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RESEARCH ARTICLE

Distributed Task Allocation for UAV Swarms with Limited Communication

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ABSTRACT
Unmanned aerial vehicle (UAV) swarms have become increasingly indispensable in both military and civilian operations. Task allocation, a crucial aspect of UAV swarm autonomy, involves assigning sequential tasks to each aircraft based on environmental constraints and swarm status. While many task allocation algorithms assume reliable communication among agents, real-world environments often present challenges such as limited bandwidth and message interference. This study presents a new distributed task assignment algorithm for heterogeneous UAV swarms, addressing various task constraints. The proposed auction-based method optimizes total cost, ensures fair workload distribution, and minimizes message size through a two-stage auction process. Comparative evaluations with existing algorithms like CBBA and the central Hungarian algorithm, under the Bernoulli communication model, consider factors such as total task cost, message size, unassignable tasks, and conflict assignments. Results indicate the proposed algorithm's effectiveness in smooth communication environments and its potential advantage in low-bandwidth environments. However, it also highlights potential conflicts in scenarios with communication disruptions. To address deviations due to communication quality, Signal-to-Noise Ratio (SNR) values are monitored throughout task execution.

Keywords: UAV swarms, Distributed computing, Auction algorithm, Task allocation, Constrained communication

1. Introduction

An Unmanned Aerial Vehicle (UAV) denotes an aircraft that operates without a human pilot onboard, either under remote control by a human operator or autonomously following pre-programmed instructions. In recent years, there has been substantial progress and utilization of UAVs across various sectors. Originally dominant in military use, UAVs have increasingly ventured into civilian domains over the last twenty years, thanks to advancements in technology, smaller sizes, and decreased component expenses, making them accessible even to hobbyists [1]. While primarily acknowledged for aerial photography, potential civilian applications encompass delivery services, agriculture, law enforcement, environmental monitoring, and entertainment [2].

Scholars have explored the prospect of collaboration among multiple UAVs, envisioning tasks including surveillance, surveying, search and rescue operations, monitoring/detection in hazardous environments, terrain mapping, and handling hazardous materials [3]. The diminishing size and costs of individual units have also spurred interest in deploying UAVs in swarms [4]. This area of research is appealing due to its potential robustness, flexibility, and scalability. Robustness in this context pertains to the redundancy offered by large numbers and decentralization. A swarm potentially can accomplish objectives that a single UAV cannot or would achieve with less efficiency.

UAV swarms may comprise either homogeneous or heterogeneous groups. Employing a homogeneous group simplifies the acquisition and utilization of a cost-effective swarm, while heterogeneous groups enhance the swarm's complexity and capability.

Advancements in artificial intelligence and machine learning are transforming combat operations, with a growing inclination toward employing autonomous robots capable of reacting and cooperating as a cohesive unit [5]. The swarm represents the next evolutionary phase in warfare. UAV systems are employed across various levels, from terrorist organizations to global superpowers, and cost-effective UAV systems serve as a means to implement swarm warfare. Already, UAV swarms are utilized in heterogeneous configurations and have been demonstrated during military exhibitions [6].

The collaboration of drones within a swarm poses additional challenges not encountered in single UAV operations. Swarms operating as a unified entity require systems for collision avoidance among the drones within the swarm itself and avoidance of obstacles encountered in the environment [7]. Failures in these systems can result in material damage and escalate the costs of developing such systems.

The global progression of UAV and swarm technologies continues, with recent advancements including Russia's "Molniya" UAV, designed to compete with the U.S. Gremlin system. It boasts 700 km/h speeds and payloads ranging from 5 to 7 kgs. Additionally, Russia's ZALA Aero has introduced the KUB-UAV, specifically tailored for naval operations. It can reach up to 130 km/h, endure for 30 minutes, and carry a three-kilogram warhead, posing a significant threat due to its rapid swarm formation capability [8]. Turkish UAV technology has also seen rapid progress, exemplified by platforms like the Bayraktar TB2, which has gained international acclaim for its efficacy in diverse military operations. China has demonstrated its dedication to swarm technology, notably in a 2017 display involving 119 UAVs, and continues to advance with companies like Zhuhai Ziyan developing versatile systems like the Blowfish family, capable of various missions with interchangeable payloads, reflecting the necessity for effective and cost-efficient solutions in future battlegrounds [9]. The U.S. deploys UAV swarms such as Predator and Reaper extensively for remote surveillance and target acquisition tasks. Similarly, Israel's UAV systems like Harop and Heron TP play active roles in defensive operations. In the civilian sphere, UAV swarms for delivery purposes, including Amazon's Prime Air, are under development.

One of the primary challenges associated with UAV swarms is the inherent difficulty in effectively coordinating them. Many coordination challenges involve solving NP-hard problems, making optimal solutions often difficult to attain and exhibiting poor scalability [10]. Among the focal points of research in UAV swarm coordination is task assignment, which presents an optimization challenge involving tasks located in varying positions and of differing significance, to be executed by UAVs with diverse capabilities and positions.

In recent years, Task Allocation (TA) has emerged as a prevalent issue in swarm robotics [11]. Given that swarm robotics applications frequently require a group of robots to perform multiple tasks, it becomes crucial to assign these tasks to robots in an optimized manner. Generally, the task allocation problem involves finding an appropriate matching or allocation, given a set of tasks, a set of robots capable of performing these tasks, and an objective function that evaluates the performance efficiency of different combinations of robots in task execution [12].

The primary factor influencing the effectiveness of a UAV swarm's mission is its ability to communicate and share information among its constituent drones. The main constraint on the size of a UAV swarm is its capacity to manage the exchange of information. Effective communication is crucial for preventing collisions among swarm drones and coordinating attack strategies. Without cohesive communication among UAVs, a swarm cannot maintain consistent functionality or achieve successful missions. Essentially, communication is a fundamental requirement for the existence and operation of a UAV swarm [13].

Existing approaches for task allocation among agents in a swarm primarily focus on distributing tasks without considering the inherent structure. They overlook factors like UAV hardware, battery levels, task time constraints, complexity, and communication bandwidth. Additionally, the impact of lossy communication on algorithm performance is often neglected in proposed algorithms.

The main contributions of this paper are the following:

- Defining the task assignment problem within the communication framework of UAV swarms.
- Introducing a novel method for task assignment in UAV swarms, with an analysis of its performance in scenarios with communication impairments.
- Demonstrating the feasibility of the proposed algorithm through comprehensive evaluations using Matlab simulations.
- Conducting a comparative evaluation of the proposed algorithm against widely utilized task assignment methods such as Hungarian and CBBA algorithms, specifically addressing communication challenges.
- The algorithm proposed is demonstrated through task allocation within drone swarms, but it offers a framework for parallel computing across various types of autonomous swarms.

