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Review

Application of Task Allocation Algorithms in Multi-UAV Intelligent Transportation Systems: A Critical Review

Marco Rinaldi [1,*], Sheng Wang [2], Renan Sanches Geronel [3] and Stefano Primatesta [1]

[1] Department of Mechanical and Aerospace Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy
[2] School of Language and Literature, Harbin Institute of Technology (Weihai), Weihai, 264200, China
[3] Department of Mechanical Engineering, São Carlos School of Engineering, University of São Paulo, Av. Trab. São Carlense, 400, Parque Arnold Schimidt, São Carlos 13566-590, SP, Brazil
* Correspondence: marco_rinaldi@polito.it

Abstract: Unmanned aerial vehicles (UAVs), commonly known as drones, are being seen as the most promising type of autonomous vehicles in the context of intelligent transportation system (ITS) technology. A key enabling factor for the current development of ITS technology based on autonomous vehicles is the task allocation architecture. This approach allows tasks to be efficiently assigned to robots of a multi-agent system, taking into account both the robots' capabilities and service requirements. Consequently, this study provides an overview of the application of drones in ITSs, focusing on the applications of task allocation algorithms for UAV networks. Currently, there are different types of algorithms that are employed for task allocation in drone-based intelligent transportation systems, including market-based approaches, game-theory-based algorithms, optimization-based algorithms, machine learning techniques, and other hybrid methodologies. This paper offers a comprehensive literature review of how such approaches are being utilized to optimize the allocation of tasks in UAV-based ITSs. The main characteristics, constraints, and limitations are detailed to highlight their advantages, current achievements, and applicability to different types of UAV-based ITSs. Current research trends in this field as well as gaps in the literature are also thoughtfully discussed.

Keywords: UAS; task allocation; aerial robotics; multi-agent system; UAV network; intelligent transportation system; MRTA; optimization; task scheduling; autonomous vehicles; auction; heuristics; dynamic task; multi-UAV; metaheuristics; software architecture; automation; drones

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1. Introduction

With the advancement of the Industry 5.0 paradigm, intelligent transportation system (ITS) technology is poised to enter the next stage: Transportation 5.0 will be dedicated to solving urban transportation challenges through intelligent technology and a multitude of autonomous robots, thereby enhancing the efficiency and safety of transportation systems [1]. Currently, unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs), i.e., drones, are being extensively utilized in ITSs as the two most promising types of autonomous vehicles [2]. Consequently, this study provides an overview of the application of drones in ITSs, with a particular focus on reviewing task allocation algorithms for UAVs.

UAVs are enhancing the level of automation in the context of intelligent transportation systems because they can either operate as an "eye in the sky" to support road transportation vehicles or carry out tasks in complete autonomy, thereby fully revolutionizing the concept of transportation service itself. For instance, in a smart city context, a multi-UAV network equipped with cameras can cooperate to report accidents to a mobility service center, thus reducing the accident response time [3]. Another example is the usage of UAVs to carry out parcel delivery tasks in traffic congested areas or difficult-to-reach areas, which results in the reduction in delivery times and traffic congestion due to delivery vans. A scalable and efficient task allocation architecture represents a crucial enabling factor for optimally coordinating the fleet of drones of the ITS, allowing the fleet to be strategically assigned to the tasks, improving the overall efficiency of the system and reducing costs. The scalability of the allocation architecture with respect to the number of agents and tasks is also a crucial factor for the deployment of large-scale UAV networks.

Generally, task allocation aims to minimize the execution time of tasks, maximize the number of completed tasks, and increase the reliability of the task allocation procedure. Presently, the applications of UAVs in ITSs primarily include delivery [4], communication [5], search and rescue, traffic monitoring, and data collection [6], to name a few.

The UAV task allocation problem in the context of intelligent transportation systems can be divided into four main categories. First, based on whether UAVs can perform multiple different tasks simultaneously, they are classified as either Single-Task-UAVs (S-T-UAVs) or Multi-Task-UAVs (M-T-UAVs). Second, depending on whether a task requires multi-UAVs to work together, it is categorized as either a Single-UAV-Task (S-UAV-T) or a Multi-UAV-Task (M-UAV-T). Third, depending on whether the drone task allocation is completed in real time, it can be categorized into Online-Task-Allocation (O-T-A) and Offline-Task-Allocation (OF-T-A). Fourth, based on the presence of dependencies between tasks, tasks can be divided into two types: Independent-Tasks (I-T) and Dependent-Tasks (D-T).

The two most used drones in the six task allocation models (S-UAV-T, M-UAV-T, O-T-A, OF-T-A, I-T, and D-T) mentioned above are S-T-UAV and M-T-UAV, and all six task allocation models involve several common objectives, including maximizing the total revenue of the task set, minimizing the flight distance, and minimizing the total cost of the fleet [7]. Some UAV task allocation issues in ITS technology are the same as those previously defined. For example, in distribution systems, due to the large-scale characteristics of some distribution problems, a fleet composed of multiple UAVs needs to cooperate to complete the set of tasks. This M-UAV-T allocation problem is defined as the Vehicle Routing Problem (VRP) [8]. In small-scale delivery systems using a single UAV, the S-UAV-T allocation problem is defined as the Traveling Salesman Problem (TSP). The task allocation problem of a UAV-based ITS is a Non-deterministic Polynomial time (NP-hard) problem. In synthesis, the UAV task allocation problem is the determination of the task sequences for a single UAV or a UAV fleet based on the scope and objectives of the entire task set, thereby ensuring its smooth and efficient completion [9]. At the same time, for the UAV to successfully complete its mission, various constraints of both the task and the UAV need to be considered, including the payload capacity, operational speed, task due date, and the maximum flight distance of the UAV.

With the rise of robotic systems technology, the concept of multi-robot task allocation has been established as a dynamic research area in the broad context of operations research applications, and some literature reviews have been recently proposed that also consider UAV-based systems [7,10–12]. But, to the best of our knowledge, the literature lacks a critical survey of the application of multi-agent system (MAS)-based task allocation paradigms to a fleet of UAVs conceptualized as an intelligent transportation network. This paper presents a survey of MAS task allocation techniques and their application to drone-based networks for intelligent transportation applications. The main contributions of this work are threefold:

- The development of a critical review about MAS task allocation methodologies focusing on multi-UAV networks. This review paper is for engineers, researchers, and scholars who need a critical overview of these emerging topics;
- The discussion of state-of-the-art allocation strategies for UAV-based ITSs, focusing on their suitability to the most established applications;
- The discussion of the challenges of task allocation algorithms for UAV-based ITSs as well as the gaps in the literature for informing future trends.

This paper is organized as follows. Game-theory-based approaches are presented in Section 2. Learning-based algorithms, auction-based algorithms, and optimization-based allocation algorithms are presented in Section 3, Section 4, and Section 5, respectively. Other hybrid approaches are discussed in Section 6. Finally, a comprehensive discussion of UAV state-of-the-art allocation techniques as well as their pros and cons, their applicability to multi-UAV ITSs, and the current gaps in this field are presented in Section 7. Our conclusions are drawn in Section 8.

