorithm showed better performance than PSO, PIO, DPSO and MPSO. In [40] the problem of task allocation in reconnaissance and attack applications of multiple UAVs is studied, proposing a chaotic wolf pack algorithm based on enhanced Stochastic Fractal Search (MSFS- CWPA). Compared to baseline Wolf pack algorithm (WPA) and two other improved Wolf pack algorithms, the QWPA and TLWPA methods, the proposed approach demonstrates better global search and performance in general. In [96] they study the problem of multi-UAV task allocation and route planning in ISR and attack applications, using Dubins curve and proposing an improved PSO algorithm. The improved algorithm has better convergence and provides better solutions than the baseline PSO. In [46] they study the dynamic task allocation of a swarm of UAVs in ISR and attack applications, used for military purposes, using a distributed, bottom up, dynamic ant colony's labor division (DACLD) approach. Compared to the WPA algorithm the proposed method has better task allocation, faster response to threats, robustness and flexibility.

Also, there are plenty of ISR or attack for multiple UAVs applications covered, like [33] where the problem of task allocation of multiple UAVs is studied, focusing on the low probability of intercept of the UAVs signals during the task allocation procedure. They propose a low probability of intercept-based task allocation (LPI-TA) algorithm, using the standard particle swarm optimization method. Simulations conducted proved the effectiveness of the algorithm. In [30] the problem of multi-UAV reconnaissance task allocation is studied, dividing the targets according to their geometric characteristics. They propose the grouping ant colony optimization (GACO) algorithm based on ACO, that has better exploration capabilities and lower cost than baseline ACO and OGA-DEMMO. As for the attack only applications, in [38] the problem of mission planning in multiple UAVs for cooperative combat tasks is covered. The problem is decomposed in task assignment, which is modeled as a multi-constraint, multi-objective, coupled integer optimization problem and the resource allocation problem which is a linear integer optimization problem. A genetic algorithm based and simulated annealing approach is used for both problems respectively. Simulations were performed to validate the effectiveness of the algorithms that proved to achieve rapid task assignment, making them suitable for complex constrained environments. In [36] they study the problem of task allocation and track planning of multiple UAVs attacking ground targets. They developed a new ant colony optimization algorithm based on adaptive parameter adjustment and bidirectional search (BSAP-ACO) for cooperative path planning together with a new improved particle swarm optimization algorithm based on guidance mechanism (GMPSO) dealing with the moving target problem. The proposed algorithms are compared with the baseline Ant Colony Optimisation (ACO) algorithm, the Dynamic feedback ant colony optimization algorithm (DFACO), the GA algorithm, PSO algorithm and the Multi-objective Particle Swarm Optimization (MOPSO) algorithm respectively, proving the effectiveness of the proposed methods. In [37] the authors study the problem of task assignment of cooperative multi-UAVs with resource constraints and precedence constraints for combat UAVs applications, like targets attacking. They propose the Fully Adaptive Cross-Entropy Algorithm (FACE), which is compared with cross-entropy (CE) method and particle swarm optimization (PSO) algorithm. The proposed technique has better performance and faster convergence than PSO and CE only in larger scale problems, while having a bit slower convergence than CE in small scale applications.

Other applications include, [97] where the authors study the problem of mission planning for heterogeneous UAVs by simultaneously dealing with sensor allocation, task assignment and collision-free path planning. They use a meta-heuristic algorithm, the two-level adaptive variable neighborhood search (TLAVNS) algorithm, where the first level is used for the sensors allocation plan and the second for the path planning. The proposed algorithm has better performance than non-adaptive variants, but a bit higher computational cost. In [48] the authors study the dynamic task allocation problem in multiple UAVs, using the distributed immune multi-agent algorithm (DIMAA) based on an immune multi-agent network framework. In simulations performed the algorithm distributed quick convergence, small loss of communication and robustness, but also a slow convergence rate in static task assignment. In [97] the problem of task allocation of UAVs and operating vehicles in electricity grid inspection procedure is studied, using K-means method and a genetic algorithm. The simulations performed proved the effectiveness and practical use of the algorithm. In [98] they study the problem of multi-UAV cooperative task assignment in battlefield applications, proposing an improved quantum genetic algorithm, using the grouping optimization strategy of hybrid frog leaping algorithm and simulated annealing. The proposed method has better local optimal solutions and increased diversity compared with multi granularity genetic algorithm and incremental learning algorithm, but with the disadvantage of higher computational complexity. In [55] the authors study UAVs usage in agricultural activities, focusing on the distance between UAVs and tasks, as well as the resources carried. They propose the Capability Value Sensitive-Collection Path Ant Colony Optimization (CVS-CPACO) method, that has better solutions and lower amount of resources are wasted compared to CPACO and modCPACO. Also, the distance of the proposed method is a bit worse than the benchmarks. In [57] they study the UAV task allocation problem for missions in complex chemical plants and city environments with dense buildings and non-negligible ambient winds. They propose a technique based on the twin-exclusion mechanism, hierarchical objective-domination operator, and segmented gene encoding (NSGA-III-TEHOD), which is an improvement of non-dominated sorting genetic algorithm III (NSGA-III). The proposed approach has better efficiency and convergence properties than NSGA-III.