The rest of this paper is organized as follows. In section 2 we discuss related work. In section 3, we describe task allocation methods. In section 4, we describe the problem. Section 5 introduces our proposed algorithm. Section 6 presents the results of the simulation. Section 7 is the conclusion and future work.

2. Related Work

In this section, we highlight recent studies on the task assignment problem in UAV swarms. Unmanned aerial vehicles have garnered significant attention due to their diverse applications. Various studies have examined the advantages and use cases of UAVs, exploring their potential in areas such as surveillance, search and rescue, and environmental monitoring. By analyzing these recent contributions, we aim to identify the current trends, advancements, and challenges in the field, and position our work within this context.

Clough [14] delves into the advantages of agents collaborating within a swarm. The benefits of using heterogeneous swarms over homogeneous ones are highlighted in recent studies, such as [15]. Heterogeneity in robotics involves employing robots with varied capabilities, features, or characteristics within a swarm. Frelinger et al. [16] demonstrated that enabling cooperative behavior through communication among weapons significantly enhances effectiveness. Despite limited sensor ranges, they share target detection information among neighboring weapons compensated for this shortfall. As a result, more targets within the designated area were successfully engaged, leading to improved overall system performance. Recent developments have also showcased the first instances of manned fighters engaging with unmanned drones [17, 18]. Edwards [19] provides an extensive study of historical battles where at least one force operated as a swarm.

The task assignment problem can manifest in different ways depending on the characteristics of the agents and the tasks. It is crucial to define the problem clearly and seek solutions accordingly to find an effective resolution. In 2004, Gerkey and Mataric [20] introduced a domain-independent classification framework for the multitask assignment problem, which remains influential in contemporary research. This classification system delineates key components such as single-task (ST) and multi-task (MT) robots, single-robot (SR) and multi-robot (MR) tasks, and instant (IA) and timed (TA) assignments. Its primary aim is to provide a structured understanding of how diverse task assignment challenges fit within the problem domain and to elucidate their relationships with solutions proposed in existing literature.

The first step in solving the task assignment problem is to express the constraints of the problem and model it accordingly. Reference [21] constructed a multi-UAV task allocation model that incorporates an interval information environment to account for uncertain factors such as revenue damage cost index, target value, and range cost index. In a similar vein, [22] tackled dynamic task allocation by breaking it down into static task allocation across multiple stages, leading to the creation of a multi-UAV dynamic reconnaissance resource allocation model, thus enhancing overall efficiency in dynamic reconnaissance tasks. Shima T [23] introduced a cooperative multiple task assignment problem model tailored for UAVs. At the same time, a subsequent paper [24] refined this model into an extended cooperative multitask assignment model, albeit with some constraints left unaddressed. Addressing the challenge of integrating new tasks or accommodating platform loss, [25] proposed a method of dynamic task local adjustment to formulate a multi base and multi-unmanned combat aerial vehicle task allocation model, thereby bolstering task allocation efficiency and platform stability.

The foundational research on the task assignment problem is documented in [26], where the initial models were developed. Further elaboration on this proposed approach can be found in [27]. Task assignment methodologies are broadly classified into two categories: centralized and decentralized.

Centralized methods are effective for determining optimal task assignments in static environments with few agents. However, as the number of agents increases and the problem becomes more complex, scaling centralized approaches becomes challenging. The seminal work in centralized task assignment, known as the Hungarian algorithm, was introduced by Kuhn, a Hungarian mathematician, in [28].

Distributed task assignment methods are more commonly used than centralized methods due to their advantages such as flexibility and scalability. In [29], the analysis of task allocation within a multi-UAV system adopts a fully distributed architecture. A key characteristic of this approach is the avoidance of centralized planning, instead relying on synchronization through token circulation. However, achieving this synchronization necessitates all-to-all communication. Auction-based algorithms represent the predominant approach for distributed task assignment, wherein agents bid on tasks and the highest bidder secures the task [30]. The determination of auction winners can be either centralized or decentralized. The inception of auction-based task assignment algorithms dates back to Dimitri's proposal in 1979 [31]. Various auction mechanisms have been employed for task allocation in multi-agent systems. In a sequential auction, the auctioneer sells a sequence of items, one item at a time, in an order chosen by the auctioneer. Lagoudakis et al. [32] compare several distributed bidding mechanisms, demonstrating that a variant of sequential auctions offers solutions that are provably close to optimal. Simmons et al. [33] introduced robots bidding to visit frontier nodes following map updates. Rekleitis et al. [34] utilized a sequence of one-round auctions to divide a Boustrophedon multi-robot coverage sweep. Similarly, Vail and Veloso [35] employed one-round auctions sequentially for role assignment in robot soccer. Approximation methods for combinatorial auctions are compared to sequential single item auctions by Cavalcante et al. [36]. Schneider et al. [37] provide experimental comparisons among various auctions, market approaches, and other multi-robot coordination mechanisms. In static multirobot task assignment, the auction-based algorithm in [38] ensures that the total travel cost of the robots is at most twice that of the optimal solution, provided all the robots are communication-connected. In [39], the auction-based CBBA algorithm, which was proposed for task assignment in static environments, has been extended for dynamic environments.

Several auction-based task assignment algorithms are customized to allocate tasks among agents in natural disasters and catastrophic situations. López et al. [40] introduced an auction system named Masictus designed to coordinate ambulances and neurologists from various ambulance trusts, particularly in instances involving stroke patients. The system employs real currency in conducting auctions to allocate ambulances that incur the lowest costs and are in close proximity to the emergency locations. Another application relating auction mechanisms to disaster management is presented by Berhault et al. [41] where combinatorial auctions are utilized to determine a schedule for a group of robots visiting target areas. Combinatorial auctions involve bidders placing bids on combinations of items to secure them. Finally, [42], [43], and [44] present various methods proposed for distributed task assignment.

Our algorithm fills a significant gap in current research by presenting a unique method for task assignment in UAV swarms, specifically designed for environments with limited communication bandwidth. Traditional task allocation algorithms typically assume stable and robust communication channels, which is often not the case in practical UAV swarm operations. Our approach, however, directly addresses these real-world communication challenges. By tackling this critical issue, our study offers an innovative solution for task allocation in UAV swarms operating under restricted communication conditions, enhancing the field with a new method that ensures efficient and effective swarm coordination.

3. Task Allocation in UAV Swarms

A primary challenge in autonomous multi-agent systems is the lack of coordination among agents, often stemming from an inefficient distribution of tasks. Task assignment plays a crucial role in determining agents' objectives and ensuring successful task completion, facilitating collaboration towards shared goals.

Task assignment involves the selection, allocation, and coordination of tasks [45]. In UAV swarms, agents, while similar in design, can vary in capabilities, necessitating task assignments compatible with their strengths. Additionally, agents may need to coordinate to tackle complex tasks requiring multiple agents, where the duration of task completion may be uncertain, making it challenging to determine when tasks might become irrelevant [46].