Challenges of Task Allocation Algorithms

According to the works of [13,14], UAV task allocation for ITSs can mainly be divided into two categories: OF-T-A (also known as static task allocation) and O-T-A (also known as dynamic task allocation). Unlike static task allocation, dynamic task allocation typically requires the use of fewer computing resources to generate real-time solutions. Centralized algorithms and distributed algorithms are the mainstream algorithms applied to static task allocation and dynamic task allocation, respectively. Currently, algorithms used for static task allocation mainly rely on biologically inspired operators, such as genetic algorithms (GAS) [15], particle swarm optimization (PSO) approaches [16], and differential evolution (DE) algorithms [17], aiming to find approximate optimal solutions in a short period of time. After more than two decades of development, although centralized algorithms have become mature, the aspects of computational time and convergence accuracy still remain significant challenges.

In comparison to OF-T-A algorithms, the development of O-T-A algorithm faces other significant challenges. Firstly, real-time task allocation increases the computational demand of solution algorithms, requiring them to solve NP-hard problems with fewer computational resources. It is well known that real-time algorithms often sacrifice decision quality to ensure their real-time performance; thus, balancing decision quality and algorithmic real-time performance is also a significant challenge. In addition, the generalization capability of the task allocation algorithms poses significant challenges in the task scheduling context of UAV-based ITSs. Determining how algorithms that perform satisfactorily in small-scale networks can adapt to large-scale drone networks has also become an emerging issue for researchers. Finally, the algorithms' robustness presents further challenges. In unexpected situations, such as the loss of control of a drone or inadequate communication network coverage, real-time algorithms should be able to make immediate decisions to ensure that the completion of the task set is not compromised. Therefore, task reallocation is also being addressed in the literature. There are different types of algorithms that are employed in state-of-the-art drone-based intelligent transportation systems, including auction (market)-based approaches, game-theory-based algorithms, optimization-based algorithms, and machine learning (ML) techniques. These approaches and their application to UAV-based ITSs are thoughtfully presented and discussed in the next sections.

2. Game-Theory-Based Algorithms

In the work of [18], the autonomous control problem based on game theory is defined and illustrated with several UAV task planning examples. Task allocation problems based on game theory are defined as decision problems either in unstructured environments (random environments) or deterministic environments with hostile agents. Afterwards, game theory algorithms have been widely studied as decentralized distributed M-UAV-T allocation algorithms [19]. In the game-theory-based UAV task allocation problem for an intelligent transportation system, each UAV is defined as a "player" who is able to make decisions and execute tasks. In real missions, due to communication limitations, players can have complete, partial, or no knowledge of the other UAVs of the network. In the M-UAV-T allocation problem based on game theory, a set of UAVs is defined as $A = \{1, 2, 3, \ldots, a_{MAX}\}$. For any UAV a, the corresponding policy set is $D_a = \{d_{a,1}, d_{a,2}, d_{a,3}, \ldots, d_{a,n}\}$. At the end of the algorithm, the benefit of a set of drones corresponding to the strategy selected by each UAV is $Z = \{z_1, z_2, z_3, \ldots, z_{a_{MAX}}\}$. The participants, the strategy set, and the revenue set constitute the three components of the game for multi-drone task allocation in ITSs. In addition, game theory can be divided into two types of models: cooperative games and non-cooperative games.

2.1. Non-Cooperative-Game-Based Task Allocation

In non-cooperative game models, each UAV will choose the strategy that is most advantageous (the strategy with the highest return) to itself while ignoring the adverse effects of this strategy on the global objective function [20]. In non-cooperative games, the system's utility function is defined as $f = \sum_i (w_i \sum_{a \in A} f_{i,a})$, where $f_{i,a}$ is a certain utility function of a UAV, and w_i is the weight of the utility function with $\sum_i w_i = 1$. In [21], the utility function set is defined as $\{f_1, f_2, f_3\}$ $=\{Time\ Cost,\ Energy\ Cost,\ Communication\ Cost\}$. Based on this set of utility functions and a strategy set composed of three policies, a non-cooperative game model is developed, and the existence of a Nash equilibrium (NE) is proven. The authors of [22] established a global benefit function consisting of an attack benefit function, a threat benefit function, an interference benefit function, a resistance interference benefit function, and a distance benefit function. At the same time, a reinforcement learning algorithm is inserted into a multi-UAV non-cooperative game model to expand the algorithm's generalization capability. In this study, the existence of an NE is also proven. Therefore, in order to improve the generalization potential of the algorithm, gradient descent methods can be combined with deep reinforcement learning algorithms, and this strategy can be applied to non-cooperative game models.

NEs exist in multi-drone task allocation schemes based on non-cooperative game models, and these schemes may contain more than one pure strategy Nash equilibrium (PSNE). The work of [23] discusses how to select the best solution from the set of PSNE solutions. The computational complexity of the algorithm is also discussed; the results indicate that using game theory algorithms in multi-drone task allocation problems can increase computational costs. A reinforcement learning algorithm is also inserted into non-cooperative game models for real-time task allocation in [24], and the results showed that non-cooperative game models based on reinforcement learning can improve the real-time performance of task allocation. Consequently, non-cooperative game models based on reinforcement learning not only have a strong generalization capability, but also have a good real-time performance which can be adopted for task allocation schemes in real time.

Table 1 provides an overview of the reviewed approaches, including the main characteristics, constraints, and limitations.

2.2. Cooperative Game-Based Task Allocation

Differently from non-cooperative games, cooperative game models focus more on the global optimum. The NE solution of cooperative games places more emphasis on global optimality and fairness among individuals. In other words, non-cooperative games emphasize the excellence of the allocation of a single UAV, while cooperative games emphasize the efficiency of the entire UAV fleet's allocation. The work of [25] studied the multi-drone task allocation problem based on cooperative games, emphasizing that the purpose of cooperative games is to generate a set of strategies for each UAV in a set of UAVs, punishing the drones assigned to incorrect strategies to ensure that the optimal task allocation scheme is found while ensuring fairness. In addition, a strategy called the coalition formation game (CFG) is also widely used in unmanned aerial vehicle task allocation models, as the CFG performs well when solving the M-UAV-T allocation problem. In [26], a CFG algorithm is developed to simultaneously optimize reconnaissance task allocation and bandwidth selection problems. The results show that the joint task allocation model based on the CFG has a superior convergence speed compared to non-joint optimization models.

Table 2 provides an overview of the reviewed approaches, including the main characteristics, constraints, and limitations.

Table 1. Characteristics of non-cooperative-game-based allocation strategies.

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[21]	Non-cooperative game with N players and 3 pure strategies	Achieved balance between energy consumption, time delay, and computational cost.	Execution delay and energy overhead	Limited generalization due to unaddressed dynamic selection of the weighting parameters
[22]	Multi-Agent Soft Actor-Critic (MASAC)	The generalization capability of the algorithm in different task allocation problems has been improved.	Dynamic model of the UAVs	Two-dimensional environment and homogeneous swarm of UAVs
[23]	Single-stage non-cooperative multiplayer game	Applying non-cooperative game models to disaster management scenarios while placing greater emphasis on fairness.	Demand vector and available resources	Negligible temporal characteristics of resource allocation
[24]	Non-cooperative and real-time approach based on deep reinforcement learning	Improved non-cooperative game models using deep reinforcement learning.	Energy power allocation and network performance	-

Table 2. Characteristics of cooperative-game-based allocation strategies.