Table 4 summarizes the main characteristics of some typical metaheuristic based approaches.

3.3.3 Heuristic Based

In most of the heuristic approaches the authors are occupied with MEC applications. In [16] they study the problem of task assignment in UAV assisted MEC networks, focusing on energy consumption and delay minimization. They proposed a heuristic based method using a differential evolution (DE)-aided algorithm and non-dominated sort process. The proposed method has lower energy consumption compared with PSO and NSGA-II and better solutions, but PSO has a much faster convergence speed. In [23] they study the problem of minimising the transmission energy of UAVs and computation energy of base stations in MEC-enabled UAV communication systems. They divide this problem into allocation optimisation and the combinatorial UAV grouping optimisation, using gradient descent and a heuristic based on simulated annealing. The proposed method has lower energy consumption compared to FDMA technique. In [10] the authors study the joint computation offloading, spectrum resource allocation, computation resource allocation, and UAV placement (Joint-CAP) problem in a UAV-MEC network. They propose a $(1 + \epsilon)$ approximation algorithm (AA-CAP) to solve the proposed Joint-CAP problem that yields solutions with bounded deviations from the optimal solution. The proposed method has reduced cost to the Least-CAP and S-MBS baselines. A different approach is [39], where the authors study the problem of cooperative tactical planning in multiple UAVs combat operations, using

Table 4 Characteristics of metaheuristic based approaches

Ref.	Application	Algorithm	Metric	Characteristics
[97]	mission planning	TLAVNS	non-adaptive variants	better performance, higher computational cost
[48]	SAR	DIMAA	simulation	good convergence, robustness, small loss of communication, slow convergence in static task assignment
[38]	target attacking	GA and SA	simulation	effectiveness, quick task assignment
[95]	ISR and attack	BAS	genetic and PSO	faster convergence, better performance
[97]	electricity grid inspection	K-means method & GA	simulation	effectiveness and practical use
[98]	battlefield applications	improved quantum GA, hybrid frog leaping algorithm, SA	multi granularity GA, incremental learning algorithm	better local optimal solutions and increased diversity, higher computational cost
[43]	ISR and attack	ISAFGA	simulated annealing	improved efficiency, lower cost
[55]	agriculture	CVS-CPACO	CPACO and modCPACO	better solutions, lower resources wasted, more distance travelled
[33]	ISR	LPI-TA	simulation	effectiveness
[42]	ISR and attack	D2PIO	PSO, PIO, DPSO and MPSO	effectiveness
[30]	ISR	GACO	ACO, OGA-DEMMO	better exploration, lower cost
[36]	ground targets attacking	BSAP-ACO	DFACO, GA, PSO, MDPSO	higher efficiency
[37]	target attacking	FACE	PSO, CE	better performance, faster convergence, slower convergence than CE in small scale
[40]	ISR and attack	MSFS- CWPA	WPA, QWPA, TLWPA	better performance, global search
[96]	ISR and attack	improved PSO	PSO	better efficiency, convergence
[57]	area monitoring	NSGA-III-TEHOD	NSGA-III	better efficiency, convergence
[46]	ISR and attack	DACLD	WPA	better task allocation, faster response to threats, robustness, flexibility

a hierarchical setup and the A-star algorithm. Simulation results prove the effectiveness of the proposed methods.

3.4 Reinforcement Learning Based Methods

Most real-world task allocation scenarios, involve highly dynamic environments, whose behaviour cannot be described by explicit mathematical models, therefore predicting future disturbances that an agent may encounter in such environments is extremely challenging. One way for agents to handle such disturbances is by taking into account their previous actions as well as those of other agents, thereby enhancing the overall efficiency of the system [99, 100].

Reinforcement learning is a commonly utilized machine learning method that allows agents to learn how to act in various states of the environment based on their experience. In this technique, the agents optimize a cost or reward function to learn from the environment that is often modeled as a Markov Decision Process (MDP). Q-learning is one of the commonly used model-free RL methods that aids agents in finding optimal solutions in MDPs [99, 100]. Reinforcement learning offers several benefits, including its ability to handle environmental uncertainties, real-time implementation (for well-trained networks), and flexibility in handling different tasks [41]. However, in large-scale complex systems, most RL algorithms typically require substantial computational power [101].

Most of the applications regarding reinforcement learning based approaches focus on MEC applications, like in [102] where the authors study the problem of computation offloading, policy and resource allocation of Edge-Internet-of-Things (EIoT) devices that in emergency cases use multiple UAVs as aerial base stations forming a network. They propose a DDPG learning framework named CCORA-DRL. The framework has higher efficiency than DQN, A3C and greedy baselines. In [103] they study the problem of UAV-enabled edge computing (UEC), where the UAVs can take computational tasks from ground local devices and from other neighbouring UAVs. They propose a DRL framework for the cooperative offloading and resource allocation process, based on a deep Q network method for both centralised and distributed network topologies. Both the centralised and distributed cooperative DRL methods outperform in terms of utility popular non-cooperative baselines, with the centralised method achieving the highest utility. In [21] the authors study the problem of mobile edge computing (MEC), using UAVs, that perform task offloading from user equipment. They propose a convex optimization based approach called Trajectory control algorithm (CAT) and a second deep Reinforcement Learning based Trajectory control algorithm (RAT), for real time decision making. These approaches were compared to baselines like local execution, random moving and cluster moving. The RAT approach has the best energy performance, compared to CAT and the baselines that have the worst. In [25] the problem of joint resource allocation of UAV based mobile edge computing (MEC) networks in maritime networks is studied, using a reinforcement learning DQN based approach. The convergence and performance of the proposed approach were validated with simulation experiments. In [9] the authors study the problem of coverage and navigation (resource allocation) of drone cells in cellular networks on the peak of communication load, using a multi-agent reinforcement learning centralised approach (MARL) with an enhanced joint action selection algorithm (enhanced hill climbing search). The proposed approach demonstrated better performance compared to classic hill climbing.

