UAV swarms & Task allocation: the way ahead in precision agriculture

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***Abstract*— Unmanned Aerial Vehicle (UAV) swarms are increasingly being used in various applications, including environmental monitoring, search and rescue operations, and surveillance. One of the primary challenges of UAV swarm technology is task allocation, which involves assigning tasks to individual drones within the swarm. Task allocation is a complex problem, and traditional algorithms may not be effective in large-scale and dynamic environments. In this paper, we introduce the concept of a task allocation model for UAV swarms aiming to optimize the task allocation process by considering the drones' capabilities and the requirements of the task while minimizing the overall energy consumption. Additionally, we discuss other challenges associated with UAV swarm technology, such as communication and routing protocols, swarm intelligence, collision avoidance, formation controls and task allocation algorithms. This research aims to identify key challenges and research gaps associated with the use of algorithms for UAV swarm task allocation and propose potential solutions and future research directions to overcome these challenges and enable the full potential of UAV swarm technology in various applications, such as precision agriculture. Specifically, in future work, we plan to evaluate the effectiveness of the proposed model using simulation experiments and compare it with existing approaches, as well as to develop a path planning algorithm based on swarm intelligence.**

Keywords—Unmanned Aerial Vehicles, multi-UAV, task allocation algorithms, cooperative task assignment, linear programming

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have gathered a considerable amount of research attention as a result of their advanced autonomous capabilities, coupled with the continued advancement and evolution of new information and communication technologies (ICT), such as machine learning (ML), artificial intelligence (AI), and embedded systems, pertaining to on-board intelligence.

The range of applications for UAVs is diverse and includes operations in search and rescue, precision agriculture, precision livestock, payload transportation, aerial photography, military operations, and extension coverage of mobile telecommunications network as depicted in Fig. 1. [1]

Fig 1. UAV application domains

For instance, in search and rescue operations, UAVs are capable of providing an aerial view of the terrain, enabling search and rescue teams to locate missing persons or stranded individuals in remote or inaccessible areas on emergency situations such as natural disasters (i.e., earthquakes, fires, etc.). In precision agriculture, UAVs equipped with sensors and cameras can collect data on crop health, soil moisture, and nutrient levels, allowing farmers to optimize and forecast crop yields and reduce water and fertilizer usage. In precision livestock, UAVs can monitor the health and welfare of livestock by providing real-time data on their location, activity levels, and vital signs. UAVs can also be utilized for the transportation of payloads to remote or difficult-to-access areas, resulting in reduced delivery times and costs. Aerial photography can be achieved through the use of UAVs, which are capable of capturing unique images and videos from different angles and perspectives, providing an innovative approach to photography and videography. Such aerial photography methods can be beneficial in monitoring projects situated in unfavorable locations, such as vast wind or solar farms. Lastly, UAVs are useful in military operations, where they can perform a variety of tasks such as reconnaissance, surveillance, and target acquisition, without endangering the lives of military personnel.

However, the deployment of a single UAV for extensive missions faces significant challenges due to both its constrained field of vision, which limits its ability to observe and monitor a wide area simultaneously, and its restricted energy reserves. As a result, relying solely on a single UAV becomes impractical and inefficient for large-scale operations. [2], [3]. In such instances, the coordination and cooperation of multiple UAVs, constituting a fleet of UAVs, lead to the timeliest efficient execution of tasks, covering large geographical areas while taking into account energy constraints while avoiding potential obstacles. Within a swarm configuration, each UAV functions as a discrete agent within a multi-agent control system. To achieve effective execution of complex missions, the individual behaviors and actions required are distributed among the agents within the swarm, allowing for coordinated efforts and resulting in collaborative behaviors that enable the swarm to effectively tackle intricate problems [4].

Moreover, the deployment of multiple UAVs can increase mission flexibility, as it allows for dynamic task allocation and reallocation based on the mission's changing requirements. Additionally, redundancy can be achieved by

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having multiple UAVs performing the same task, ensuring mission completion even when one or more UAVs fail.

The deployment of UAV swarms presents several challenges that must be addressed to ensure their successful deployment in real-world scenarios, which are interdependent and interrelated as depicted in Fig.2.