Approaches to task allocation in UAV swarms typically fall into two categories: centralized methods and distributed methods.

Centralized task assignment algorithms involve a central coordinator agent is communicating with all other agents, manages negotiations and makes decisions on task assignments. While capable of producing optimal or near-optimal assignments, these algorithms require continuous and reliable communication between each robot and the central server to gather global information. This reliance on effective communication often leads to significant central node overhead, complex computation, and a single point of failure [47]. Moreover, certain multi robot task assignment problems are proven to be NP-hard, demanding high computational capacity from the central server [48]. Consequently, centralized methods face scalability issues with increasing numbers of robots and/or targets, and they are not suitable for scenarios where robots may encounter local or outdated information due to imperfect communication.

The Hungarian algorithm [28], introduced by the mathematician Kuhn in 1955, is a foundational centralized method for task assignment. This algorithm, known for its simplicity and wide applicability, efficiently solves assignment problems in polynomial time.

In contrast, distributed methods eliminate the need for a central agent, with task allocation occurring through negotiations among agents. Distributed systems operate under the principle that no agent possesses complete information about the system or control over other agents' actions [49]. In such systems, UAVs communicate with each other to exchange information, leveraging their autonomous capabilities to enhance assignment efficiency [50]. Decentralized algorithms empower each robot to plan its route based on locally available information.

In recent years, auction-based distributed techniques, renowned for their computational efficiency, have gained traction in addressing the task assignment problem within distributed environments. These approaches involve UAVs determining their bids for individual tasks based on internal valuation or cost metrics. Depending on whether the objective is to maximize value or minimize cost, the task is awarded to the highest or lowest bidder, respectively [51].

CBBA (Consensus Based Bundle Algorithm), an approach rooted in open incrementality, has emerged as a prominent method for task assignment, as outlined in [52]. Within CBBA, each agent maintains a list of tasks potentially allocated to them, and the auction mechanism operates at the task level rather than the package level. CBBA comprises two key stages: bundling and conflict resolution. Unlike other consensus algorithms, CBBA focuses on achieving consensus on the winning bid instead of individual agent strategies. Leveraging a parallel task assignment model, CBBA exhibits faster convergence compared to serial auction algorithms. Its primary objective is to allocate tasks without conflicts, ensuring that each task is assigned to only one UAV. However, in practical scenarios, certain tasks may necessitate collaboration among multiple UAVs with diverse capabilities. To address this, CBBA-based applications adopt a strategy of duplicating these collaborative tasks with corresponding dimensions [53]. For instance, if task j requires n UAVs for cooperative execution, it is replicated into n identical tasks $(j_1, j_2, j_3, \cdots, j_n)$, treating each as a separate task during the assignment process.

Various methodologies exist in the literature to tackle the task assignment problem, encompassing centralized, distributed, and hybrid approaches, each with distinct characteristics. The selection of the optimal task assignment algorithm for UAV swarms hinges on specific application requirements, swarm size, communication capabilities, and environmental considerations. Table 1 presents a comparative analysis of centralized, distributed, and hybrid task assignment algorithms, highlighting their key features.

Table 1. Task Assignment Approaches

Feature	Centralized	Distributed	Hybrid
Scalability	No	Yes	Yes
Robustness	No	Yes	Yes
Flexibility	No	Yes	Yes
Handling unknown conditions	No	Yes	Partially
Communication obligation	High	Low	High
Team size	Small	Big	Medium
Global information need	Yes	No	No

UAV swarms are often deployed in environments where communications are unreliable. Communication can be unreliable due to weather and environmental factors such as obstacles, distance between robots, and interference. Communication may also be blocked intentionally to maintain confidentiality.

The challenge of limited bandwidth or data rate in wireless communication becomes significant when dealing with large numbers of agents operating within communication range. The constraints of current communication technology are often overlooked in the development of algorithms for aerial swarm applications. Many of these algorithms assume an arbitrarily large bandwidth for communication, assuming that neighbor information is continuously available to an agent or at every time step [54]. Recent surveys [55] indicate that decentralized topologies are underutilized due to limitations in current technology. Successful experiments reported in the literature usually involve limiting the number of agents or implementing larger safety distances with relatively low speeds to accommodate delays or dropouts [56].

In the context of a task assignment problem, the most challenging scenario arises when an agent cannot establish communication with other agents and must navigate to all designated targets. While many task allocation methodologies presuppose flawless inter-agent communication among Unmanned Aerial Vehicles (UAVs), positing an ideal connection with unlimited bandwidth for ensuring consistent situational awareness (SA) before allocation, contemporary communication technologies fall short of meeting this criterion [57].

In instances of inconsistent communication, the effectiveness of the task assignment algorithm assumes critical significance. In line with this, within the purview of this research endeavor, section 6 comprehensively examines the performance of the proposed algorithm in an environment characterized by weakened communication and potential message loss.

4. Problem Statement

In this section, initially, the mathematical model and constraints are delineated for the task assignment problem in UAV swarms amidst dynamic environments. Subsequently, the communication model employed for assessing the efficacy of the proposed task assignment algorithm is illustrated.

4.1. Task Allocation Problem

The essence of the task assignment problem lies in matching a set of tasks with a corresponding set of agents, driven by an objective function. Within a UAV swarm context, N UAVs exist, each possessing distinct capabilities. Represented as A, this collection constitutes N heterogeneous UAVs, as formulated in Equation 1.

$$A = \{1, 2, \dots, N\} \tag{1}$$

The system encompasses M dynamic tasks, with the task set denoted as T. This is represented by Equation 2. These tasks exhibit heterogeneity, meaning there is no uniform type; rather, UAVs with fitting capabilities are requisite for task execution.

$$T = \{1, 2, \dots, M\} \tag{2}$$

The quantity of potential assignments achievable within a swarm is contingent upon the count of agents and tasks. If the agents within the ensemble are homogeneous, the number of feasible assignments, denoted as S, is defined by Equation 3.

$$S = N^M \tag{3}$$

When the agents in the swarm exhibit heterogeneity, the count of feasible assignments is articulated by Equation 4.

$$S = \prod_{i=1}^{n} N_i^{M_i} = N_1^{M_1} \times N_2^{M_2} \times N_n^{M_n} \tag{4}$$

where n represents the number of groups within the swarm. Each N_i agent group is tasked with executing the M_i task group.

The primary objective of task assignment is to allocate tasks in a manner that maximizes the total benefit derived from the UAVs. This objective is expressed mathematically in Equation 5.

$$max \sum_{i=1}^{N} \sum_{j=1}^{M} x_{ij} R_{ij} \tag{5}$$

If task *j* is assigned to agent *i*, then x_{ij}=1; otherwise, x_{ij}=0. R_{ij} denotes the utility value agent *i* will attain if assigned task *j*.