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[25]	Joint Bandwidth Allocation and Coalition Formation (JBACF) algorithm	Improved the algorithm's generalization ability in task allocation problems and maximized the benefits of the task.	Bandwidth	Does not include trajectory optimization or information fusion
[26]	Coalition Formation Game	Achieved balance between task completion time and energy consumption.	Task completion degree, UAV energy loss	-

3. Learning-Based Algorithms

For real-time task allocation (O-T-A), the learning-based algorithm is another good approach. Compared to traditional artificial neural networks and deep neural networks, reinforcement learning can handle complex tasks and continuously optimize strategies from the optimization process, making it widely used by researchers in real-time task allocation problems for multi-UAVs. In order to solve the M-UAV-T allocation problem, a deep reinforcement learning algorithm is proposed in [27] with the aim of improving the computational efficiency and the convergence accuracy of the task allocation algorithm. Unlike game-theory-based methods, reinforcement-learning-based algorithms typically establish a nonlinear model based on the task allocation problem, as shown in Equation (1).

$$min f = \sum_i (w_i \cdot f_i),\ subject\ to: \quad b \leq B_{max} \tag{1}$$

The objective function aims to minimize the cost of the problem, which is the same as the reward function in game-based models. $b \leq B_{max}$ denotes a set of constraints considering the boundary conditions.

In addition, the work of [28] also aims at improving the convergence accuracy of the algorithm, thus developing an improved reinforcement learning algorithm. The reinforcement learning algorithm introduces the transfer learning theory. After finding a similar UAV task allocation model in the policy library, the algorithm transfers the training parameter results of the previous source task to the new model through transfer learning. The simulation results show that the algorithm not only effectively improves the performance of UAV task allocation schemes, but also has a strong generalization capability. The authors of [29] developed a multi-agent reinforcement learning method aimed at generating task allocation schemes for heterogeneous UAV fleets. This algorithm can run in locally known environments and has strong robustness.

Table 3 provides an overview of the reviewed approaches, including the main characteristics, constraints, and limitations.

Table 3. Characteristics of learning-based allocation strategies.

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[27]	Deep Q-learning approach	UAVs learn the network state and adapt their locations	Considered all constraints of UAV-based networking tasks.	-
[28]	Deep migration reinforcement learning algorithm based on QMIX	Compared with heuristic algorithms, this method can improve solving efficiency without increasing solving time.	UAV range constraint	Does not consider time constraints for practical scenarios
[29]	Multi-agent reinforcement learning	It can be used in dynamic task scenarios and can achieve real-time task allocation.	Considers the uncertainty of dynamic tasks	-
[30]	Gradient descent method based on deep reinforcement learning	UAVs can automatically and dynamically adjust task allocation strategies in real time.	Time delay of UAV data transmission	Verified only for a specific application scenario

4. Market-Based Algorithms

Auction-based algorithms are widely used for task allocation in drone applications. These algorithms are based on economic principles, as they are alternatively called market-based algorithms, with agents using a negotiation protocol to bid in an auction for task allocation, informed by their local perception of the environment. The agents aim to complete the task assigned with the highest utility or lowest cost by bidding based on the cost or utility they calculate. According to the agents' utility functions, a global objective function is optimized. According to [31], auction-based algorithms present several advantages, including a high solution efficiency and moderate computational costs, in addition to having a dynamic protocol, as they can include or remove new tasks from the allocation procedure.

The literature presents several works related to auction methodology. A time-sensitive sequential auction (TSSA) algorithm considering time window constraints is proposed in [32] for task allocation in a multi-agent system. An auction-based algorithm for multi-agent task allocation is also proposed in [33]. In this way, auction-based task allocation has received increasing attention since there are different factors that may be considered, including UAVs' capability, battery consumption, execution time, and path routes, among others. The work of [34] proposes an auction-based algorithm for multiple UAVs. A multi-layer cost computation strategy is developed to handle multiple constraints and determine the bid's value.

Most of the proposed auction algorithms yield a poor performance for multi-dynamic tasks for multiples drones. To address this issue, a hybrid auction algorithm, based on a decision mechanism and an enhanced objective function, is proposed in [35]. The work of [36] exploits a dynamic decentralized auction-based algorithm for multi-agent systems, such as UAVs. A dynamic task allocation protocol is used, since the agent utilities may change throughout their path towards their targets. This strategy aims to assign a maximum of one task to each member of the fleet, while the same task can be allocated to multiple agents. Thus, the task utilities are calculated according to the agent's states; i.e., they depend on both the rewards from the accomplishment of the assigned tasks and the costs associated with their execution. Differently from game-based algorithms that may not always achieve high levels of global utility, the auction-based algorithm is able to greedily achieve global utility, due to its simplicity and fast convergence.

The use of different auction-based algorithms to solve a heterogenous task allocation problem for multiple UAVs in a drone delivery context is investigated in [37]. The strategy is used to minimize the battery consumption of a UAS-based parcel transportation service by allocating delivery tasks with due date constraints to multiple drones that demand a lower consumption of energy. The allocation of charge tasks is also addressed. These auction-based algorithms were implemented by means of both single-item and multiple-item strategies. Scalar constrained optimization problems are solved by each agent to calculate the UAV's bid for each task. For delivery tasks, the protocol's bid is related to the consumption of energy, while the flight time is chosen for charge task bids. Path planning is also included in the framework to compute the risk-aware path for each task-UAV bid by means of a 2D risk map of the operational area.

The work of [38] investigates the use of a second price auction algorithm for drone intelligent transportation. A deep learning methodology is also included to enhance the auction algorithm's robustness by revenue optimality. In addition, an improved implementation of an auction algorithm for drone delivery is addressed in [39]. Lightweight distributed task allocation is proposed for this application, simplifying the management of delivery and charge tasks with minimal energy consumption. Each agent runs a decentralized protocol, running path planning and optimization algorithms. In contrast to conventional auction-based methods for task scheduling, each agent is designed to function as both the network's auctioneer and bidder, depending on the task type. Recent works combine the auction-based algorithm with other methodologies, as seen in [40–42].

Table 4 provides an overview of the reviewed approaches, including the main characteristics, constraints, and limitations.

Table 4. Characteristics of auction-based allocation strategies.

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[32]	Time-Sensitive Sequential Auction	Improved allocation of tasks that have time constraints	Time window deadlines	-
[33]	Auction	Increases robustness and non-exclusive task assignment	Battery consumption, execution time, and path	Poor performance when tasks could saddle agents with leaden tasks
[34]	Auction-based Multiple Constraints	Solves multiple constraints and provides a way of calculating the price of a bid	Sensor, time window, and fuel cost	Most of the parameters are variable, but the area is fixed. The effectiveness is not investigated.
[35]	Hybrid Auction Algorithm	Promotes its performance and robustness in dynamic task assignment and avoids obstacles	Mission cost, coverage factor	Each UAV can only perform limited tasks and must return to the base to replenish resources
[36]	Greedy Coalition Auction	Allows for dynamic task allocation for spatially distributed multi-agent systems with a positive time efficiency	Path and targets	In the presence of large fleet of autonomous systems, scalability issues may arise due to the high computation cost