In [24] the authors study the problem of task offloading and resource allocation in Space-air-ground integrated power Internet of Things (SAG-PIoT) networks, using Lyapunov optimisation to decompose the joint optimisation problem. Especially for the task offloading QUARTE is proposed, which is a DRL actor critic based method capable to deal with the curse of dimensionality, while taking into consideration queue information, being ideal for dynamic task allocation. The proposed approach has better performance, convergence speed and lower energy consumption compared to baseline DAC and EMM algorithms. In [13] they study the problem of cooperative multi-UAV enabled IoT edge network for dynamic task offloading and resource allocation, proposing a MADRL method. They utilize the MADDPG algorithm, forming the aforementioned problem as a stochastic game and focusing on energy consumption and computation delay minimisation. The proposed method demonstrated better performance and lower cost than single agent DDPG and greedy methods. A different application is studied in [41] where the authors study the problem of ISR and attack with uncertainty, using a reinforcement learning approach. The task allocation problem is formed as MDP and a Q-learning based fast task allocation algorithm is developed, using neural network approximation. The algorithm is real time implementable. The algorithm compared to discrete particle-GuoTao-simulated annealing (DPSO-GT-SA) has better performance with uncertainty. Also, the algorithm with prioritized experience replay converges faster than the one with random experience replay.

Table 5 summarizes the main characteristics of some typical learning based approaches.

3.5 Hybrid Methods

In addition to the aforementioned methods for solving task allocation problems, there exist hybrid approaches that are a combination of some of these methods.

The authors of [47] investigate the issue of task allocation for SAR missions and propose a CBBA-based approach. They combine this approach with the Ant Colony System (ACS) algorithm and a greedy-based strategy to enhance the inclusion phase of the CBBA. This approach has lower makespan, travel distance and number of exchanged messages, compared to baseline approaches such as, the Hungarian algorithm (HA), the decentralised greedy algorithm (DGA), the repeat auctions algorithm (RAA) and the spatial

Table 5 Characteristics of RL based approaches

Ref.	Application	Algorithm	Metric	Characteristics
[102]	MEC	CCORA-DRL	DQN, A3C and greedy	higher efficiency
[103]	MEC	DQN based	non-cooperative baselines	higher utility
[21]	MEC	CAT, RAT	local execution, random moving and cluster moving	lower energy consumption
[25]	MEC	DQN based	simulation	convergence, performance
[9]	MEC	MARL and hill climbing	hill climbing	better performance
[41]	ISR and attack	Q-learning based	DPSO-GT-SA	better local optimal solutions and increased diversity, higher computational cost
[24]	MEC	QUARTE	DAC, EMM	better performance, convergence speed and lower energy consumption
[13]	MEC	MADDPG based	DDOG, greedy	better performance and lower cost

queuing-based algorithm (SQA). On the other side, this approach provides suboptimal (near optimal) solutions and has bigger number of exchanged messages compared to the firefly algorithm-quantum artificial bee colony-multi robot task allocation (FA-QABC-MRTA), even though it has lower makespan and travel distance. In [31] they propose a framework based on an auction system based on market economy and a biologically inspired pheromone map for solving the problem of area exploration, connectivity management and mission allocation, simultaneously, for multiple UAVs on ISR applications. Their approach has good coverage performance, better efficiency, presenting positive correlation between connectivity and area coverage, compared to a random explorer algorithm, but the connectivity maintenance mechanism reduces the area covered by the drones and a calibration phase is needed before use.

3.6 Other Approaches

There are also some other approaches that could not fit in the above categories. In [60] they study the method of block information sharing for decentralised dynamic task allocation in structures assembly of aerial robots. This method is based on the one to one strategy that shares information between neighbouring agents helping them to reallocate tasks. Their method converges to an optimal solution, under certain circumstances, but the block size of the agents, for which there is not yet an optimal method for its calculation, has a key role in the balance between convergence time and robustness. For big size blocks might be cost expensive and can lead to a decrease in efficiency and fault tolerance. In [104] the authors work on the coverage path planning problem for heterogeneous UAVs, having a bounded number of regions. They propose a new clustering - based algorithm that classify regions based on using relative distances, called spatial-temporal clustering-based algorithm (STCA). This approach provides sub-optimal solutions, but can guarantee coverage of all regions under specific assumptions. In [45] they study the problem of multi-target task assignment with fuzzy inference using a Mamdani-type fuzzy inference system, for the application of ISR and attack of UAVs. In [51] the authors study the problem of task allocation in SAR applications, proposing a communication protocol that improves the Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) protocol achieving task allocation in a distributed way. The efficiency of the approach was validated by simulations as well as field experiments.