The task assignment problem constitutes an optimization challenge, typically geared towards maximizing resource efficiency or achieving optimal outcomes within specific constraints. The assignment problem is fundamentally linked to linear optimization, making it a fundamental difficulty. This issue commonly arises in scenarios where multiple tasks require the allocation of resources, necessitating a strategic assignment approach.

The constraints and assumptions defined for the problem within the scope of the study are as follows:

Various types of aircraft possess distinct capabilities tailored to specific missions. Aircraft must be assigned tasks that align with their respective capabilities to ensure effective execution. Each agent is associated with an ability matrix (A) that delineates its abilities. If agent *i* can perform task *j*, $a_{ij} = 1$, otherwise $a_{ij} = 0$.

$$A_i = [a_{i1} \quad a_{i2} \quad \cdots \quad a_{in}] \tag{6}$$

One aircraft must be assigned to each mission, this constraint is expressed in Equation 7.

$$\textstyle\sum_{i=1}^{N} x_{ij} = 1, j \in T \tag{7}$$

A time frame is established for each task in Equation 8, within which the task must commence. Additionally, each task demands a duration t_{td} for completion. Upon reaching the task location, the UAV is obligated to remain at the task position for this specified duration of time.

$$t_{start_j} \leq t_{d_{ij}} \leq t_{finish_j} \tag{8}$$

where $[t_{start_j}, t_{finish_j}]$ represents the time frame of task *j*, and $t_{d_{ij}}$ represents the commencement time for agent *i* to execute task *j*.

The allocation of tasks to UAVs should be balanced, aiming to distribute the workload evenly among the UAVs. This constraint is articulated in Equation 9.

$$|s_i| - |s_k| \leq B, i \neq k \quad i,k \in \mathrm{A} \tag{9}$$

where $|s_i|$ is the number of tasks in the task list of drone *i*, $|s_k|$ is the of tasks in the task list of drone *k* and B is the threshold value for the difference in the number of assigned tasks.

The total distance traveled by the UAV must not exceed the range of the UAV. This constraint is expressed mathematically by Equation 10.

$$\sum_{j=1}^{M} S_{ij} x_{ij} \leq D_i \tag{10}$$

where D_i is the maximum range of the UAV, S_{ij} is the distance that UAV *i* must travel to perform task *j*.

A UAV is capable of executing only one task at a time, and its speed remains constant throughout the task.

4.2. Communication Model

There are two basic ways to deal with poor communication. The first method involves the negotiating agent waiting until it receives messages from all agents in each round, akin to the TCP message transfer protocol. Alternatively, in the second method, the negotiating agent operates under the assumption that each round has a fixed duration. If it fails to receive an offer from an agent within this time frame, it interprets this as a communication issue [51]. Given the uncertainty regarding whether agents in UAV swarms are within communication range, the second method was favored within the study's scope.

During the simulations conducted for the study, the Bernoulli communication model was utilized, assuming that agents communicated within a fully connected graph structure. The fully connected graph structure is illustrated in Figure 1.

The Bernoulli Communication Model represents a framework for communication wherein information is transmitted through random variables. Developed to assess information transmission efficacy, this model derives its name from the mathematician Jakob Bernoulli.

In this framework, the information to be transmitted, denoted by the random variable X, adheres to a specific probability distribution. Typically, this distribution follows a Bernoulli distribution, often expressed as P(X = 1) = p and P(X = 0) = 1-p, where p signifies the probability of successfully transmitting a bit. The fidelity of information transmission hinges upon the characteristics and distribution of this random variable, with the communication channel's effectiveness contingent upon the state of said variable.

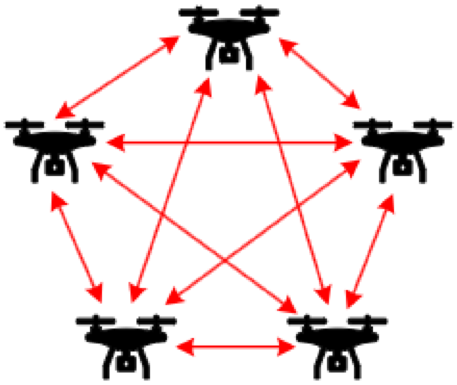

Figure 1. Fully Connected Communication Graph

The Bernoulli Communication Model finds application in scenarios involving stochastic communication channels, offering a simplified depiction that overlooks real-world factors such as range effects, directional influences, and bandwidth limitations. Nevertheless, it proves beneficial in contexts where communicating entities are proximal within their communication range. Its straightforward structure renders it a valuable analytical instrument, particularly in error analysis and performance evaluations across diverse communication systems, including wireless and radio communication networks.

To evaluate the communication channel quality parameter, first, the path loss of the channel was calculated by measuring the distance between agents. For path loss, it has been shown that the two-ray path loss model gives superior approximations of the aerial vehicle communication channel modeling in comparison to the free-space path loss model [58]. The two-ray path loss model calculates the path loss between a transmitter and a receiver considering both the direct line-of-sight (LOS) path and a reflected path. The equation for the two-ray path loss model is as Equation 11.

$$P_r = P_t - 20\log\left(\frac{\lambda}{4\pi d} * 2\sin\left(\frac{2\pi h_r h_t}{\lambda d}\right)\right) + G_t + G_r + AWGN \tag{11}$$

where P_r is the receiving power, P_t is the output power of the transmitter, λ is the wavelength of the transmitted signal, d is the distance parallel to the ground between the aircraft, h_t is the ground clearance of the transmitting aircraft, h_r is the receiving aircraft's ground clearance, G_t is the gain of the transmitting antenna, G_r refers to the gain of the receiving antenna. In channel modeling, it is assumed that there is no interference except thermal noise to obtain more repeatable results during simulation studies. The communication channel parameters are chosen as follows; thermal noise (W/Hz)=4.143×10^{-21}, N_0=-174 dBm, bandwidth=47 MHz, output power=10 W, antenna gain=1 dB.

5. Proposed Approach

One of the main contributions of the research lies in presenting an algorithm featuring a two-stage auction process for task assignment within heterogeneous unmanned aerial vehicle swarms. This section elucidates the proposed task assignment algorithm.

5.1. Utility Function Design

Within auction-based task assignment algorithms, the utility function serves as a crucial metric for prioritizing and assigning tasks based on specific criteria. Typically, a benefit value is computed for each task, and aggregating these values guides the assignment process, ensuring optimal task allocations. This section elaborates on the design of cost and utility functions incorporated within the proposed algorithm.