Table 4. *Cont.*

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[37]	Greedy Auction	Able to effectively handle the complexity and heterogeneity of the problem	Energy efficiency, task due dates, safe path planning	Distributed implementation is not addressed
[38]	Learning-Based Second Price Auction	Enables the algorithm to be truthful, distributed, and scalable	Energy consumption	The data performance is limited to investigate the proposed conditions
[39]	Multi-Auctioneer Market-Based	Enables one to tackle tasks with temporal constraints, minimizing the heterogeneous fleet of UAVs' energy consumption	Comprehensive optimization of energy consumption, hard task due dates	Robustness to lossy communication network is not addressed
[40]	Neural Myerson Auction	Designed for UAV charging scheduling. It can provide collision avoidance to build secure and privacy-preserving systems	Energy consumption and cluster selection	The external forces, such as wind and other physical factors, are not considered
[41]	Improved Multi-Objective Auction	Improves the setting of the quotation threshold parameters by the distance factor and designs an adaptive operator strategy	Distance and target	-
[42]	Combinatorial Double Auction	Yields a set of feasible solutions for undertaking complex winner determination problem models	Costs and market satisfaction	Unavoidable limitation regarding the data simulation procedures

5. Optimization-Based Algorithms

The optimization methodology is widely used in applied mathematics to find the optimal solution to a specific problem. The goal of the optimization is to reduce costs or maximize profit through an objective function, aiming to find the best solution from a set of possible solutions. Various constraints can be applied to optimize the cost function and achieve an improved solution. A variety of optimization techniques are evaluated, including three main groups: deterministic, metaheuristic (or stochastic), and heuristic. Methods based on deterministic optimization do not consider randomness; i.e., the output is equal when the same initial condition is adopted. Graphical methods, sequential and linear programming, and mixed integer linear programming (MILP) are some examples of deterministic techniques. Stochastic methods, on the other hand, include randomness in the algorithm, leading to different outcomes even in the presence of the same initial conditions. Evolutionary algorithms, swarm intelligence, Monte Carlo methods, and simulated annealing are some of the current examples for this group of algorithms. Furthermore, heuristic algorithms are an interesting alternative to deterministic methods (that yield a high computational cost), providing fast solutions in good computational time. Heuristic algorithms use practical approaches and shortcuts to obtain solutions that are not necessarily optimal, but sufficient for finding good local solutions.

5.1. Deterministic

A cooperative task allocation technique is investigated for multiple drones in [43]. Three constraints are implemented to successfully carry out the cooperation, including a special time window, variant equipment, and a specified execution sequence. Then, a multilayer objective function formed by four optimization functions, such as the completion time, target reward, UAV damage, and total range, is designed to investigate heterogenous allocation plans. The dynamic model of the UAV is represented by $U_{DM} = (X_j^U, \phi_j, v_j, R_j^{limit}, S_j^U)$, where the terms correspond to the position, heading angle, speed, minimum turning radius, and maximum range, respectively, while the allocation variable is defined to establish the relation between UAVs and tasks as follows:

$$x_{jk} = \begin{cases} 1: \; allocate\ task\ M_k\ to\ drone\ U_j \\ 0: \; otherwise \end{cases} \tag{2}$$

The use of two MILP models, where the first is used for the clustering problem and the second for the delivery route problem, is investigated in [44]. The clustering stage, designed by means of a MILP model, determines the specific locations of a group of data. The second MILP is then employed to find optimal routes from the drone delivery. The objective function minimizes the total distance, which is defined by $\min z = \sum\sum distance_{ij} \cdot X_{ij}$, subject to $\sum X_{ij} = 1$ and many other constraints.

A mixed-integer nonlinear programming (MINP) problem is employed to reduce the energy consumption of multiple drones in [45]. A movement model of a drone cluster is designed based on a two-dimensional random walk model, while the sequence-dependent computing task assignment (CTA), based on multiple UAVs, is employed to enforce the task assignment decision of heterogenous UAV clusters. Energy consumption, transmission power, and sequence-dependent start time are some of the items included in the CTA. The random model describes the behavior of the nodes to determine the next movement. The position density function can be expressed by $f_X(X) = f_S(X) + f_P(X) + f_M(X)$, which is formed by three states, i.e., stationary, suspended, and moving. Similarly to the previous work, the task allocation model assumes $X_{ij} = 1$ if task i is handled by the drone j, and $X_{ij} = 0$ otherwise.

There is an abundancy of works in the literature that employ the Hungarian algorithm for the task assignment of multiple aerial vehicles. The Hungarian algorithm for task assignment is studied in [46]. In this case, all drones cooperatively compute a global assignment to optimize a common criterion (distance), considering a finite set of local computations and communications. Likewise, the work in [47] proposes a decentralized Hungarian algorithm to find the optimal assignments, with an improvement in computational time. The Hungarian algorithm shows superiority in scalability when multiple drones are assumed to participate in the assignment of tasks. A Hungarian algorithm with the aim to find optimal drones' charge stations in a smart city context is also proposed in [48]. Drones usually return to their preassigned stations when using conventional strategies, regardless of the distance of the drones from the station. In this case, the Hungarian algorithm based on energy and distance enables the drones to find an optimal charge station before performing their missions. However, a scarce number of works in the literature consider additional strategies for collision avoidance and the minimization of the idle time between tasks. For instance, in a multiple-drone transportation problem, to be assigned the next task, the drones must wait until the last drone completes the corresponding mission. The work in [49] proposes a fast and energy-efficient strategy, based on the Hungarian algorithm, to minimize the unnecessary idle time between stages. Before the implementation of the Hungarian algorithm, an assignment algorithm is designed to optimize the maximum movement distance among UAVs in a swarming scenario. The algorithm aims to improve the operating time by reducing the maximum movement distance, while a multilayer methodology (a swarming flight system) is used to avoid collisions.

Table 5 provides an overview of the reviewed approaches, including the main characteristics, constraints, and limitations.

Table 5. Characteristics of deterministic-based allocation strategies.

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[43]	Multi-Objective Optimization	Enables the use of adaptive parameter control and multiple tasks and agents to speed up the convergence of the algorithm	Completion time, target reward, UAV damage, and total range	Dynamic location, unexpected tasks, and additional UAVs are not investigated
[44]	Mixed-Integer Linear Programming	Improves the efficiency of cluster selection and product distribution	Distance of pharmacies, cluster location, distance between clusters	-
[45]	Sequence-Dependent Task Assignment	Reduces the consumption of heterogeneous UAV clusters by mapping relationship between UAVs and sequence-dependent tasks	Task assignment, bandwidth, and energy	The computing speed varies differently for a different number of tasks
[46]	Hungarian Algorithm	Optimizes a given global criterion within a finite set of local computations and communications over a peer-to-peer network	-	The interface does not allow a user to modify the score unless the modification occurs after a prespecified time duration
[47]	Hungarian Algorithm	Improves the performance, converging speed, and optimality of the assignments	Number of agents	-
[48]	Hungarian Algorithm	Enables the drones to find an optimal charge station before performing their missions	Energy consumption and distance	Preassigned matching might demand more energy and have a higher computational cost
[49]	Hungarian Algorithm	Improves operating time and considers collision avoidance	Costs and energy consumption	The energy consumption is not fairly distributed among all the drones

5.2. Heuristic

Besides the use of single and multiple drones for intelligent transportation, they can also be combined with other vehicles, such as trucks, to improve transportation efficiency. The combined truck–drone system guarantees that the trucks are responsible for the largest part of the path, while the drones are employed to facilitate last-mile transportation to the customer. The work of [50] investigates the use of simultaneous objective functions to minimize the energy spent by the trucks, the drone consumption, and the number of trucks. An improved artificial bee colony algorithm is designed to tackle multiple constraints of the proposed problem. The proposed methodology is based on decision variables as follows:

$$x_{ijk} = \begin{cases} 1,\ if\ truck\ k\ travel\ from\ vertex\ i\ to\ j \\ 0,\ otherwise \end{cases}$$
$$j_{ik} = \begin{cases} 1,\ if\ vertex\ i\ is\ served\ by\ vehicle\ k \\ 0,\ otherwise \end{cases} \tag{3}$$