4 Discussion

The computational complexity of algorithms, optimality of solutions, and scalability of approaches used are fundamental criteria for assessing the task allocation process in UAVs. Additionally, the ability of algorithms to handle uncertainties and the effectiveness of communication schemes utilized significantly impact the overall system performance.

4.1 Complexity, Optimality and Scalability

The computational cost of task allocation is influenced by various factors such as the complexity of the algorithm employed, the frequency of the algorithm's usage, and the computational cost of the communication scheme utilized. This refers to the amount of information exchanged between agents in order to achieve successful task allocation [105, 106].

The optimality of the solutions is another crucial factor to consider in task allocation procedures. By optimality, we refer to the extent to which the solution found maximizes the overall utility of the system, while taking into account the system's characteristics such as noise, uncertainty, and inaccuracy of the information available to the agents. The quality of the solution can be affected by the frequency of algorithm execution, which should be sufficient to ensure dynamic, rather than static, solutions, as well as the ratio of tasks that can be reassigned. As the complexity of tasks and the number of agents involved increase, the scalability of the algorithms becomes vital in ensuring their effectiveness. [2].

4.1.1 Auction Based

Most of the auction based methods found are CBBA and CNP methods improvements, therefore follows a detailed presentation of their complexity, optimality and scalability.

CBBA Based Most of the CBBA approaches found concern SAR missions and also there are some regarding ISR and SEAD military applications. The most frequent baselines used are baseline CBBA and PI algorithms. Most of the auction based approaches presented, are improved versions of these algorithms, that usually exhibit higher efficiency and scalability. Even though few demonstrate lower computation cost, most of them have the disadvantage of higher computational cost and complexity. This is the case for the EPIAC approach [44], where the computational complexity is dominated by $\mathcal{O}(\sum_{j=1}^{N_t} h_{ij}|a_i|^2 M_1 \sigma N_u)$, where N_u is the number of the UAVs, N_t is the number of the tasks, a_i is the task list, h_{ij} is a set of constants and σ is the complexity of computing the score of a task.

CNP Based In general, techniques based on Contract Net Protocol (CNP) are very effective in task reallocation, but they heavily rely on the communication scheme among the agents, leading to high computational burden. Additionally, message congestion has been observed as a problem with CNP. While some improved CNP algorithms have been proposed to address this issue and achieve higher efficiency with lower computational cost than baseline CNP, the problem of message congestion remains a topic of ongoing research. Some approaches, such as the one proposed by [76], attempt to address this problem, but further investigation is needed.

4.1.2 Game Theory Based

The game theory approaches that have been presented demonstrate greater efficiency than the baseline approaches, producing suboptimal solutions that are closer to the optimal solution. Furthermore, in general, some game theoretic algorithms exhibit better efficiency compared to auction-based approaches. In terms of complexity, the Apollonius circle-based Active Pursuer Check (AAPC) [80], has complexity of $\mathcal{O}(n_a^2)$, where n_a is the number of pursuers. Also, in [81] where a Bayesian coalition game approach is used the complexity is $\mathcal{O}(|\Pi|2^T)$, where Π is the set of possible environments, with each environment specifying a coalition game and T is the number of tasks. As we see the complexity is also proportional to the number of possible environments. In [28], the authors propose a potential game theory based approach that has complexity of $\mathcal{O}(N)$, where N is the number of agents. Therefore, as we see, the complexity varies from fast algorithms to exponential ones, that are unsuitable for large scale systems. Some game theoretic approaches though, can have comparable or lower complexity than CBBA based ones and can be suitable for large scale systems like [28].

4.1.3 Optimisation Based

Most of the optimisation based methods found include deterministic optimisation, heuristics and metaheuristics methods, therefore follows a detailed presentation of their complexity, optimality and scalability.

Deterministic Optimisation Based For the deterministic optimisation based approaches we notice that they are used mainly for MEC scenarios, with common baselines being random and greedy task allocation algorithms. The approaches usually have high efficiency but very high complexity and cost. In [17] the authors propose two alternating optimisation algorithms. The first algorithm has complexity of $\mathcal{O}(I^{max}2^{N(S+UT)})$. and the second algorithm has complexity of $\mathcal{O}(I^{max}(J^{max}N^3T^3+N^3(S+UT)^3+N^2UST))$, where I^{max} is the number of the algorithm iterations, J^{max} is the number of the iterations of the successive convex approximation algorithm used, N is the number of services, S is the number of user equipments and T is the number of slots existing. We have to note that the first algorithm has higher efficiency than the second one that has lower complexity and finds a suboptimal solution. In [8], the authors propose an algorithm for solving the resource allocation problem and another one for trajectory optimisation, using jointly alternating optimization and successive convex approximation (SCA). The first algorithm has complexity of $\mathcal{O}((MKN)^{3.5}\log^2(1/\epsilon))$ and the second one of $\mathcal{O}(K^{3.5}\log^2(1/\epsilon))$, where M is the number of UAVs, K is the IoT devices, N is the number of time slots and ϵ is the given solution accuracy. In [19] a dynamic programming bidding method together with alternating direction method of multipliers (ADMM) with a conflict resolution phase is used. The complexity of the algorithm is $\mathcal{O}(K_aMR+Q)$, where K is the number of division area, M is the number of the UAVs, R is the number of iterations to solve and Q is the number of conflicts. In [14] they propose a modified K means clustering algorithm to balance tasks, matching theory based modified-Hungarian-based dynamic many-many matching (HD4M) for channel allocation and an alternative iterating method for power control of UAVs. The complexity of the method is $\mathcal{O}(M\lceil(M/N)\rceil L_1 + NM^{3.5}L_3\log_2([h_{\max}-h_{\min}]/\epsilon))$, where M is the number of IoT devices, N is the number of UAVs, L_i are the numbers of iterations of algorithm i, H_{min} is the minimum altitude of the UAVs, h_{max} is the maximum altitude of the UAVs. It is apparent that the majority of approaches exhibit high polynomial or exponential time complexity, rendering them impractical for deployment in large-scale systems.

