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Auction-based distributed task allocation algorithm for drone swarms

Dron sürüleri için müzakere tabanlı dağıtık görev atama algoritması

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Abstract

Drone swarm research has surged due to their superior task performance. This paper introduces Harmony DTA, an auction-based algorithm for task allocation in heterogeneous drone swarms. Prior research primarily focuses on minimizing overall costs associated with assignments. In contrast, Harmony DTA not only minimizes total costs through an enhanced cost calculation function, but also ensures equitable distribution of workload among drones. Additionally, the proposed two-stage auction process reduces the total message size utilized during communication. Simulations and field tests were conducted to assess the effectiveness of the proposed algorithm. In addition, the performance of the algorithm was evaluated by comparing it with the CBBA (Consensus-Based Bundle Algorithm) algorithm in cases where all messages are transmitted between agents and some messages are not transmitted due to communication problems. Based on the simulation findings, the suggested algorithm demonstrates an ability to address the assignment problem with a mean cost reduction of 20% and a mean reduction in message size of 50% compared to CBBA in scenarios without communication issues. However, in situations where communication obstacles lead to some messages being untransmitted between agents, Harmony DTA exhibits inferior performance to CBBA, attributed to conflicting assignments arising from the absence of a consensus phase.

Keywords: Drone swarm, Task allocation, Distributed computing, Auction algorithm

Öz

Dron sürüleri üzerine yapılan araştırmalar, üstün görev performansları nedeniyle ivme kazanmıştır. Bu makale, heterojen drone sürülerinde görev dağılımı için açık artırmaya dayalı bir algoritma olan Harmony DTA'yı tanıtıyor. Literatürde var olan araştırmalar öncelikle görevlerle ilgili toplam maliyeti en aza indirmeye odaklanmaktadır. Harmony DTA ise gelişmiş maliyet hesaplama fonksiyonu aracılığıyla yalnızca toplam maliyeti en aza indirmekle kalmaz, aynı zamanda iş yükünün dronlar arasında adil bir şekilde dağıtılmasını da sağlamaktadır. Ayrıca önerilen iki aşamalı açık artırma süreci, iletişim sırasında kullanılan toplam mesaj boyutunu da azaltmaktadır. Önerilen algoritmanın etkinliğini değerlendirmek için simülasyonlar ve saha testleri yapılmıştır. Ek olarak algoritmanın performansı CBBA (Konsensus Tabanlı Demet Algoritması) algoritmasıyla ajanlar arasında tüm mesajların iletildiği ve haberleşme sorunları nedeniyle bazı mesajların iletilmediği durumlar için de karşılaştırılarak değerlendirilmiştir. Elde edilen simülasyon sonuçlarına göre önerilen algoritma haberleşme sorunsuz ortamlarda CBBA'ya göre ortalama %20 daha düşük maliyet ve ortalama %50 daha az mesaj boyutu ile atama problemini çözebilmektedir. Haberleşme sorunu nedeniyle ajanlar arsında bazı mesajların iletilemediği ortamlarda ise Harmony DTA, fikir birliği aşamasına sahip olmaması nedeniyle çakışan atamalar yaparak CBBA'ya göre daha kötü performans sergilemektedir.

Anahtar Kelimeler: Dron sürüsü, Görev Atama, Dağıtık hesaplama, Açık artırma algoritması

1 Introduction

With advancements in technology, drones have found applications in various fields including military, agriculture, transportation, security, damage assessment, and photography. A drone swarm refers to a network of multiple drones capable of autonomous collaboration to achieve a shared objective. Each individual drone within the swarm is referred to as an agent. The utilization of drone swarms is gaining attention due to their ability to perform tasks more effectively than a single drone, particularly in hazardous military operations [1].

A swarm is typically described as a cohesive assembly collaborating cohesively to accomplish a particular goal or behavior. Similarly, the concept of a drone swarm denotes a network composed of numerous drones equipped with communication abilities, autonomous functionality, and aligned towards a common aim.

The agents within the swarm is equipped with sensors, tools, or weaponry tailored to its specific purpose. For instance, combat drones are outfitted with weapons, reconnaissance drones feature advanced sensors for threat detection, among other functionalities. These individual drones can collaborate within the swarm to undertake more complex tasks [2]. The fault tolerance of a drone swarm significantly surpasses that of a single drone, as the failure of one drone does not impede the overall task execution of the swarm. It is anticipated that in the near future, drone swarms

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will supplant conventional unmanned aerial vehicles and other costly weapon systems [3].

The primary factor that impacts the success of a drone swarm in achieving its objectives is the efficiency of intercommunication and information sharing among its individual drones. The main limitation on the scale of a drone swarm is its ability to manage the flow of information effectively [4]. One of the primary drawbacks associated with drone swarms is the inherent difficulty in coordinating them effectively. Many coordination challenges such as task assignment entail solving NP-hard problems, rendering optimal solutions often elusive and exhibiting poor scalability [5].