The objective function is defined as follows :

$$\min\ \alpha \sum\sum\sum x_{ijk} w_{t_k} t_{ij} + \beta \sum\sum x_{0jk} 2tp_i \left(\frac{1}{yd_k}\right) wd_k + \gamma \sum x_{0jk}$$

where w_{tk} and w_{dk} denote the energy consumption coefficient for each truck k and each drone d_k, respectively. The term tp_i corresponds to the vertical trip distance for each customer i; the serving duration is expressed by s_i. The term yd_k denotes the flight speed, while t_{ij} denotes the travel distance. Finally, α, β and γ denote the weight coefficients of the total energy consumption. The objective function is then subject to different constraints such as the minimization of the truck's energy consumption, the maximum capacity of the trucks, the delivery of each parcel to each customer, the serving duration, etc.

A hybrid genetic algorithm (HGA) for a vehicle–drone cooperative system is investigated in [51]. The hybrid algorithm is used to minimize both the total operational cost and the total delivery time. The HGA is formed by the genetic algorithm and local search technique, modeled with a set of 16 local operators, a penalization mechanism, and a restoration method, to balance the exploration of the search space considering feasible and infeasible solutions. The minimum cost is represented by the function $cost(TD, DD) = cost\ (TD) + cost\ (DD) + cost_w(DD)$, where $cost\ (TD)$, $cost\ (DD)$, and $cost_w(DD)$ correspond to the costs of truck, the drone, and the waiting time, respectively. The minimum time is denoted by $time(s) = max\big(t_{n+1},\ t'_{n+1}\big)$. Similarly, an HGA is proposed in [52] to improve the cooperation between ground vehicles and multiple drones. The HGA aims to optimize the final delivery time by selecting the appropriate paths for the truck–drone system. The method is divided into three stages: population initialization, crossover, and education. Initially, anchor points are chosen to obtain optimized solutions. The remaining stages involve both reducing the computation time and avoiding stopping at local optimal solutions. A low visit cost crossover (LVCC) algorithm is employed to appoint genetic fragments based on nodes' anchor points.

A variant of the genetic algorithm, also known as the 2D quantum genetic algorithm (2D-QGA), is developed in [53] to solve a multi-task allocation problem in a 2D space. The objective function is designed to reduce the distance between drones and tasks by assigning tasks to corresponding drones according to their mutual distance. Compared to a conventional GA, the 2D-QGA algorithm achieves a higher convergence rate, lower computational cost, and smaller population size. Considering the set of tasks, expressed by T, the allocation problem can be defined as $J = \sum\sum x_{ij}d_{ij}$, such that $\sum x_{ij} \geq 1$ and $x_{ij} \in \{0,1\}$. As observed, x_{ij} is a binary variable that denotes the allocation, while d_{ij} corresponds to the distance between the i^{th} drone and the j^{th} task. Since the evaluation of different paths' lengths can directly influence the efficiency of the multi-drone task allocation problem, an improved genetic algorithm is designed in [15]. The objective function is designed to improve the drone's reward and consequently reduce the fuel consumption. Compared to conventional GAs, the proposed strategy reduces the allocation time due to a novel acceptance criterion, increases the diversity of the population (thanks to the double-chromosome encoding logic), and improves the efficiency with a reduced convergence time. The adaptive genetic algorithm (AGA) can also be used for cooperative multiple-task assignment, as in the work in [54]. The multi-type gene strategy is designed for establishing a deadlock-free encoding strategy, while the AGA is developed to dynamically adjust the number of crossover and mutation operators.

A fast heuristic approach, based on multi-armed bandit selection (MABL), is designed in [55] for deliveries using a truck and drones. The MABL algorithm is used to select the customer and the corresponding delivery alternative (the truck or drones). By selecting the truck's trip, a residual scheduling problem may be solved, i.e., the time between each stage of the mission. Greedy approximation is also used to optimize the time associated to the solution, by dividing all events into four priority classes, including urgent landings, starts, normal landings, and servicing the truck. The classes are ordered from those with a lower contribution to those with a more significant contribution to the total delivery time, and then those with the greatest contribution are prioritized. A mathematical programming formulation of a multiple-flying-sidekick travelling salesman problem (mFSTSP) is also proposed in [56]. The formulation includes some service-based constraints, like drone launching and retrieval, the total delivery time, the battery discharge, the integration between the truck and the drones, and the use of multiple drones. Some heuristic approaches are employed to solve the scheduling problem: a local search method, two evolutionary-based methods, and a greedy solution. The algorithms are designed to optimize the total completion time, i.e., the latest arrival time of either the drone or the truck. Similarly, two heuristic algorithms based on Compatible Delivery-Max Battery (CD-MaxB) and Compatible Delivery-Min Battery (CD-MinB) are employed to optimize the delivery time of the drone [57]. The constraints are related to the drone capacity, battery re-charging, and available flight time.

The work of [58] proposes an adapted greedy algorithm for different delivery scenarios to investigate the unit cost. In this work, a constant number of drones is assumed. However, in real situations, there are several other constraints that must be investigated. A hybrid multi-objective optimization algorithm is developed in [59] to minimize the total cost of distribution and optimize the satisfaction of a customer in a collaborative routing problem. The hybrid strategy is formed by a population-based algorithm and a Pareto local search (PLS) algorithm. Collaborative routes are selected according to the minimum transportation cost and the maximum customer satisfaction, which can be expressed as follows:

$$\begin{aligned} f_1 &= \sum\sum \mathrm{c_t}\delta_{ij}x_{ij} + \sum\sum\sum\ \sum\ c'_d\left(\delta'_{ij} + \delta'_{djk}\right)y_{dijk}, \\ f_2 &= \sum\sum \mathrm{x_{ij}}.\ \mu_j\left(t_j\right) + \sum\sum\sum\ \sum\ y_{dijk}.\mu_j\left(t'_{dj}\right) \end{aligned} \tag{4}$$

where the terms c_t and c'_d correspond to the transportation cost of the truck and the drones per unit of distance. The customer satisfaction assumes a value of one if a vehicle arrives within the time window $[a_i, b_i]$ and zero otherwise. The work of [60] investigates a multiple-drone delivery scheduling problem (MDSP) for a last-mile package delivery scenario. The heuristic algorithms are employed in two different scenarios using single and multiple drones. The objective function minimizes the reward of a fleet of drones' routes as $\max\sum\sum p_j x_{ij}$. The constraints are related to the energy budget $\sum w_j x_{ij} \leq B$, the use of at most one drone $\sum x_{ij} < 1$, and exclusivity of assignment of the same task to each drone $x_{ij} + x_{ik} \leq 1$ and $x_{ij} \in \{0, 1\}$.

Likewise, a sequential greedy algorithm is employed in [61] for multiple drones in a parcel delivery context. The algorithm determines the estimated arrival time for each agent and task to determine both the next task to be allocated and the coalition leader, while minimizing the time of arrival. Due to the battery limitation, some constraints are included in the objective function to account for both time and battery constraints. Moreover, the assignment allocation, based on a greedy algorithm, is evaluated in [62] under different constraints for a cooperative flight of multiple drones. The strategy combines task allocation with the breadth-first travel method and the greedy algorithm. The objective function determines the shortest plan or flight time and ensures a cooperative flight between them.