Heuristics Usually techniques with optimal solutions to the task allocation problem, like deterministic optimisation ones might have even an exponential computation cost. On the other side, heuristic techniques provide suboptimal solutions, but have minimal computation cost compared to them. Also, it was noticed that some heuristic techniques can be more efficient and less computationally expensive than some genetic and auction based approaches [107]. In [10] the authors study the problem of joint computation offloading, spectrum resource allocation, computation resource allocation, and UAV placement (Joint-CAP) proposing the (AA-CAP) algorithm. The complexity of the algorithm is $\mathcal{O}((|B|+log(|U|+2))|U|C_{N_1}^{N_2})$ where B is the set of base stations, U is the set of internet of things devices, C is the computing capacity of the base station, N_1 is the set of candidate positions for UAVs in the XY-plane and $N_2 = B - 1$. Generally, heuristic methods can be used on large scale systems with algorithms in literature exhibiting complexity of $\mathcal{O}(n)$ or $\mathcal{O}(nlog(n))$.

Metaheuristics Some of the methods presented exhibit lower complexity and improved scalability compared to the baseline techniques. However, some of these methods are suboptimal or assume no failures in the communication procedure between the agents. Furthermore, many methods show better scalability and efficiency than certain greedy and auction-based approaches such as CNP.

In general, metaheuristic techniques are considered to be cost-effective, robust, and efficient, but they can sometimes lead to conflicts between tasks, assign unnecessary tasks to agents, and respond slowly to changes in the environment. The metaheuristic techniques were mostly used in military applications like ISR and attack among others. Some of the methods presented exhibit lower computational cost and are more scalable compared to the baseline techniques. However, some of these methods are suboptimal or assume no failures in the communication between the agents. Furthermore, many methods are more scalable and efficient than certain greedy and auction-based approaches such as CNP. In [42] the authors propose the dynamic discrete Pigeon-inspired Optimization (D2PIO) algorithm. The computational complexity of the algorithm is $\mathcal{O}(N_c(N_P \log N_P + DN_P + L_f N_P + L_{di} N_P + L_{dy} N_P))$, where, N_c is the total iteration, N_P is the population size of the pigeons, D the dimension of the parameter vectors, L_f the computational cost of the objective function J, L_{di} is the computational cost of the discrete mechanism and L_{dy} is the computational cost of the dynamic mechanism.

4.1.4 Reinforcement Learning Based

In general, reinforcement learning approaches are known for their high efficiency, potential for online implementation, and ability to adapt to environmental disturbances. It has been observed that many techniques outperform baseline algorithms such as simulated annealing, hill climbing, and greedy algorithms. In addition, some methods have demonstrated greater efficiency than frontier-based and Hungarian methods. Although some approaches have lower computational costs than market-based methods, computational cost and increased dimensionality remain significant challenges in some reinforcement learning techniques. Also, most of the approaches found were regarding MEC applications and most of the algorithms had higher efficiency and some of them had also lower cost, than the baseline methods.

The authors of [21] propose a deep Reinforcement Learning based Trajectory control algorithm (RAT), for real time decision making. The computational complexity is $\mathcal{O}\big((\sum_{l=1}^{L} n_l \cdot n_{l-1} + NM)T\big)$, where L is the number of network layers, n_l is the number of neurons in the l-th layer, N is the number of user equipments, M is the number of UAVs and T is the number of time slots. In [13] they propose a MADRL method utilizing the MADDPG algorithm. The proposed method demonstrated a training procedure complexity of $\mathcal{O}(Z_{eps} H Z_l N |L|^2)$, where $|L|$ is the number of the agents, Z_{eps} is the number of training episodes, H is the batch size, N is the number of hidden layers and Z_l is the agent cost. In [102] the authors propose a DDPG based learning framework named CCORA-DRL. The complexity of the framework is $\mathcal{O}(C \times |S| \times |A|)$, where C is the number of UAVs cluster heads, S denotes the state set and A denotes the action set. As we see the complexity varies from $\mathcal{O}(n)$ to $\mathcal{O}(n^2)$, with n being the number of agents, making some approaches online implementable and some others not ideal for large scale systems.