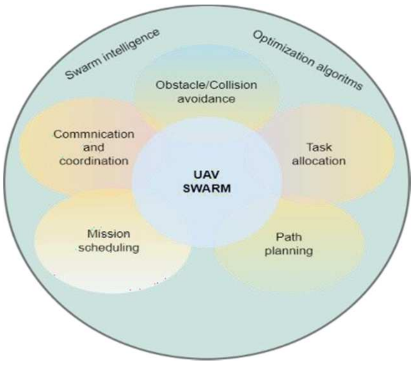

Fig 2. Interdependence among challenges in a UAV swarm

One of the most significant challenges is the need to ensure reliable communication and coordination of UAVs in dynamic and uncertain environments. This challenge is compounded by several factors, including limited range of wireless communication, susceptibility to interference, and bandwidth constraints. In addition to communication and coordination challenges, effective task allocation is another critical challenge as it involves assigning tasks to UAVs based on factors such as task priority, agent capability, and communication constraints. This challenge is particularly significant in heterogeneous swarms where UAVs have varying capabilities and limitations [5].

The energy constraints of UAVs, particularly in battery-powered drones, pose yet another critical challenge. These constraints limit the endurance and range of UAVs, necessitating the optimization of their energy consumption. For example, [6] is a comprehensive survey which extensively explores energy optimization techniques specifically designed for UAV-based cellular networks, with a primary emphasis on addressing the critical need to enhance capacity in mobile communication networks, especially during mass gathering scenarios (such as music concerts, sports competitions, and fairs). The survey delves into an in-depth examination of diverse UAV types and elucidates their respective power supply options and charging mechanisms. According to the authors, UAVs can be powered by an array of sources including batteries, grids, fuel cells, renewable energy sources, and hybrid systems. Additionally, the article delves into the pivotal role played by UAV-BSs (Base Stations) in wireless communication networks and comprehensively covers various UAV deployment strategies, such as standalone UAV deployment and UAV deployment alongside fixed BSs. The survey then shifts focus towards energy optimization techniques that are specifically tailored for UAV-based cellular networks. It classifies these techniques into four main categories: 1) minimizing energy consumption at the BS, 2) minimizing energy consumption at the user equipment (UE), 3) optimizing resource allocation, and 4) optimizing network topology. The article provides an extensive overview of popular algorithms utilized for energy optimization, encompassing both traditional approaches such as dynamic programming and more advanced machine learning algorithms like deep reinforcement learning. Furthermore, the authors highlight and address the common challenges and open research problems that are currently impeding the widespread adoption of UAVs in cellular networks. These challenges encompass various aspects, including the limited battery life of UAVs, interference from other wireless devices operating in the same frequency band, the complex task of efficient resource allocation, security and privacy concerns, regulatory restrictions, and the cost-effectiveness of deploying and operating UAV-based cellular networks. Resolving these challenges is of utmost importance to enhance the efficacy, reliability, and wider implementation of UAV-based cellular networks.

Mission scheduling, routing, and path planning are other challenges that must also be addressed. In dynamic environments, the availability of resources and the mission objectives may change over time, making mission scheduling and routing more challenging. Additionally, the integration of multiple sensors into UAVs for tasks such as target detection and tracking present additional challenges.

Sensor fusion involves the complex task of combining data from diverse sensors (i.e., LiDAR, RADAR, camera, ultrasonic sensors etc.) each with their own unique properties and limitations, necessitating advanced algorithms and techniques to ensure accurate interpretation of the data. Precise sensor synchronization is crucial to maintain temporal alignment of the collected data, minimizing discrepancies and delays in sensor readings. Calibration and alignment procedures are essential to achieve accurate and consistent measurements across different sensor types. Real-time or near-real-time processing and fusion of data from multiple sensors require efficient computational algorithms and resources. The assignment of sensor measurements to appropriate targets and the tracking of their positions over time pose additional challenges, particularly in complex and dynamic environments with multiple targets and occlusions. Occlusions can occur due to various factors such as other objects, buildings, vegetation, or even atmospheric conditions. Furthermore, accounting for environmental factors such as lighting conditions, weather variations, and environmental obstacles demands adaptive strategies to optimize sensor performance. Successfully addressing these multifaceted challenges is imperative to fully harness the potential of integrating multiple sensors into UAVs for target detection and tracking, thereby enabling advanced situational awareness and informed decision-making capabilities.

Moreover, ensuring the safety of UAV swarms in the presence of obstacles and other air traffic is crucial. The development of reliable obstacle detection and avoidance systems, as well as collision avoidance algorithms, is essential to ensure the safety and effectiveness of UAV swarms.