Table 6 provides an overview of the reviewed approaches, including the main characteristics, constraints, and limitations.

Table 6. Characteristics of heuristic-based allocation strategies.

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[50]	Improved Artificial Bee Colony	Improved global search abilities	Energy consumption of drones and trucks, number of trucks	Only a static scenario is considered
[51]	Hybrid Genetic Algorithm	Enhances the convergence as well as the use of an adaptive penalization mechanism to dynamically balance the search between feasible/infeasible solutions	Truck travel time, drone travel time	If the drone travel time constraint is not enforced, the algorithm could have infeasible solutions
[52]	Hybrid Genetic Algorithm	Improves the efficiency	Distance cost, time	-

Table 6. *Cont.*

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[53]	2D Quantum Genetic Algorithm	Improves the execution time, convergence iteration, minimum cost, and population size	Distance between drone and task position	Limited to problems with 2D representation
[15]	Improved Fusion Genetic Algorithm	Improved population diversity, global search ability, and overall effectiveness	Number of tasks, number of UAVs, reconnaissance capability	Regarding local optimal solution, the fitness value is not efficiently optimized
[54]	Adaptive Genetic Algorithm	Enhances the optimization and convergence	Task coupling	Predefined trajectories must be used to perform the assigned tasks; thus, it is not able to provide path adjustment
[55]	Fast Heuristic Algorithm	Presents more accurate solutions with lower amount of time	Time	The algorithm is limited to different extensions, including delivery time windows and multiple UAVs
[56]	Heuristics Algorithms (Local Search, Evolutionary, Greedy)	Enhances the exploration of search space, more flexible, and better computational efficiency	Service time of truck–drones delivery operations	Limited to static operational conditions
[57]	Compatible Delivery—Max/Min Battery	Enables one to improve the optimal solution	Number of UAVs, battery capacity, payload weight, time	Does not consider scheduling of deliveries for multiple warehouses, taking location and resources as constraints
[58]	Greedy Algorithm	Positive efficiency	Battery, energy cost, and time	The proposed algorithm are all bounded approximations and cannot be used to get arbitrarily close to the optimal solution
[59]	Hybrid Multi-Objective Optimization	Improves the performance and enables one to balance the convergence and the diversity of the hybrid algorithm	Departure time, arrival time, order of visit, spatial coordination, and time	Does not assume the effects of parcel weights on the flight time and energy consumption of the drones
[60]	Greedy Algorithm	Enables one to find optimal solution with minimum overall reward	Energy cost, time interval, and rendezvous times	Does not investigate a more realistic scenario, such as multi-depot multitrack scenarios, multiple deliveries at the same time, or battery recharging
[61]	Sequential Greedy Algorithm	Enables one to perform binary optimization	Battery and recharging station	-
[62]	Greedy Algorithm	Enables one to find optimal solution of multiple types of subtasks and improve the effectiveness of the solution	Number of UAVs and flight time	The algorithm considers only a few factors in the distribution of regional tasks, and the optimization distribution is not obtained

5.3. Metaheuristic

The swarm intelligence algorithm is inspired by cooperative activities in nature, such as the behavior of bees or ants in colonies. The algorithm's concept is motivated by the natural distribution and self-organization of the labor in those colonies, including the relationship between individuals as well as the social behaviors within the colony [63]. This concept is currently being employed to combine multiple drones with a positive efficiency, by minimizing the flight time (optimal path) and, thus, reducing the cost of the operations. Conventional particle swarm optimization algorithms are often designed for multi-UAV task allocation problems. The work of [64] investigates the use of an objective function to complete all desired missions within a minimum time deadline. Moreover, an improved algorithm based on multi-objective particle swarm optimization (MOPSO) is developed in [65] for multi-UAV task allocation. The multi-UAV task allocation is formed by (V, T, C), where the terms V, T, and C correspond to the set of UAVs, the set of tasks, and the speed of each UAV, respectively. The objecive function is designed in order to account for both the flight distance and mission execution time. This function is subjected to some constraints, such as $\sum t_{\{i,j\}} = 1$ and $d_i = D(V_i,\ T_{i1}) + \sum D\left(T_{ij} + T_{i(j+1)}\right) + D(V_i, T_{ik})$, to allocate only one task for each UAV and calculate the maximum distance that the UAV can travel, respectively. Regarding the d_i constraint equation, V_i is related to each UAV, T_{ij} is related to the corresponding task, $\sum D\left(T_{ij} + T_{i(j+1)}\right)$ is related to the distance between both points T_{ij} and $T_{i(j+1)}$, and $D(V_i, T_{ik})$ is related to the distance between the UAV V_i and the task T_j. The results show that the proposed algorithm is able to speed up the convergence rate, expand the search area, and also prevent the algorithm from stopping at local optimal solutions.

A multiple-ant-colony algorithm is employed for task allocation in a fleet of multiple UAVs in [66]. The proposed strategy enables the multiple colonies to work together, meaning the algorithm does not need to perform a collision check, and to decrease the rate of convergence. The objective function is designed to optimize the time that the UAVs need to complete the assigned tasks. On the other hand, conventional ant colony algorithms may present several challenges, including difficulty in finding the optimal path and the large number of iterations for the initial convergence; i.e., they are characterized, in general, by a low rate of convergence. In this sense, an obstacle avoidance factor is included in the state transition probability of ants, which enables the reduction in the deadlock number and speeds up the process of searching for new paths for multiple UAVs [67]. An improved pheromone factor is also calculated, based on a Gaussian distribution, to make this factor dynamically change over time in an adaptive way. These improvements allow the algorithm to obtain the corresponding path in an easier way as well as to speed up the convergence rate of the ant colony optimization (ACO) algorithm. Moreover, a min-max ACO is also employed in [68] to solve a cooperative task allocation problem for multiple UAVs. The goal of this strategy is to minimize the maximum cost of each individual salesman to balance the overall workload in the fleet. Then, the algorithm aims to determine the ordered sequence of tasks performed by each UAV of the network, $U = (U_1, U_2, \ldots,\ U_n)$, and the task list $T = (T_1, T_2, \ldots,\ T_n)$ to minimize the global cost (according to the flight distance). The optimization can be expressed by $\min(P) = \max\left(\sum\sum x_{ijk}\, D_{jk} P_i\right)$, where x_{ijk} equals one in case of a UAV performing task T_j; otherwise, x_{ijk} equals zero. Finally, $D_{jk}P_i$ corresponds to the cost of the UAV from T_j to T_k along its task path P_i. Several constraints are also included as boundary conditions for the solution, including that each task must be performed by at most one UAV, the UAVs should depart from the depot before performing tasks, and the UAVs should return to the depot after accomplishing all their tasks.

A variant of ACO, called the grouping ant colony optimization (GACO) algorithm, is investigated in [69] for heterogeneous targets with multiple drones. Likewise, a multi-objective function is developed in [70] to solve a cooperative task allocation problem for multiple drones. Multiple objectives are employed to guide decision makers through a set of solutions that balance multiple objectives. Therefore, the proposed strategy improves the efficiency and diversity of the solutions.