The cost function is utilized to compute the task expenses of the UAV, which include two elements: balance cost and distance cost. The cost of task j for agent i, denoted as $\boldsymbol{C_{ij}}$, is computed using Equation 12, where $\boldsymbol{w_1}$ and $\boldsymbol{w_2}$ are the coefficients for distance and balance costs, respectively.

$$C_{ij} = w_1 C_{ij}^D + w_2 C_{ij}^B \tag{12}$$

The balance cost $\left(C_{ij}^B\right)$ for UAV i performing task j is determined using Equation 13, which takes into account the task load of the UAV.

$$C_{ij}^B = \frac{|b_i|}{MT_i} \tag{13}$$

where $|\boldsymbol{b_i}|$ represents the number of elements in the task list of UAV i and $\boldsymbol{MT_i}$ denotes the maximum number of tasks that UAV i can add to its task list.

The distance cost $\left(C_{ij}^{D}\right)$ of UAV *i* for task *j* is determined by Equation 14, which considers the distance of the UAV to the task location.

$$C_{ij}^{D} = \frac{d_{ij}}{MFD_i} \tag{14}$$

where MFD_i represents the distance of UAV *i* to the farthest task, while d_{ij} denotes the distance between UAV *i* and task *j*.

The cost matrix for agent *i* is expressed as depicted in Equation 15.

$$C_i = [C_{i1} \quad C_{i2} \quad \dots \quad C_{iM}] \tag{15}$$

Employing the defined cost function, the local utility value is computed according to Equation 16, where R_{ij} represents the utility value for agent *i* of task *j*.

$$R_{ij} = V_j e^{-\tau*(tc_{start}-(tp_{start}+tp_{duration}))} - C_{ij} \tag{16}$$

where V_j represents the initial reward value of task *j*, while τ denotes the time penalty coefficient. Additionally, tc_{start} refers to the earliest time at which agent *i* can commence task *j*, tp_{start} represents the time required for the agent to initiate the last task on the agent's path, and $tp_{duration}$ signifies the duration of the last task on the agent's path.

Two different reward matrices are utilized in the algorithm: normal (R_{ij}^{N}) and synergy (R_{ij}^{S}) . The normal reward matrix is computed using the cost matrix acquired by the agent in the respective iteration for tasks that have not yet been assigned.

In calculating the synergy reward matrix, the initial step involves the computation of a new synergy cost matrix, which is based on the assumption that the agent successfully completes the task with the highest reward in the normal reward matrix. Subsequently, the synergy reward matrix is determined based on this cost matrix using Equation (16). The utilization of the synergy reward matrix aims to capture the synergy between tasks, particularly their proximity to one another. This approach facilitates the agent in receiving their next assignment with maximum income by leveraging task synergies. If there are only two tasks remaining unassigned, the synergy reward matrix is not calculated.

5.2. Auction Process

The auction process comprises two distinct phases: the pre-auction phase and the synergy-auction phase. In the proposed two-stage auction process, agents strive to incorporate the second most beneficial task into their path alongside the primary task, rather than adopting a purely greedy approach of solely pursuing the most beneficial task at each iteration. This approach aims not only to minimize the overall system cost but also to reduce the message size required to address the problem effectively.

Pre-auction phase: in this phase, the UAV identifies the highest value (f_i) task (j_i) in the normal reward matrix and computes its bid (δ_i) for f_i. Subsequently, the drone broadcasts an auction message for task j_i. The calculation of δ_i is determined by Equation 17, where s_i represents the utility value of the agent's second-best task.

Once all agent's auction messages are received, the UAV proceeds to check whether other UAVs have initiated auctions for the same task. Should multiple UAVs commence an auction for a task, the UAV boasting the highest reward value (MaxReward) wins the task. In instances of equal reward values, the UAV with the lower ID wins the task. This process is termed the pre-auction phase. Subsequently, the winning drone communicates its success to other swarm agents via a Pre-Auction Result message.

$$\begin{gathered} \delta_i = f_i - s_i \\ j_i = \arg\max_{j=1,\dots,n} \left\{R_{ij}^{N}\right\} \\ f_i = \max_{j} \left\{R_{ij}^{N}\right\} \\ s_i = \max_{j \neq j_i} \left\{R_{ij}^{N}\right\} \end{gathered} \tag{17}$$

Furthermore, the winner drone in the pre-auction phase has the opportunity to bid for the synergy task in the subsequent stage. Conversely, the drone that loses the preliminary auction is ineligible to bid for the synergy task. The outlined procedure for the preliminary auction phase is outlined in Algorithm 1.

Algorithm 1. Pre-Auction Phase

Input: Unassigned task
Output: Pre-Auction Mes., Pre-Auction Result Mes.
if $length(P_i) < MT_i$ **then**
  $auction = 1$
  $Calculate : R_i^N$
  $j_i = argmax_j(R_{ij}^N)$
  $f_i = max_j(R_{ij}^N)$
  $s_i = max_{j \neq ji}(R_{ij}^N)$
  $\delta_i = f_i - s_i$
  $MaxTask = j_i$
  $MaxReward = f_i$
  $MaxTaskInc = \delta_i$
  SEND (*PreAuction Message*)
else
  $auction = 0$
end if
  RECEIVE (*PreAuction Messages*)
if $MaxTask_i = MaxTask_k, \forall k \in T$ **then**
  Find : *WinnerAgent*
else
  Agent wins the PreAuction Phase
end if
  SEND(*PreAuction Result*)

Synergy-Auction phase: in this phase, agents place bids for synergy tasks. Should an agent secure a task during the pre-auction phase, bids for synergy tasks are extended during the synergy-auction phase. Upon receiving a Pre-Auction Result message from another UAV pertaining to the task with the highest value in the synergy revenue matrix, the drone subsequently submits its bid for the corresponding task to the winning drone. The computation of the bid for the synergy task is based on the synergy revenue matrix, as detailed in Equation 18.

$$
\begin{gathered}
\gamma_i = g_i - h_i \\
j_i = \arg\max_{j=1,\ldots,n}\{R_{ij}^S\} \\
g_i = \max_j\{R_{ij}^S\} \\
h_i = \max_{j \neq j_i}\{R_{ij}^S\}
\end{gathered}
\tag{18}
$$

Upon receiving offer messages for synergy tasks, the agents winning the respective tasks are identified for the initial iteration. If $\delta_i > \gamma_i$ for the relevant task, the agent who broadcasts the auction message wins the task. Conversely, if a synergy offer results in $\gamma_i > \delta_i$, the agent making the offer wins the task. Should the agent who initiated an auction for the most valuable task receive no bids, they emerge as the winner.

Following the culmination of the synergy-auction phase, all agents disclose the tasks they have secured through the dissemination of the Synergy-Auction Result message. For agents unable to secure a task, the task ID is set to 0, and the message is broadcasted accordingly. Upon receiving this message, agents proceed to eliminate the corresponding task from the unassigned task list. This protocol serves to mitigate potential disagreements between agents and ensures an accurate record of unassigned tasks is maintained. The comprehensive procedure for the synergy-auction phase is delineated in Algorithm 2.