Motivated by the above, the rest of this paper is organized as follows: the related work on challenges is presented in Section II with particular emphasis on proposed task allocation techniques and algorithms for UAV swarms. In Section III, the proposed mathematical model on task allocation is presented and the problem formulation is described. Finally, in section IV, concluding remarks are made and future work is discussed.

II. RELATED WORK

A. Overview on challenges

Extensive research has been conducted with particular emphasis on routing algorithms for UAV swarms, as routing protocols are deemed crucial to maintain dependable information exchange within the swarm. For instance, in [7] the authors focus on UAV swarm communication architectures and routing protocols from both academic and engineering perspectives. The study conducts a comprehensive analysis, comparison, and discussion of literature review related to different proposed architecture and routing mechanisms in UAV swarms to provide a detailed overview of deploying effective communication architectures and reliable routing protocols. Similarly, authors in [8] perform a comprehensive analysis and qualitative comparison of routing protocols in UAV networks, dividing them based on network architecture and data forwarding, and subcategorizing them based on topology, position, hierarchical and deterministic, stochastic, and social networking approaches. Additionally, in [9], the authors introduce the concept of the Internet of Drones (IoD) as a category that belongs to the Internet of Things (IoT) and present the routing of UAVs as a challenge in wireless sensor networks (WSNs). The article focuses on IoD-oriented and innovative routing protocols, instead of traditional IoT and WSN protocols, while also discussing the challenges and future directions of IoD research.

Moreover, the contemporary notion of wireless communication networks, namely 5G and 6G, has significantly permeated the field of protocols selected by researchers for scientific purposes on UAV swarms. For instance, [10] explores the integration of autonomous services to swarm of UAVs for network management in 6G technology. According to the authors, the deployment of UAVs as flying base stations (BSs) utilizing physical layering techniques like mmWave and massive MIMO (Multiple-Input Multiple-Output), cognitive radios, and other advanced technologies enables the fulfillment of data-intensive service requirements. The authors discuss the challenges faced by swarm of UAVs operating in 6G mobile networks, such as security and privacy, intelligence, and energy-efficiency issues. The paper provides an overview of how the 6G wireless network can be used to connect blockchain and AI/ML with UAV networks. By incorporating these technologies, ultra-reliable, intelligent, secure, and ubiquitous UAV networks can be established. The authors present key findings on the integration of these technologies with UAV networks utilizing the 6G ecosystem. They conclude by highlighting potential research challenges and future prospects in this rapidly developing field.

Effective communication protocols are crucial for addressing the challenges of UAV swarms. A swarm network architecture can be broadly categorized into interactive or decentralized and non-interactive or centralized types and hybrid [11]. In the interactive approach, UAVs operate autonomously and coordinate their operations via a collaborative approach to tracking, monitoring, and exchanging information. This approach enables members to select the best method for completing a mission while encountering obstacles. Members of standalone UAVs can directly communicate with each other without mediation by a central ground control station, forming a Flying Ad Hoc Network (FANET) topology [12]. However, the quality of communication that can be achieved in a FANET topology depends on several parameters, such as the mobility of UAVs, the availability of bandwidth, environmental and geographical constraints, and achieving synchronization between swarm members. For example, this paper [13] presents a thorough review of wireless communication technologies that support communication in UAV applications. The authors discuss the essential factors that require attention when designing an effective and dependable communication system for autonomous UAVs, such as mobility, reliability, and efficiency. Furthermore, the paper emphasizes the significance of collaboration and information sharing in multi-UAV systems and how a communication system can aid task allocation.

Moreover, the concept of *swarm intelligence* refers to the collective behavior that arises from the interactions of multiple individual agents or organisms. In this context, each agent adheres to simple rules, and the entire group exhibits complex and intelligent behavior. UAV swarms are a rapidly expanding field that utilizes swarm intelligence in which a group of UAVs operates in a coordinated manner to achieve a common objective. Inspired by the behavior of social animals like bees, ants, fish and birds, the collective behavior of UAV swarm offers several advantages over traditional single-drone missions, such as increased efficiency, robustness, and scalability.

The main purpose of the paper [14] is to provide a comprehensive survey of recent advances and future trends in UAV swarm intelligence. The paper presents a hierarchical framework perspective to classify UAV swarm intelligence research into five layers: decision-making layer, path planning layer, control layer, communication layer, and application layer. The authors provide an in-depth literature review of each layer and discuss the relationship between them. Additionally, they identify research trends and limitations in UAV swarm intelligence in dynamic and uncertain environments as well as on complex tasks and suggest possible future directions. According to the authors, current research directions include swarm architecture, swarm combat effectiveness and mission assessment, scheduling and management technology for complex tasks, and intelligent decision-making and game technology, all aimed at enhancing the capabilities of UAV swarm intelligence.