Furthermore, trucks and drones can collaborate for intelligent transportation. The work of [71] assesses different metaheuristic algorithms to solve the formulated variant of the traveling salesman problem (TSP) in case of drone-based delivery. Firstly, the algorithm generates the truck delivery path as a classical TSP. Secondly, the calculated path is divided into the delivery paths of the truck and the drone, leading to an initial solution. Additional techniques, based on self-adaptive neighborhoods, are then employed to optimize the total delivery time. Also, a hybrid metaheuristic algorithm to optimize both truck and drone paths is proposed in [72]. The adapted SimWWO metaheuristic algorithm aims to optimize the drone's path and uses a further method to calculate the truck–drone intersections by exploiting a convex relaxation technique. Compared to the conventional WWO algorithm, a population reduction policy is employed (instead of the refraction operation) to reduce the population size from a higher limit to a lower limit by eliminating the inferior solution, as noted by $N_p = N_p^{max} - (t/t_{max})\left(N_p^{max} - N_p^{min}\right)$.

A multi-task method, based on the Monte Carlo tree search algorithm (MCTS), is developed in [73] to investigate the performance of a logistic system based on multiple drones. The proposed task allocation method allocates charge stations to the drones in order to perform a longer-range mission constrained by a limited payload capacity and battery life. The proposed objective function aims to accomplish the task while reducing the consumption of energy. Two stages are employed to design an efficient method, including the creation of sub-task groups to minimize the search range, and the use of MCTS to minimize the energy consumption. The objective function is defined as follows:

$$C = \sum\sum c_{ij} x_{ij} \tag{5}$$

which is subject to the following constraints:

$$\begin{gathered} \sum x_{ij} \leq P_{max} \\ \sum x_{ij} \leq 1 \\ x_{ij} \in \{0,1\} \\ E\left(x_{i(j-1)}\right) - c_{ij} > 0 \end{gathered} \tag{6}$$

where $x_{ij} = 1$ indicates the assignment of a task, and $x_{ij} = 0$ indicates the non-assignment of a task. The constraint equations are used to assign one drone to each task and to ensure that the drone has enough energy in its battery to reach the task location.

Table 7 provides an overview of the reviewed approaches, including the main characteristics, constraints, and limitations.

Table 7. Characteristics of metaheuristic-based allocation strategies.

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[64]	Particle Swarm Optimization	Improves the convergence	Time	High computational time
[65]	Multi Objective Particle Swarm Optimization	Improves the convergence and prevents the algorithm from falling into the local optimal solution	Task coordination, flight distance, and time	The objective functions cannot reach the maximum or minimum value at the same time
[66]	Multiple Ant Colonies	Improves the overall efficiency	Path length	In contrast to real situations, the edges of the obstacles are assumed to be regular

Table 7. *Cont.*

Ref.	Algorithm	Characteristics	Main Constraints	Limitations
[67]	Ant Colony Optimization	Enables one to easily find the corresponding path and speeds up the convergence rate	Number of tasks	The energy consumption is neglected
[68]	min-max Ant Colony Optimization	Improves the overall performance	Task path and cost of each UAV	The task allocation is only assumed for homogenous UAVs
[69]	Grouping Ant Colony Optimization	Improves the optimality and convergence efficiency	Fuel consumption, path length, and flight speed	-
[70]	Multi-Objective Ant Colony Optimization	Improves the convergence speed, solution quality, and solution diversity	Task benefit, UAV damage, and total range	The payload is limited by small size and low weight
[71]	Population-based and Solution-based Algorithm	Improves efficiency and enables the self-adaptive selection of the search neighborhood	Time	A limited number of parameters for the SA variant are investigated
[72]	Adapted SimWWO Metaheuristic	Improves efficiency	Delivery time	The study is limited to one single drone to be sent and received by the truck
[73]	Monte Carlo Tree Search	Improves selection and records historical simulation informational	Flight distance, speed, and time	A controlled scenario is chosen to investigate the proposed algorithm

6. Hybrid Allocation Algorithms

Hybrid allocation strategies are also designed to improve the transportation efficiency for UAV-based ITSs by merging different types of allocation algorithms.

The work of [74] combines mixed-integer linear programming (MILP) and a simulated annealing (SA)-based heuristic algorithm to find optimal routes for a drone delivery application. Both battery consumption and payload weight are considered to calculate the drone's energy consumption. MILP is employed to minimize costs and the delivery time up to a budget constraint, while the SA is used to find suboptimal solutions of practical scenarios, i.e., the relation between the delivery time and budget. As a drawback, the SA algorithm fails to utilize geographical information to attenuate the choice of impractical routes. Hybrid algorithms can also be used to investigate the optimization of the service itself, as in [75]. Particle swarm optimization (PSO) and the grey wolf optimizer (GWO) are combined to minimize the number of deployed drones, cost, and flight time. The proposed algorithm incorporates different strategies, such as interval transformation, dynamic weighting rules, and a nonlinear convergence factor, to enhance the performance accuracy and to lower the cost.

The work of [76] combines the Hungarian algorithm (HA) and machine learning (ML) to optimize the task assignment problem in a drone delivery application. Different mathematical models, such as linear and polynomial regressions, are used to generate distinct cost functions, based on distance and time metrics. Once the cost function is estimated, the Hungarian algorithm is employed for solving the drone intelligent delivery problem. The Hungarian algorithm is defined by a matrix of costs, which represents the cost of each agent or task.

Similarly, the combination of a multi-agent RL algorithm and a conflict-free method is investigated in [77] to optimize task allocation and path planning for multiple drones. The strategy guarantees that the shortest path is chosen for the drones, while multi-agent proximal policy optimization (MAPPO) enables collision avoidance between the drones.

The work of [78] investigates the design of a rapid allocation algorithm, based on the combination of a greedy auction algorithm and a reassignment strategy. The combination of both strategies enables swift and effective responses, which result in a rapid and efficient completion of tasks while preventing the occurrence of deadlocks. In addition, neural networks are widely employed for task allocation [79]. An assisted learning invasive encroachment neutralization (ALIEN) technique is designed for a secure drone transportation system. The objective function of the ALIEN algorithm aims to maximize the security of the drone transportation system, and it is represented by $I_{max} = t_i D_i + t_i D^d_{r\lambda_i} + t_i D_{Ni}$, where the decision variables represent drone detection, object recognition, and neutralization, respectively.

Moreover, the maximum task allocation algorithm is proposed in [80]. The maximum task allocation algorithm for multiple UAVs under time constraints has been significant in meeting requirements for quality of service. The TRMaxAlloc algorithm is designed based on two phases: assignment and reassignment. The PI algorithm is used, in the first stage, to allocate the tasks to the drones, while, in the next stage, the proposed TRMaxAlloc algorithm enables the creation of feasible time slots for the unassigned tasks. As a result, the assignment enables each task to be completed before its corresponding deadline with a lower time cost. Each UAV is assigned to several tasks, as described by the task list $\{s_1, s_2, \ldots, s_N\}$. Then, the cost function, expressed as $J = max\ |s_i|$, aims to optimize the task allocation problem.