6. Simulation Experiments

We conducted three sets of simulations to assess the efficacy of our proposed task assignment algorithm, the Central Hungarian algorithm, and CBBA. Initially, we utilized our algorithm to assign 10 tasks to 5 aircraft, presuming no communication issues among the UAVs, to showcase its adeptness in heterogeneous task allocation. Following this, we employed Monte Carlo simulations across 100 scenarios without communication constraints, comparing our algorithm's performance with centralized and CBBA algorithms of regarding total task cost and message size. This comparison aimed to scrutinize assignment efficiencies in unfettered communication scenarios. Lastly, we analyzed scenarios where message transmission between aircraft was partial, comparing outcomes with Central Hungarian and CBBA algorithms, particularly focusing on unassigned and conflicting tasks, to evaluate assignment capabilities under communication limitations.

In the simulations, UAVs and assignments were distributed randomly across a 100x100 km. The UAVs move at a speed of 80 km/h and fly at an altitude of 1000 m. The UAV group consists of two types: reconnaissance and payload UAVs. Tasks are categorized into intelligence gathering (IG) and delivery (DL), each with specific time windows for execution; otherwise, they cannot be performed. Reconnaissance UAVs are dedicated to intelligence gathering tasks, while payload drones are equipped for deliveries. In simulation and field tests, certain constants are fixed: w_1=0.7, w_2=0.3, and τ =0.1. Users have the flexibility to adjust these constants based on task demands and UAV swarm characteristics. MATLAB software was utilized for simulations, executed on a personal computer featuring a 2.53 GHz Intel processor, 12GB of memory, and running the Windows 10 operating system.

Algorithm 2. Synergy-Auction Phase

Input: Pre-Auction Result, Unassigned task list
Output: Synergy-Auction Result
if *length* (*UnassignedTask*) < 2 **then**
  auction = 1
  Calculate : R_i^S
  $j_i = argmax_j(R_{ij}^S)$
  $g_i = max_j(R_{ij}^S)$
  $h_i = max_{j \neq ji}(R_{ij}^S)$
  $\gamma_i = g_i - h_i$
  SynergyTask = g_i
  SynergyTaskInc = γ_i
  SEND(*Bidding Message*)
else
  auction = 0
end if
Find : *WinnerAgent*

6.1. Heterogeneous UAV Swarm Task Assignment

Utilizing the algorithm introduced in this section, we assigned the 10 tasks outlined in Table 2 to the 5 aircraft specified in Table 3. The resulting aircraft routes obtained from the assignment are as follows: for agent 1, the route is 5, 2, and 1; for agent 2, it is 4 and 3; for agent 3, it is 9, 7, and 10; for agent 4, it is 6; and for agent 5, the route is 8. These routes are visually depicted in Figure 2.

As depicted in Figure 2, the proposed algorithm has successfully completed the task assignment process for the specified scenario without any conflicts. In the figure, the x and y axes correspond to the longitudinal and lateral positions of the aircraft, respectively, while the z axis represents the time constraints associated with the tasks.

Table 2. Task Parameters

ID	The coordinates of the task	Type	Time window of task validity	t_{td}
1	[117.92, 382.28]	IG	[69.04, 74.04]	5
2	[257.68, 479.90]	IG	[47.79, 52.79]	5
3	[527.33, 519.80]	IG	[99.35, 104.35]	5
4	[769.09, 615.00]	IG	[83.26, 88.26]	5
5	[167.90, 430.83]	IG	[10.22, 15.22]	15
6	[267.62, 384.62]	PL	[67.12, 82.12]	15
7	[678.08, 463.60]	PL	[20.89, 35.89]	15
8	[291.03, 238.99]	PL	[49.70, 64.70]	15
9	[464.14, 44.05]	PL	[15.12, 30.12]	15
10	[549.71, 632.80]	PL	[45.50, 60.50]	15

Table 3. UAV Parameters

Parameter	Value
The number of UAV	5
Type of UAV 1	Reconnaissance
Type of UAV 2	Reconnaissance
Type of UAV 3	Payload
Type of UAV 5	Payload
Type of UAV 5	Payload
Initial position of UAV 1	[365.07, 517.17, 0]
Initial position of UAV 2	[598.60, 726.87, 0]
Initial position of UAV 3	[707.61, 58.52, 0]
Initial position of UAV 4	[191.20, 740.49, 0]
Initial position of UAV 5	[719.82, 404.64, 0]

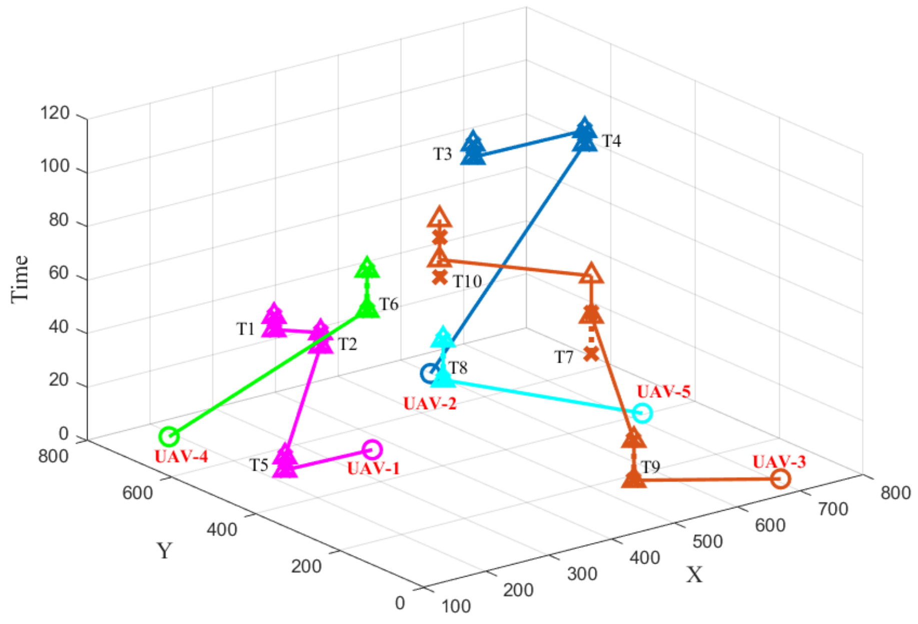

Figure 2. Agent Routes

6.2. Comparison with Similar Algorithms

In the subsequent phase of simulations, the performances of the proposed algorithm, as well as the Central and CBBA algorithms, were evaluated through Monte Carlo simulations. The objective was to allocate 20 tasks to 20 aircraft within a fully connected network structure, assuming no communication issues. Comparative analysis among the algorithms encompassed total mission cost, total message size (measured in bits), and communication channel signal-to-noise ratio (SNR) parameters. Monte Carlo simulations were executed across 100 different scenarios, with aircraft and mission locations being randomly generated for each scenario.