4.1.5 Hybrid

The goal of hybrid approaches is to use two or more techniques aiming to combine their advantages and increase the efficiency or decrease the computational cost of the case these methods were used alone. The approaches found are a combination of auction based with metaheuristic approaches that is a common combination for task allocation algorithms. The proposed approach in [47] combines CBBA with the Ant Colony System (ACS) algorithm, and a greedy strategy is employed during the inclusion phase of CBBA. The worst-case computational complexity of this approach is $\mathcal{O}({n_t}^3)$, where n_t is the number of survivors (tasks).

4.1.6 Other Approaches

In [104] they propose a new clustering - based algorithm called spatial-temporal clustering-based algorithm (STCA). The complexity of the algorithm is $\mathcal{O}(m^2)$, where m is the number of the regions that the UAVs do a search task.

In Table 6 a summary of the complexity of the aforementioned algorithms is presented. As we can see the complexity varies a lot even between methods of the same category. However, deterministic optimization-based approaches, followed by CBBA-based algorithms, and hybrid approaches tend to have the highest computational costs. In contrast, heuristic-based approaches and metaheuristic-based approaches generally have the lowest with reinforcement learning and game theory ones being in the middle but not with high difference.

4.2 Communication

In many task allocation methods, effective communication between agents is crucial for their coordination and overall performance. The objective is for agents to exchange necessary information about their state and the environment using minimal bandwidth and without causing congestion in the communication network [108]. Communication used in task allocation methods can be either explicit or implicit. Explicit or direct communication involves exchanging messages between agents through a communication network and dedicated protocols, which is the most commonly used method in existing coordination approaches. On the other hand, implicit communication involves obtaining information about other

Table 6 Complexity of some characteristic task allocation algorithms

Category	Algorithm	Complexity
CBBA based	EPIAC [44]	$\mathcal{O}(\sum_{j=1}^{N_t} h_{ij}\|a_i\|^2 M_1 \sigma N_u)$
Deterministic optimisation	Alternating optimisation based [17]	$\mathcal{O}(I^{max} 2^{N(S+UT)})$, $\mathcal{O}(I^{max}(J^{max} N^3 T^3 + N^3(S + UT)^3 + N^2 UST))$
	Alternating optimization, SCA [8]	$\mathcal{O}((MKN)^{3.5} \log^2(1/\epsilon))$, $\mathcal{O}(K^{3.5} \log^2(1/\epsilon))$
	ADMM [19]	$\mathcal{O}(K_a MR + Q)$
	Modified-Hungarian-based [14]	$\mathcal{O}(M\lceil (M/N)\rceil L_1 + NM^{3.5} L_3 \log_2([h_{\max} - h_{\min}]/\epsilon))$
Game theory based	AAPC [80]	$\mathcal{O}(n_a^2)$
	Bayesian coalition game based [81]	$\mathcal{O}(\|\Pi\| 2^T)$
	Potential game theory based [28]	$\mathcal{O}(N)$
Metaheuristics	D2PIO [42]	$\mathcal{O}(N_c(N_P \log N_P + DN_P + L_f N_P + L_{di} N_P + L_{dy} N_P))$
Heuristics	AA-CAP [10]	$\mathcal{O}((\|B\| + log(\|U\| + 2))\|U\| C_{N_1}^{N_2})$
Learning based	RAT [21]	$\mathcal{O}\big((\sum_{l=1}^{L} n_l \cdot n_{l-1} + NM)T\big)$
	MADDPG based [13]	$\mathcal{O}(Z_{eps} H Z_l N \|L\|^2)$
	CCORA-DRL [102]	$\mathcal{O}(C \times \|S\| \times \|A\|)$
Hybrid	CBBA based with Ant Colony System [47]	$\mathcal{O}({n_t}^3)$
Other	STCA [104]	$\mathcal{O}(m^2)$

agents in a multi-agent system and the environment, through the agents' perception of the environment using sensors. Implicit communication can be active if the agents use information left by other agents in the environment, which are techniques mostly inspired by nature, or passive if the agents use only their sensors to perceive changes in their observation spaces [109]. Another communication scheme used is the blackboard scheme, where agents' characteristics such as location and target point are added to a shared file on the blackboard along with other relevant information.

Auction-based techniques often employ explicit communication methods, with mesh, row, star, circular, and hybrid network topologies being commonly used. Among these, the row topology appears to have the best performance, while mesh topology may have lower computational cost in some cases. Asynchronous communication schemes are also employed to reduce communication costs, as there is no need for specific time slots. In metaheuristic-based approaches, the token ring architecture or blackboard schemes are often used for communication. Reinforcement learning methods, on the other hand, mostly use implicit communication schemes, although some methods utilize explicit communication between UAVs, particularly in MEC applications.

Not all of the aforementioned task allocation methods give specific description of the communication technique used, if any, therefore a detailed representation of the communication techniques of the rest of the methods follows in the next paragraphs.