A real-time market-based task allocation mechanism is proposed in [81] for a dynamic coalition formation (DCF) problem. Autonomous agents can collaborate independently, creating an optimal global coalition structure to efficiently execute the emerging tasks. The auction algorithm is used for real-time assignment, and a mutual-selection method is employed for obtaining an improved performance in terms of the agent utilization rate and task completion rate. In addition, the work of [82] investigated the combination of a distributed evolutionary algorithm and a greedy algorithm to simultaneously optimize multiple objective functions. This combined methodology aims to improve the model's local optimizing ability with different constraints, such as spatial constraints, time costs, and energy consumption. The proposed strategy aims to efficiently solve large-scale task allocation problems with enhanced and more diverse non-dominated solutions.

7. Discussion

For the sake of completeness, before delving into a discussion of the reviewed methodologies along with the applicability of the task allocation methods to the most established applications of UAVs in the context of ITS technology, the main applications of UAVs in the context of ITS technology are listed as follows:

- Search and rescue (SR) [83–86];
- Delivery (D) [87–89];
- Traffic monitoring (TM) [90];
- Inspection (I) [91–93];
- Disaster response (DR) [94–96];
- Surveillance (S) [97,98];
- Coverage (C) [99,100];
- Data collection (DC) [101];
- Smart mobility (SM) [102];
- Agriculture (A) [103–105].

For each application listed above, refer to the cited works for additional examples concerning applications of task allocation methodologies. Also, refer to the works in [106–110] for comprehensive surveys regarding UAV civilian applications.

The primary objective of this paper is to serve as a state-of-the-art reference for researchers and engineers about the science of task allocation applied to various UAV-based ITSs. Such technology is foreseen to become popular in the next decades in different contexts: smart cities, urban air mobility, smart logistics, connected vehicles, etc.

The main conclusions drawn from this survey are summarized as follows:

- Market-based allocation algorithms are, in general, less computationally demanding than other methods, but the bidding procedure has to be designed carefully to avoid unfair allocations. Market-based allocation architectures should be developed for applications with a high level of autonomy and inherent dynamicity (e.g., parcel delivery, traffic monitoring, search and rescue, and passenger transportation), with the drones being able to adjust their bids based on their current status as well as both the service demand and the environmental conditions;
- Optimization-based approaches produce more efficient allocation but should be used to allocate tasks to UAVs in static scenarios with well-defined constraints (e.g., inspection and data collection). The main drawback is the scalability of these approaches with larger fleets due to their computational complexity. Also, complex application scenarios may be difficult to model, and discrepancies between a real application and a simulation model may severely affect the quality of the obtained solution;
- Learning-based task allocation algorithms are suitable for highly dynamic scenarios in which the UAVs can exploit large datasets of past experiences to adapt to variable environmental conditions. A preferable application can be identified as the UAV traffic monitoring service. On the other hand, a learning-based task allocation architecture is not suitable for every type of scenario involving environmental variability; for instance, considering a critical emergency scenario such as disaster response, the trustworthiness of UAV task allocations plays a crucial role, thereby limiting the deployment of such an allocation architecture. Also, the questionable level of generalizability to unseen conditions may be a limiting factor;
- Game-theory-based approaches are well suited for applications in which the UAVs can compete against one another or cooperate in the completion of a task with well-defined utilities. Coverage and traffic monitoring tasks represent a valid example since the UAVs of the ITS can compete for the best coverage/monitoring location. The limitations of a game-theory-based task allocation strategy in UAV-based ITS contexts are both the computational burden with large fleets and the capability of the utility function to adequately represent the real-world reward related to the allocation;
- The design of a hybrid allocation architecture incorporating multiple approaches is the most promising strategy for leveraging the characteristics of each method, thus enhancing the capability of the allocation algorithm to meet the requirements of (i) the environment, (ii) the service, and (iii) the UAV-based ITS. Also, hybrid allocation algorithms feature a higher generalization capability with respect to both the service and the robot type.

Finally, Table 8 summarizes the characteristics of the allocation methods in terms of computational cost, efficiency in finding optimal solutions, scalability to large fleets, capability of handling dynamic tasks, robots, and environments, and the most suitable application domains in the context of UAV-based ITSs.

Table 8. Characteristics of the allocation methods in terms of computational cost, efficiency, scalability, effectiveness in handling dynamic tasks and dynamic robots, and application domains. The evaluation of the algorithms' characteristics is expressed as follows: very low (+), low (+ +), intermediate (+ + +), high (+ + + +), and very high (+ + + + +).

Algorithm	Cost	Efficiency	Scalability	Dynamic Tasks and Robots	Dynamic Environment	Application
Auction	+	+ +	+ + + +	+ + + +	+ + + +	D, TM, SR
Learning	+ + +	+ + + +	+ + +	+ + + + +	+ + + + +	TM, DR, A
Game Theory	+ + +	+ + + +	+ + +	+ + +	+ + +	C, TM, DC
Deterministic	+ + + + +	+ + + + +	+	+	+	I, DC
Heuristic	+ +	+ + +	+ + + +	+ + +	+ +	D, C
Metaheuristic	+ + +	+ + + +	+ + +	+ + +	+ + +	D, C

8. Conclusions

The use of unmanned aerial vehicles has gained significant attention in the context of intelligent transportation. The use of different sensors and high-resolution cameras enables the drones to support road transportation vehicles and to be used for a variety of parcel delivery tasks, among other applications. However, a scalable and efficient task allocation architecture must be designed for optimizing the coordination of the fleet of drones of an intelligent transportation system. Generally, task allocation is used to minimize the execution time of the tasks with a reliable and well-defined procedure. A categorization can be defined depending on the number and type of vehicles and tasks employed, including single-task UAVs or multi-task UAVs, single-UAV tasks or multi-UAV tasks, online or offline task allocation, and independent or dependent tasks. In addition, a combination of multiple UAVs and trucks as well as the inclusion of several constraints can significantly improve the overall efficiency. Therefore, the constant development of task allocation enables us to create more efficient methodologies that cover a large variety of scenarios.

In this sense, this paper provides a comprehensive literature review of how such approaches are being utilized to optimize the allocation of tasks in UAV-based ITSs. Market-based algorithms, game-theory-based algorithms, optimization-based algorithms, machine learning techniques, and other hybrid methodologies are reviewed and discussed. Furthermore, the main applications of unmanned aerial vehicles in ITSs are presented as well as the suitability of the task allocation algorithms presented throughout the paper with respect to the different applications. The main characteristics of, limitations of, and differences between the algorithms are highlighted, showing their main uses over the last few years. Understanding the main characteristics and the applicability of each type of allocation enables engineers and researchers to properly choose the most appropriate type of task scheduling logic. Moreover, the emerging trends and gaps in the literature are also discussed.

In conclusion, we stress the importance of considering the requirements of the service as well as the environmental conditions and the operational capability of the UAV-based intelligent transportation system when designing a task allocation strategy.

As a further consideration, it is worth noticing that the design of communication channels and their security are fundamental for both implementing (if the allocation architecture is fully decentralized) and validating (if the allocation architecture is centralized or distributed) the allocation of tasks in a fleet of UAVs. Also, the security of the communication channels is a significant challenge for achieving a safe, regulatory-compliant, and resilient real-world deployment of a UAV-based ITS. The efficiency of the task allocation process can be heavily influenced by aspects such as the security of the communication channels as well as their fallibility.

Future survey-based research will focus on investigating how the UAV communication protocol can influence the efficiency of the task allocation architecture in terms of both security and robustness to fallible communication networks. Also, conceptual modelling frameworks used to implement task allocation algorithms in UAV-based ITSs may also be discussed.

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