Swarm intelligence for multi-UAV collaboration is a promising research area, but there are several open issues and gaps that need to be addressed. One significant challenge, according to [15] is ensuring collision avoidance, especially in dynamic environments where communication is limited, and the number of UAVs is large. Developing effective algorithms that can guarantee the safe navigation of UAVs, even in the presence of obstacles and unpredictable changes in the environment, is critical. In [16] the authors present an extensive examination of collision avoidance strategies employed in unmanned vehicle systems, with a specific focus on UAVs. They classify the various collision avoidance techniques and conduct a comparative analysis of the approaches under consideration, taking into account different scenarios and technical aspects. The utilization of diverse sensor types for collision avoidance in the context of UAVs is also explored. They categorize the approaches into geometric and force-field methods, optimization-based methods, and sense-and-avoid approaches based on their algorithmic design complexity level. Among these, the geometric and force-field methods exhibit the highest complexity level, while the sense-and-avoid approaches rank lowest in terms of complexity in this comparison. In addition, the authors discuss the challenges of developing effective collision avoidance systems for UAVs, which include on-board payload limitations, power constraints, reduced visibility due to bad weather, and complications in remote monitoring.

Task assignment is another important issue that requires balancing workload among UAVs while optimizing the swarm's overall performance and minimizing costs. Designing intelligent algorithms that can allocate tasks to UAVs based on their capabilities, preferences, and availability is essential. For example, a comprehensive survey of task assignment algorithms developed for UAV networks is presented in [17]. The authors provide a detailed explanation of the operational features, benefits, and limitations of various algorithms designed for this purpose. The study also compares these algorithms in terms of their performance characteristics. The authors highlight the challenges involved in task coordination among multiple UAVs and suggest possible future directions for research in this area. The primary contribution of the study is a thorough examination of the basic principles, benefits, limitations, and potential improvements of each algorithm discussed. However, the algorithms that are presented mainly focus on single UAV applications.

In [18], the application of autonomous control of multi-UAV systems in complex environments is explored. To enable fully autonomous control, the authors emphasize the importance of cooperative task assignment. However, according to the authors, challenges associated with this approach, including global planning of the environment, task requirements, and UAV resources, must be addressed. To address the challenges associated with multi-UAV cooperative task assignment, the authors suggest three promising directions for future research. These include cooperative task assignment in a dynamic complex environment, in an unmanned-manned aircraft system, and in a UAV swarm. More details about proposed task allocation algorithms will be discussed in the next section.

Additionally, *path planning* is a challenging task that requires finding optimal or near-optimal paths for UAVs while avoiding obstacles, threats, and satisfying constraints such as fuel, time, and distance. Developing efficient algorithms capable of handling the complex dynamics of the swarm is crucial for successful path planning. This article [19] offers a comprehensive review of the latest research on the application of AI to path planning in UAV swarms. The authors explain that UAV swarms have many benefits, including faster flight times and reduced operational costs, making them useful in applications such as transportation, logistics, and emergency response, where efficient path planning is critical. They also provide a detailed summary of relevant papers based on AI approaches such as Reinforcement Learning, Evolutionary Computing, Swarm Intelligence, and Graph Neural Networks, as well as the type of flight environment and field of use. Despite the potential benefits of using AI techniques for path planning in UAV swarms, there are still challenges to overcome. The authors acknowledge the lack of standardization in the field, making it difficult to compare results across different studies. Additionally, there are limitations to current AI algorithms that require further research.

Formation reconfiguration is another critical issue in multi-UAV collaboration. Changing the swarm's shape and size according to task requirements and environmental changes while maintaining cohesion and coordination is essential. The article presented in [20] provides a thorough analysis of communication networks and formation control strategies employed in UAV swarms. The authors introduce and compare commonly used UAVs, followed by a detailed explanation of the formation task, from assignment to transformation. Additionally, the article evaluates the existing formation control strategies and communication networks for UAV swarms, revealing that distributed formation control is superior to centralized methods and represents the future trend in this field.