The total task cost cumulative probability density function (CDF) graph is provided in Figure 3. Total mission cost represents the collective distance traveled by each aircraft. The total task cost achieved by the proposed algorithm, due to its two-stage auction structure, outperforms CBBA and maintains a satisfactory proximity to the centralized solution.

The CDF graph in Figure 4 illustrates the total number of bits, signifying the overall size of messages transmitted during task assignment. This comparison enables us to assess the efficiency of various methods in terms of resource utilization. By quantifying the amount of data exchanged throughout the task assignment process, we can gain insights into the feasibility and scalability of implementing the proposed algorithm in real-world communication networks with limited bandwidth. As depicted in the figure, the proposed algorithm demonstrates the capability to address the problem with significantly smaller message sizes, attributed to the developed cost function, auction structure, and message format enhancements.

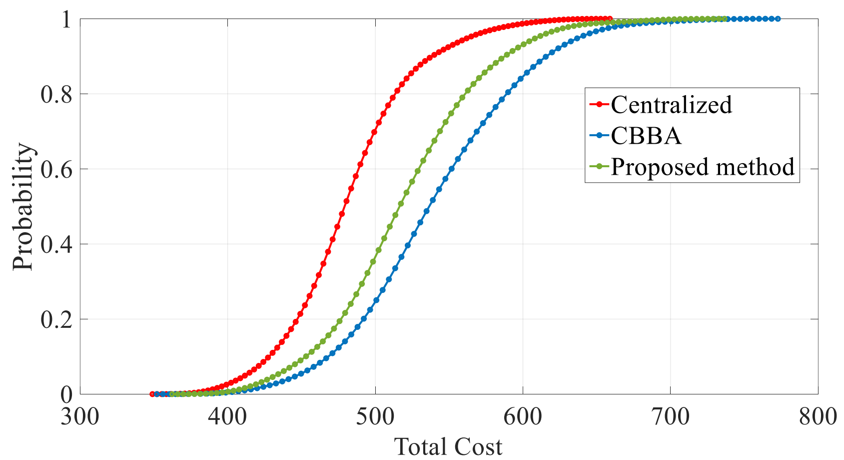

Figure 3. CDF of the Total Mission Cost

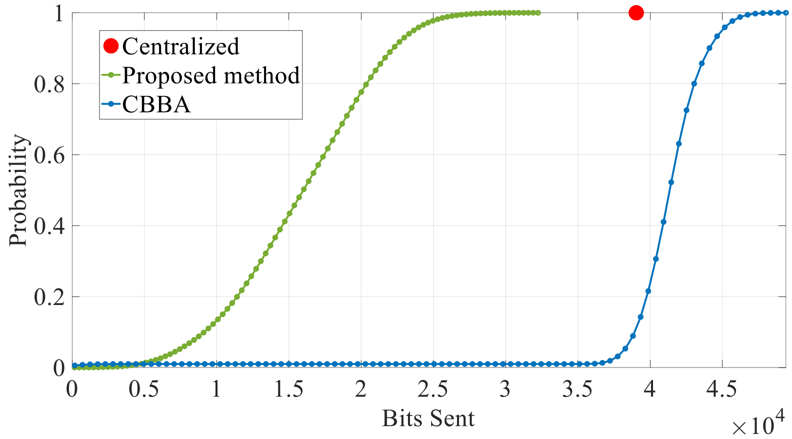

Figure 4. CDF Graph of Total Bits Sent

The comparison of average Signal-to-Noise Ratio (SNR) values of the communication channel is illustrated in Figure 5. Across all three algorithms, a consistent trend emerges where SNR values exceed 0 dB in 90% of the simulation runs. Notably, both CBBA and the centralized approach demonstrate SNR values surpassing 5 dB with nearly 0.8 probability. Conversely, Harmony achieves similar SNR values with slightly higher probabilities, around 0.9, thus creating a probability gap of approximately 0.1 to 0.2 for the same SNR values. Furthermore, in direct comparison to the other algorithms, Harmony showcases SNR values 2 dB higher for equivalent probabilities, underscoring its superior performance in maintaining reliable communication channels under various conditions.

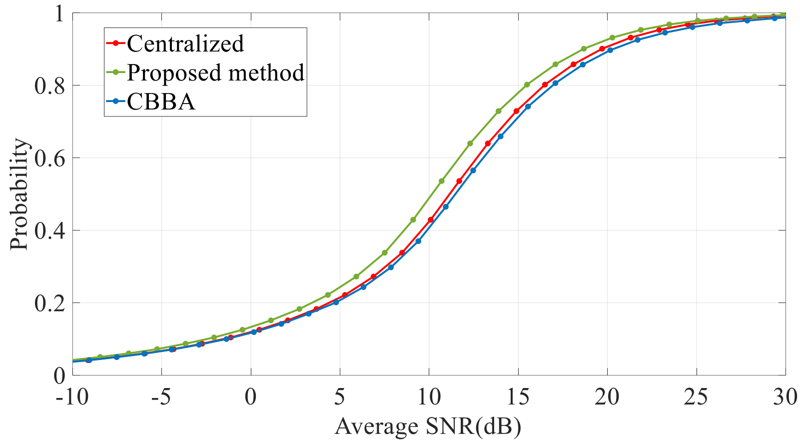

Figure 5. CDF Graph of the Average SNR

6.3. Comparision with Similar Algorithms Under Limited Communication

In this section, the proposed algorithm is evaluated against centralized and CBBA algorithms under scenarios where some messages may not be transmitted, employing the Bernoulli communication model. Simulations were conducted with varying probabilities of message non-transmission (0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%), and the algorithms were compared based on the number of unassigned tasks and conflicting tasks parameters.

Figure 6 displays the outcomes of simulating the allocation of 10 tasks among 5 agents under conditions of limited communication. In centralized assignment, where tasks are delegated by a single agent, conflict task assignment remains absent despite potential increases in communication errors. However, as the number of agents unable to communicate with the central agent rises, the count of unassigned tasks also escalates. In contrast, in CBBA, there is no notable change in the number of unassigned tasks even with heightened probabilities of communication error. Moreover, due to its consensus-based assignment approach, the fluctuation in the number of conflict tasks remains minimal even with elevated error rates. Although the proposed algorithm maintains a steady count of unassigned tasks within acceptable limits despite heightened communication error rates, its absence of a consensus stage results in an increase in conflict task assignments as the probability of communication errors rises.