4.2.1 CBBA Based

In [66] where an extended PI algorithm is used, communication schemes such as mesh, row, and hybrid (row-tree) were utilized, and they demonstrated comparable performance. Among them, the row communication scheme exhibited a greater success rate in solving problems with the best solution, while the hybrid and mesh approaches followed. In [50] where the CBBA-TCC algorithm is used, row, star, circular and mesh communication types were used, with row type achieving the best performance, while the other types had almost similar performance. Another improved CBBA method in [34] uses asynchronous communication for the conflict mediation phase, decreasing communication cost. In the improved CBGA method [73] a communication matrix is used for the conflict resolution phase and the communication network is fully connected. Moreover, in EPIAC method [44] mesh, row, circular and star topologies are tried. Mesh seems to need the fewest iterations to converge, having the smallest run time, while star topology needs the most iterations and highest run time.

4.2.2 Game Theory Based

In a potential game theory based technique [28] the UAVs use a shared communication channel to offload tasks by multiplexing accessing. Only the queuing status from ground stations is needed, so the communication cost is decreased compared to baseline PSO-SA. Also, in [82] where the authors propose one cooperative and another one competitive game theoretic algorithm, the UAVs can only communicate with their neighbours having only partial information about their missions.

4.2.3 Metaheuristics Based

In the DACLD method [46] all UAVs can freely communicate with each other, while in another swarm-GAP based method [110], a token protocol with a ring architecture is used (token ring). In this method, the communication cost was increased compared to the baseline and a perfect communication scheme was assumed. In DIMAA [48] the blackboard communication scheme is used, where agents' characteristics such as location and target point are added to a shared file on the blackboard along with other relevant information. Here agents can communicate only with neighbouring agents.

4.2.4 Reinforcement Learning Based

In a MADDPG based method [13], the UAVs that belong to a cluster are connected to each other with D2D communication, while in a DQN based method, [103], UAVs communicate with each other, but have different computation and communication capacities.

4.2.5 Hybrid

In ACS-MRTA [47], UAVs can communicate with every other UAV, having a fully distributed solution to the task allocation problem. Moreover, in the auction based and pheromone map approach [31], the communication utilized the Pheromone Map Model, which involves the placement of virtual markers by agents to indicate mission and network states, which are then detected by other agents. This technique helps to minimize direct communication between agents.

4.2.6 Other

In the Block information sharing method [60], each UAV communicates with the neighbouring UAVs only, with limited communication range, forming a communication graph. The whole graph is divided into blocks, that the agents belonging to them can communicate with each other. The information amount every UAV can accept is unbounded, unlike a real world scenario.

Consequently, explicit communication has a higher level of accuracy compared to the implicit approach, but it comes at the cost of higher communication cost, which is particularly problematic for larger systems. On the other hand, the implicit approach is more stable and resilient to faults, despite its lower accuracy. Therefore, a combination of these methods is often recommended to take advantage of their respective strengths and improve overall system performance [109].

Table 7 provides an overview of the communication schemes used by some typical task allocation methods of UAVs. Popular techniques include the social network technique, the pheromone map model, the blackboard scheme, and graph-based techniques.

4.3 Uncertainty

Considering uncertainty is essential for efficient and reliable task allocation in practical applications. However, many existing approaches, particularly distributed ones, are limited in their ability to handle uncertainty and often rely on oversimplified assumptions about the environment. Uncertainty may arise from sensor inaccuracies, agent failures, environmental disturbances, and more [53, 111]. Previous research has shown that considering reliability beforehand is essential, as neglecting the possibility of failure can lead to performance deterioration [112]. For instance, in [113] it is proved that the Asynchronous Consensus Based Bundle Algorithm (ACBBA) produced inefficient task assignments in environments with uncertainty in the communication process, especially for a large number of agents. This is the reason why there are differences between the theoretical performance of the algorithm in comparison to more realistic scenarios. It is difficult to incorporate uncertainty in time critical task allocation tasks when optimisation techniques are used, since the uncertainty needs to be represented within the system and usually some uncertainties cannot be expressed analytically. On the other side, even when possible, the dimensionality of the problem increases a lot, hence the computational cost increases too [53].

Generally, uncertainty is a topic that is not usually taken into consideration in a lot of the task allocation techniques discussed above. Nevertheless, it is very important, because of the complexity of task allocation of UAVs, especially when real life scenarios are taken into consideration. Therefore in the following paragraphs are presented some of the approaches that incorporated uncertainty.

4.3.1 CBBA Based

As for auction based techniques, PI seems to perform better than CBBA for probabilistic task allocation with tasks with tight deadlines, but robustness of the algorithms and

Table 7 Communication type of some representative task allocation algorithms

Category	Algorithm	Communication
CBBA based	Extended PI [66]	Mesh, row, and hybrid (row-tree)
	CBBA-TCC [50]	Row, star, circular and mesh.
	Improved CBBA [34]	Asynchronous communication.
	Improved CBGA [73]	A communication matrix with fully connected network.
	EPIAC [44]	Mesh, row, circular and star.
Game theory based	Potential game theory based [28]	Shared communication channel with multiplexing.
	Competitive / cooperative [82]	Only communicate with neighbouring UAVs.
Metaheuristic based	DACLD [46]	All UAVs communicate with each other
	Swarm-GAP based [110]	A token protocol with ring architecture
	DIMAA [48]	Blackboard communication scheme.
Learning	MADDPG based [13]	D2D communication.
	DQN based [103]	All UAVs communicate with each other.
Hybrid	ACS-MRTA [47]	All UAVs communicate with each other.
	Auction based and pheromone map [31]	Pheromone Map Model.
Other	Block information sharing [60]	Only communicate with neighbouring UAVs.