However, several challenges exist in UAV swarm formation control, including communication networking, collaborative task assignment, trajectory planning, and autonomous formation control. The objective of formation control is to ensure that the UAV swarm moves in a specific formation by controlling their relative positions and velocities. This capability enhances the reconfiguration ability and structure flexibility of the swarm, thus increasing the efficiency and robustness of task completion. During formation, UAVs must autonomously navigate between various locations to avoid collisions with obstacles and other members of the swarm. Moreover, collision avoidance between UAVs within the swarm is also a crucial consideration. In case some UAV members fail or are damaged, the swarm must reconstruct the formation effectively based on the remaining UAVs.

While communication protocols play a critical role in facilitating coordination and information exchange among UAVs in a swarm, designing protocols that are efficient, reliable, and adaptable remains challenging, particularly in dynamic and complex environments. There are several open issues and gaps in the field of communication protocols for UAV swarms. For instance, selecting an appropriate communication architecture that suits diverse scenarios and mission requirements is crucial as it impacts the scalability, robustness, latency, and overhead of the system. Another open issue is the design of routing protocols that ensure dependable end-to-end data transmission in UAV swarms, given challenges such as high mobility, limited bandwidth, variable link quality, network partitioning, and security threats. Additionally, enabling learning-based communication protocols for UAV swarms is another open issue that would enhance their adaptability and flexibility in complex and uncertain environments. Notwithstanding, there exist several unresolved matters and discrepancies that necessitate attention, with collision avoidance constituting a substantial challenge in rapidly changing settings where communication is restricted, and the quantity of UAVs is considerable. In addition, developing effective algorithms based on swarm intelligence decrease the completing time of tasks while also formation control techniques can ensure the safe movement of UAVs, even when there are barriers and unforeseen alterations in the surroundings.

B. *Related work on task allocation*

Task allocation algorithms for UAV swarms are a complex and challenging area of research for engineers and researchers alike. The efficient and effective allocation of tasks among swarm members is essential to ensure the successful completion of mission objectives. However, this task allocation process must consider several critical factors, including task priority, swarm size, communication constraints, and resource limitations. Additionally, the algorithms must be able to adapt to changing environmental conditions and unexpected events, such as equipment failures or weather changes.

In [21] a novel task allocation algorithm for a swarm of UAVs inspired by the behavioral characteristics of wolf packs is presented. The algorithm aims to address challenges of dynamic task allocation, path planning, and coverage search algorithms in UAV swarms. The proposed multi-agent system simulates the UAV swarm as a wolf pack, considering several parameters, including the number of UAVs and targets, the search range of the UAVs, and the order constraints for task allocation. Order constraint refers to the requirement that certain tasks must be performed in a specific order. In the context of the algorithm, it means that the UAVs must perform tasks A, B, and C in a specific sequence for each target. The algorithm must consider this constraint when assigning tasks to UAVs to optimize task allocation performance. The authors conducted simulations using MATLAB and compared their results with those obtained from other algorithms such as random allocation and greedy algorithms. While the proposed algorithm outperforms existing algorithms in simulations, there are still challenges to be addressed for real-world applications. These challenges include path planning, which affects both execution time and task completion ratio, and coverage search algorithms, which ensure efficient completion of all tasks in real-world scenarios.

In [22], the authors propose a task allocation strategy for UAV swarms based on the Multi-Discrete Wolf Pack Algorithm (MDWPA) to address the problem of task allocation in complex dynamic environments. The algorithm uses discretization of wandering, calling, sieging behavior, and new individual supplements to improve accuracy, robustness, and convergence rate. The authors use Orthogonal Experiment Design (OED) and analysis of variance to compare the performance of MDWPA with six other algorithms, namely PSO, GA, Wolf Pack Algorithm (WPA), PSO-GA-WPA, chaotic-local-search-based JADE (CJADE), and Enhanced Binary Opposition-based Competitive Mutation Algorithm with Randomization (EBOCMAR). The experimental results show that MDWPA outperforms the other algorithms in terms of function mean, function standard deviation, function maximum, and mean time. The article also discusses challenges and open issues related to task allocation in UAV swarms, including efficiently allocating tasks with limited resources and handling uncertainties in the environment or incomplete information about the tasks. The authors suggest that future research should focus on developing more practical situations to further improve existing models.