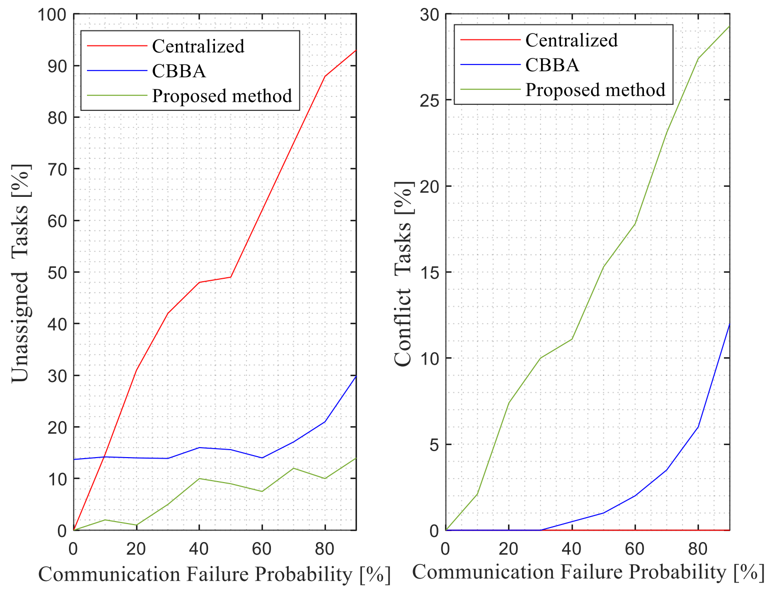

Figure 6. Assigning 10 Tasks to 5 Agents Under Limited Communication

Figure 7 presents the simulation results of distributing 100 tasks among 5 agents while varying the communication error rate in a similar manner as in Figure 6.

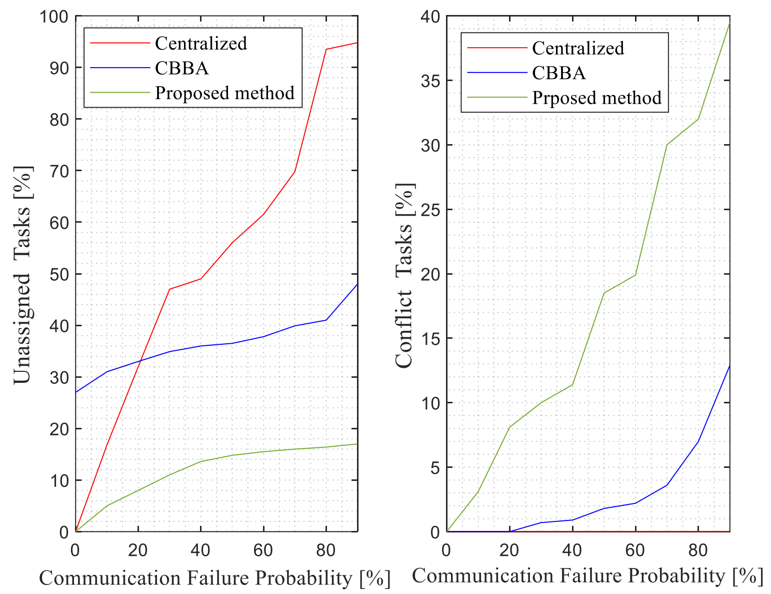

Figure 7. Assigning 100 Tasks to 5 Agents Under Limited Communication

The outcomes derived from three sets of simulations are as follows:

In situations devoid of communication issues, the centralized algorithm adeptly tackles the assignment problem with the least overall cost. However, due to the necessity for all agents to relay their cost matrices to the central agent, the collective message size expands significantly. Instances where communication obstacles arise and certain messages fail to transmit highlight a vulnerability of the centralized algorithm to single-point errors. Consequently, under such circumstances, while conflict assignments are absent due to assignments originating from a singular point, the count of unassigned tasks escalates.

CBBA, in contrast, often incurs higher task assignment costs compared to both the centralized and proposed algorithms under ideal communication conditions. Additionally, CBBA may encounter situations where it fails to assign certain tasks altogether. This is compounded by the necessity of transmitting three large datasets among agents during the consensus phase, resulting in a substantial total bit usage, which is especially problematic in bandwidth-constrained environments. Notably, CBBA's performance and system-wide efficiency are significantly impacted by bandwidth availability. However, in scenarios where communication issues arise and messages fail to transmit, CBBA demonstrates resilience by executing the assignment process with fewer unassignable and conflicting tasks, albeit requiring extended iterations. Thus, CBBA appears more suitable for environments without bandwidth constraints but with potential message loss risks.

The proposed algorithm excels in resolving the assignment problem with lower costs compared to CBBA, particularly in scenarios without communication hindrances. Its performance is commendably close to that of the centralized approach. Moreover, owing to its two-stage auction mechanism and message structure, it achieves problem resolution with minimal bit usage, offering a distinct advantage in bandwidth-constrained environments. In environments where all messages can be reliably transmitted, the proposed algorithm demonstrates superior performance. However, when communication issues arise and messages fail to transmit, the algorithm faces challenges. Even if the proposed algorithm manages to assign all tasks under such circumstances, conflicts may arise due to the absence of a consensus stage. As the probability of communication errors increases, the incidence of conflict assignments also rises.

7. Conclusion

In this research endeavor, a novel approach is introduced for the distributed task assignment within UAV swarms. The efficacy of the proposed algorithm is scrutinized across varying conditions, including scenarios of poor communication. The algorithm's core objective revolves around curtailing message sizes exchanged between agents, thereby minimizing the overall bit consumption during assignment through a two-stage auction process. This process involves drones bidding on tasks while considering synergistic tasks, steering clear of a purely opportunistic approach of selecting tasks solely based on immediate benefits.

To gauge the performance of the proposed algorithm, Monte Carlo simulations were conducted under differing communication scenarios, ranging from seamless communication to various levels of message loss. These results were juxtaposed against those obtained from the central Hungarian algorithm and CBBA.

The findings underscore the superiority of the proposed algorithm in resolving assignment quandaries with reduced costs compared to CBBA, particularly evident in communication-unfettered environments. Notably, its performance closely rivals that of the centralized approach. Furthermore, owing to its innovative two-stage auction mechanism and streamlined message structure, the algorithm achieves problem resolution with minimal bit utilization, offering a distinct advantage in bandwidth-constrained settings. In environments conducive to reliable message transmission, the proposed algorithm exhibits superior performance.

However, challenges emerge when communication issues disrupt message transmission, potentially leading to conflicts even if all tasks are successfully assigned. This underscores the necessity for a consensus stage, particularly in scenarios with heightened probabilities of communication errors.

Future investigations will incorporate a consensus stage to bolster the algorithm's performance under limited communication conditions. Following this augmentation, the algorithm's resilience in communication-constrained environments will be evaluated across diverse communication network topologies.

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Author(s) Contributions
All three authors contributed equally to the study.

Conflict of Interest Notice
The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical Approval and Informed Consent
It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

Availability of data and material
Not applicable.

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