especially for PI has not been researched a lot. Generally, robustness is essential for time-critical applications like SAR or military applications where a low percentage of mission failure is demanded [53]. In [53] they propose different robustness modules for PI algorithm using a combination of expected value and the worst-case scenario metric to handle task costs uncertainty. They use probabilistic sampling assuming uncertain variables of the task allocation procedure modeled with a Gaussian distribution. They conclude that baseline CBBA is more robust than baseline PI, since baseline PI cannot handle well uncertainty. When the robustness scheme is incorporated, both algorithms have better performance with PI performing better than CBBA, while the solution quality is not affected by the robustness module. Also, CBBA with the robustness module is better at handling uncertainties than baseline robust CBBA originated in [72]. Scalability, though, is still a problem with robust PI having higher computational cost than the baseline versions. In [71] they assume uncertain duration of the task execution, since in real life environments each task duration can be usually considered as a random process. They propose a robust MDP based CBBA extension, that transforms the reward function by incorporating the expected values of MDPs, improving robustness, while maintaining convergence. This approach also has better performance than baseline CBBA and better performance and lower computational cost than baseline robust CBBA, but higher cost than baseline CBBA, since the construction model of the MDPs is computationally expensive rendering it unsuitable for large scale systems, like robust baseline CBBA.

4.3.2 Game Theory Based

In a real MEC environment assisted by UAVs, tasks are uncertain because of their randomness and mobility. In [81] the authors propose a Bayesian coalition game based on possible environments with belief update scheme that acquires the probability of the environments related to the uncertainty of the tasks. They found out that, since the uncertainty of the tasks is related to the environment classification, if the detail in the classification of the environment is increased, this leads to a better optimized coalition structure having the disadvantage of increasing the complexity as well.

4.3.3 Metaheuristics Based

In [36] the authors study the problem of task allocation and track planning of multiple UAVs attacking ground targets. When the target is moving there is uncertainty that makes the battlefield environment even more complex. They developed an adaptive parameter adjustment and bidirectional search (BSAP-ACO) for cooperative path planning together with a new improved particle swarm optimization algorithm based on guidance mechanism (GMPSO) dealing with the moving target problem. They propose an online task reassignment method for time-sensitive uncertainty that guarantees

Table 8 Comparison of the main task allocation methods

Algorithm category	Efficiency	Scalabilty	DTA	Computational cost
CBBA Based	★★★	★★	★★	★★★★
Game Theory	★★★★	★★★	★★★	★★★
Optimisation	★★★★★	★	★★	★★★★★
Heuristics	★★★	★★★★	★★	★
Metaheuristics	★★★★	★★★★	★★★	★★
Learning	★★★★	★★★	★★★★	★★★

that if the moving target state changes, the track of the UAVs is replanned and task assignment can be accomplished again.

4.3.4 Reinforcement Learning Based

In [41] the problem of surveillance and attack of targets with UAVs is studied in the presence of environmental uncertainties, like the local weather with uncertain wind speed and rainfall. They propose a task allocation algorithm based on the method of Q-learning that has better performance under uncertainty than DPSO-GT-SA.

The study presented in [112] investigates the effect of uncertainty on multi-agent systems (in terms of failures to task allocation components), utilizing non-Markovian states and a heuristic approach. They found that simplifying assumptions, such as using Markovian states, can result in inaccurate representation of system performance. Furthermore, they demonstrated that more sophisticated heuristics that better describe the physical environment and uncertainties can lead to improved performance in certain problem categories. Therefore, incorporating uncertainty can enhance performance in many applications, but there is a trade-off between efficiency, robustness, and convergence time. This balance must be carefully considered, taking into account the available computational power and the specific requirements of each application.

5 Conclusion

Table 8 provides a summary of the main performance characteristics of the most prominent task allocation techniques, graded on a scale from one (low value) to five (very high value). It is observed that CBBA based techniques typically have a high computational cost, rendering them unsuitable for large scale systems. Similarly, deterministic optimization techniques are also very computationally expensive and not scalable, despite their great efficiency. Conversely, heuristic and metaheuristic approaches can provide fast solutions with moderate to good efficiency at a low computational cost, and they are suitable for use in large scale systems due to their good scalability. Game theory and reinforcement learning approaches have moderate costs, very good efficiency, and scalability, and they can be employed in medium to large scale environments, depending on the specific task allocation problem. Reinforcement learning techniques, in particular, are highly effective in dynamic task allocation and dynamic environments.

Improved task allocation algorithms are essential for real environments with high uncertainties and complex tasks, especially with the increasing computational power and evolving technology of UAVS. Real-time implementation of these algorithms may also be necessary. RL methods have gained attention in this field due to their adaptability to such environments, and they have been widely researched by the scientific community in recent years. In addition, game theory and metaheuristic approaches also show great potential for these systems. According to [114], combining RL and game theory-based techniques enhances RL in the multi-agent case (MARL), making it a very promising approach for task allocation methods. However, since each UAV application is unique and has its own characteristics, one method may be more suitable than others.

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