Another example using an optimization approach in task allocation challenge is presented in [5]. In more detail, the authors present a novel dynamic task allocation mechanism for a heterogeneous UAV swarm operating in unknown environments. The proposed mechanism considers parameters such as the number of UAVs, targets, and communication design to optimize resource utilization while ensuring mission completion rates in real-time scenarios. To solve the dynamic task allocation problem in real-time, the authors introduce a discrete solution method based on the binary wolf pack algorithm (BWPA), a metaheuristic optimization algorithm inspired by the hunting behavior of wolves. The mechanism adopts a multi-objective optimization approach that considers both target cost-effectiveness ratio and task execution time window. The authors conducted experiments to evaluate the effectiveness and dynamic adaptability of the proposed mechanism, using performance metrics such as mission completion rate, average mission time, and resource utilization rate. The results showcased the superiority of the proposed mechanism over existing methods, including ACO, PSO, Generic Algorithm (GA), and Improved Binary Wolf Pack Algorithm (IBWPA), in terms of mission completion rate and resource utilization rate. This study addressed challenges such as the complexity of the dynamic task allocation problem in unknown environments, limited resources, and communication constraints. The proposed mechanism aimed to optimize resource utilization and ensure real-time mission completion rates.

However, the authors acknowledged certain limitations and open issues. These included assuming a static environment with stationary targets and perfect communication between UAVs. Future research could explore the development of a more sophisticated dynamic task allocation mechanism that can handle moving targets and communication constraints. Additionally, the authors suggested leveraging machine learning techniques to further enhance the performance of their proposed mechanism.

In [23] a novel task allocation algorithm based on particle swarm optimization (PSO) for multi-agent systems engaged in cooperative timing missions is proposed. The algorithm aims to address the challenges associated with task allocation, such as communication and synchronization among agents, by utilizing PSO-based optimization. The authors adopt a centralized approach where a single agent is responsible for task allocation among other agents. They modify the conventional PSO-based algorithm by incorporating graph theory to reduce computational load and achieve a near-optimal solution with less computation time. The algorithm considers critical parameters such as number of agents and tasks, required agents for each task, the time when the last team member arrives for the task, speed, and distance between the current location of the agent and the task. To evaluate the algorithm's performance, the authors employ several performance metrics such as task completion time and average number of tasks completed by each agent. They conduct numerical simulations on MATLAB and compare their results with those obtained from other methods such as genetic algorithms and ant colony optimization (ACO). The findings reveal that the proposed algorithm outperforms other methods in terms of efficiency and effectiveness. One of the primary challenges in this study is the NP-hard nature of the problem, which requires significant computational resources and time to find an optimal solution. To address this challenge, the authors propose the use of PSO-based optimization as an alternative method to obtain near-optimal solutions while reducing the computational load.

However, the authors address two main open issues that need to be considered for their proposition. The first is the scalability of the algorithm, as the computational load and communication cost increase with the number of agents. The second issue is related to communication protocols used in multi-agent systems, which can affect task allocation and synchronization. Additionally, while PSO-based optimization is effective, it may not guarantee global optimality, so future research should focus on developing hybrid algorithms.

Another solution based on PSO is presented in [24]. In more detail the authors introduce a novel approach, called auction quality clustering discrete particle swarm optimization (A-QCDPSO), for dynamic task allocation of multiple UAVs in a changing battlefield environment. QCDPSO is an innovative approach that combines the auction mechanism and the discrete particle swarm optimization (DPSO) algorithm to tackle the challenges of dynamic task allocation for multiple UAVs. This hybrid architecture incorporates a dynamic subpopulation strategy and a market auction mechanism based on the DPSO algorithm. The market auction mechanism plays a crucial role in ensuring a high-quality initial solution by initializing specific particles. It addresses the task coordination issue by enabling UAVs to bid on tasks with a focus on maximizing efficiency. This ensures that the task coordination process operates effectively and efficiently. To enhance performance, the dynamic subpopulation strategy divides particles into different subpopulations based on their fitness values. This strategy helps improve the speed of convergence and prevents premature convergence, leading to better optimization outcomes. The performance of A-QCDPSO is evaluated using an efficiency function model based on the principle of maximum efficiency of matrix full arrangement and performance metrics such as effectiveness and timeliness are used for comparison with other solutions. The simulation experiments demonstrate that A-QCDPSO outperforms other algorithms in terms of finding a better solution in a shorter time. The authors also address challenges such as the limitation of the maximum number of tasks that UAVs can perform and unexpected situations such as sudden failure of UAVs and new emergency tasks.

Similarly, the authors in [25] propose an improved genetic algorithm based on the beetle antennae search algorithm for multi-UAV task allocation. The algorithm considers the number of UAVs, the type of mission, and the flight environment to optimize task allocation. They introduce a new method called twice crossing operators, which increases the diversity of target sequence arrangements, and dynamically adjusts the mutation probability to contribute to the global optimality of the population. To evaluate their proposed method, the authors use performance metrics such as task completion rate, average task completion time, and total distance traveled by UAVs. They compare their solution with other approaches such as random assignment and greedy algorithms and demonstrate that their proposed method outperforms other approaches in terms of task completion rate and average task completion time while minimizing total distance traveled by UAVs.

However, regarding open issues of this approach, further investigation must be addressed in terms of the use of other optimization algorithms such as ACO and PSO, as well as taking into account the impact of communication constraints on task allocation and the use of ML techniques to improve the performance of their proposed method.

In [26] a novel approach to optimize the performance of multiple UAVs in time-critical combat environments with multiple constraints is presented. The authors propose the Orchard Picking Algorithm (OPA), which assigns tasks to heterogeneous UAVs by denoting multiple targets and tasks as fruits on multiple fruit trees. The algorithm efficiently addresses the task requirements and has high calculation efficiency without the need for a complex cost function. The authors consider several parameters in their algorithm, including the number of UAVs, the number of targets, the distance between targets and UAVs, the ammunition capacity of each UAV, and the task requirements for each target. To evaluate the performance of their approach, the authors compare it with other solutions such as Particle Swarm Optimization (PSO) and Tabu Search Algorithm (TSA) using task completion time and success rate as performance metrics. TSA is a metaheuristic optimization algorithm that is inspired by the tabu search strategy. The results show that the proposed approach outperforms PSO and TSA in terms of both task completion time and success rate.

Finally, the authors identify several areas that require further investigation for their proposed approach. One limitation of the Orchard Picking Algorithm is that it assumes perfect communication and sensing capabilities, which may not be realistic in real-world scenarios. Additionally, the algorithm assumes a static environment where targets do not move, and a centralized control system where all UAVs are controlled by a single entity. These assumptions may limit the applicability of the algorithm in certain scenarios.

Prior research in the field of task allocation for multiple UAVs has suggested that current solutions may not be capable of effectively addressing complex tasks. However, a recently proposed algorithm, as presented in [27], aims to offer a viable solution to this challenge. In particular, the authors propose a novel algorithm based on deep transfer reinforcement learning, which leverages the experience gained from previous tasks to improve allocation efficiency. The algorithm employs QMIX, a deep reinforcement learning algorithm, to learn network parameters from source tasks and migrate them to new tasks. This approach overcomes local optimization by combining global knowledge with local exploration. Authors consider parameters such as the number of UAVs, starting point coordination, UAV's current position, speed, maximum flight range without refueling, current flight range, number, position and the emergency level of rescue areas, as well as the list of needed materials. They also highlight the need to enhance similarity calculation methods between new and source tasks, as existing methods may not identify source tasks with high similarity. The authors compare their algorithm's performance using a custom Python-based custom made simulator with other heuristic methods using relevant metrics such as task completion time and energy consumption. The results demonstrate that their algorithm outperforms traditional heuristic methods in terms of allocation efficiency while maintaining similar running times. However, the article acknowledges that local optimization remains a significant challenge that needs to be addressed in future research. Moreover, straightforward similarity calculation methods may not always identify relevant source tasks, emphasizing the need for developing more advanced algorithms to tackle these challenges.

One of the significant challenges in designing task allocation algorithms is the constraint of limited energy resources. While incorporating complex ML algorithms may reduce execution time by increasing computing resources, it can also deplete energy reserves due to the high computational demands involved. For this reason, the authors in [28] propose an energy-aware joint routing and task allocation algorithm for multi-UAV assisted mobile edge computing (MEC) systems. The objective of this algorithm is to minimize energy consumption while completing data collection and processing tasks for IoT devices. The algorithm considers factors such as hovering energy, flight energy, and the number of UAVs required for each task. To evaluate the performance of their proposed algorithm, the authors compare it with neighbor Greedy search algorithm (GSA) using metrics such as total energy consumption, average task completion time, and the number of completed tasks. They demonstrate that their algorithm outperforms other solutions in terms of energy efficiency while maintaining a similar level of task completion rate, using MATLAB. However, the authors also highlight several challenges associated with UAV-assisted MEC systems. These include communication delays between UAVs and IoT devices, limited battery life of UAVs, and the need for real-time decision-making in dynamic environments. To further improve the performance of UAV-assisted MEC systems, the authors suggest that future research should focus on addressing these challenges.

Another example of multi-UAVs task allocation algorithm in MEC systems is presented in [29]. In this article, the authors propose a novel approach to tackle the challenges associated with processing data locally on Internet of Things (IoT) devices, given their limited computation capacity and battery lifetime. They present a UAV-aided MEC system that optimizes task offloading decisions, resource allocation mechanisms, and UAV trajectory to minimize energy consumption while meeting IoT devices' latency requirements. To solve the non-convex problem, the authors use the Block Successive Upper-bound Minimization (BSUM) method and compare their proposed algorithm's performance with other existing solutions, including Block Coordinate Descent (BCD) based solution, equal resource allocation, and remote task execution schemes. Simulation results indicate that their proposed algorithm reduces total energy consumption by 10.54%, 18.49%, and 40.67% compared to the other solutions, respectively. Additionally, the authors emphasize the benefits of using UAVs in mobile edge computing systems, as they can increase network capacity and offer services to mobile users with or without infrastructure coverage. The proposed system exploits UAVs' mobility to optimize resource allocation and task offloading decisions, thereby minimizing energy consumption.

However, deploying this system in real-world scenarios faces challenges, such as regulatory issues related to UAVs' deployment in urban areas. Additionally, there are technical challenges related to optimizing resource allocation and task offloading decisions in dynamic environments where network conditions may change rapidly.

III. Discussion And Proposed Task Allocation Model

The aforementioned algorithms address various aspects such as workload balancing, energy optimization, and task completion rate improvement. However, limitations exist, including assumptions of static environments and perfect communication, as well as their implementation on real-world scenarios. Further research is needed to explore communication constraints and integrate machine learning techniques. Evaluation of these algorithms is commonly done using MATLAB and Python-based custom-made simulators across domains like military operations and rescue operations. Additionally, optimizing energy consumption is crucial for UAV swarms, specifically when they aim to extend the coverage of mobile networks.

In the domain of precision agriculture, UAV swarms face constraints related to energy, communication and coordination, task allocation, obstacle avoidance, sensor fusion, and cost effectiveness. These challenges have contributed to hesitancy and reluctance among professionals in adopting UAV swarm technology. Despite a comprehensive literature review, there is a notable dearth of research focusing on the application of UAV swarm in precision agriculture. In this perspective, in the context of smart ecosystem "VELOS" for providing recommendations for the application and scheduling of fertilizers for plant protection in bean cultivation [30], we propose the "UAV as a service" concept, where users can access and utilize UAV resources and functionalities on-demand, tailored to their specific needs and requirements. Following, we aim to provide novel task allocation algorithms with main goal to minimize energy consumption specifically tailored for precision agriculture, considering farmers' requests or missions generated from VELOS smart ecosystem. In more detail, end-users can submit customized requests for monitoring crop health or detecting diseases/pests, through the Human Machine Interface (HMI). The proposed model aims to bridge the gap by providing efficient task allocation solutions in precision agriculture, ultimately enhancing agricultural practices and productivity.

In conclusion, ongoing research focuses on addressing limitations, optimizing energy consumption, and improving task management. Future research should focus on addressing communication constraints, leveraging machine learning techniques to improve algorithm performance, and developing solutions that are adaptable and efficient in real-time, dynamic environments. By considering these aspects, we can enhance the reliability and effectiveness of task allocation algorithms across diverse domains, such as precision agriculture.

IV. Conclusion And Future Work

The development of a task allocation algorithm for UAV swarms presents significant limitations that must be carefully addressed for practical implementation in real-world scenarios. This paper conducts a comprehensive literature survey to examine the challenges associated with UAV swarms, with a specific focus on task allocation algorithms. In particular, the design of a task allocation system necessitates addressing various interconnected challenges, including communication, coordination, and range extension. While the majority of proposed task allocation algorithms have predominantly focused on military operations, driven by the criticality of time constraints, this paper introduces UAV as a service in the precision agriculture context and highlights energy constraints as a major issue to be considered when designing task allocation mechanisms. To this end, we aim to develop a novel model specifically tailored for task allocation in UAV swarms. The objective of this model is to optimize task allocation while concurrently minimizing energy consumption in precision agriculture applications, aiming to address the existing research gap in this domain. Future work entails evaluating the proposed model's efficacy through simulation experiments, comparing it to existing approaches, and developing a swarm intelligence-based path planning algorithm to measure UAV energy consumption and select mission-appropriate strategies based on the end-user's requests.

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