Task assignment serves as the foundation of a drone swarm's operation. In a swarm system, task assignment essentially involves solving an optimization problem to ensure that tasks of varying positions and significance are effectively carried out by drones possessing diverse positions and capabilities.

Algorithms employed to address the task assignment problem are generally categorized into two main groups: centralized and distributed algorithms.

Centralized task assignment algorithms operate with a central coordinator agent responsible for communicating with all other agents. This coordinating agent facilitates negotiations among the other agents and makes decisions regarding task assignments. Typically, a utility function covering all considered agents is employed in this process. As task assignment occurs centrally, conflicts during assignment are avoided, and there is no need for a consensus stage, enabling the attainment of optimal solutions. However, drawbacks include the vulnerability of the entire system if the coordinator agent becomes damaged. Furthermore, centralized algorithms are better suited for systems with fewer agents due to the high computational costs involved [6].

Distributed task assignment algorithms operate without a coordinator agent, and tasks are distributed among agents through negotiations among themselves. Numerous distributed decision-making algorithms have been developed to address the limitations of centralized decision-making algorithms and mitigate the risk of single-point errors in the system.

Market-based task allocation algorithms exemplify notable instances of distributed algorithms. Auctions form the cornerstone of these algorithms, where agents participate in bidding for tasks, and the highest bidder wins the task.

The task assignment problem, being a combinatorial optimization issue, holds fundamental significance, with any linear optimization problem being potentially linked to it. Consequently, various approaches have been suggested in the literature to address this fundamental problem.

Kuhn's Hungarian algorithm [7], introduced by the Hungarian mathematician Kuhn in 1955, represents the first approach to task assignment. This method, widely employed for solving assignment problems, is characterized by its simplicity and accessibility. In small systems operating within static environments, centralized methods are viable for identifying optimal task assignments. However, as the number of agents grows and problem complexity escalates, centralized approaches become impractical to scale effectively.

An algorithm for the genetic algorithm-based solution of the task assignment problem is presented in [8]. Given the complexity where some tasks necessitate the involvement of more than one agent for completion, the algorithm accommodates this requirement.

Freitas et al. [9] introduced an algorithm designed for the efficient and decentralized identification and allocation of tasks within UAV swarms. The primary focus of the research is on minimizing message size through the implementation of a low-level protocol for distributed task assignment in multi-UAV networks.

In [10], an auction-based algorithm tailored for task assignment is introduced, accounting for the diverse capacities of heterogeneous agents and the varied requirements of heterogeneous tasks.

Exploration missions in unknown environments, as studied in [11] and [12], involve agents autonomously generating and selling missions through single-item auctions. However, managing rewards for agents necessitates a central decision maker.

Effective bidding rules play a crucial role in achieving near-optimal solutions in task assignment. [13] and [14] specifically focus on devising bidding rules for navigation tasks. Their proposed method entails a multi-round auction process, where each agent bids on its most cost-effective task.

In [15], two distinct greedy-based centralized auction algorithms are introduced for assigning heterogeneous tasks in heterogeneous multi-agent systems. The objective is to distribute tasks in a manner that minimizes energy consumption during task execution, while also considering the maximum completion time for the tasks.

IDMB [16] represents a market-based task assignment algorithm. In this approach, each agent is initially assigned a task with a number identical to its ID. Subsequently, each agent serves as a negotiator for its respective task, while the remaining agents function as bidders for this task.

In [17], two objective functions were delineated to address the MRGAP (Multi-Robot Generalized Assignment Problem), which includes fitness constraints signifying that not all tasks can be assigned to every agent. These objective functions were amalgamated using the weighted sum method. The primary objective function seeks to minimize the sum of squares of the agents workloads, while the secondary objective aims to minimize the total number of agents assigned tasks. A centralized solution approach is employed in this context.

The CBBA (Consensus Based Bundle Algorithm) [18] is a widely utilized market-based multitask sharing algorithm, which is an expanded iteration of the CBAA (Consensus Based Auction Algorithm) designed for addressing the multiple assignment problem. In the CBBA framework, each agent maintains a list of tasks that could potentially be assigned to them. The auction process operates at the task level rather than the package level. CBBA comprises two primary stages: bundle construction and conflict resolution. During the bundle construction phase, each agent constructs a bundle using a greedy approach and continually updates it throughout the assignment process, adding tasks until the bundle reaches its capacity. In the conflict resolution phase, agents exchange three datasets containing information on the winning agents, winning bids, and bid update time. Following predefined rules, agents update the winning bid and winning agent lists, ensuring consensus among all agents regarding the winning agent for the tasks.

The majority of studies in the literature on task assignment in multi-agent systems accept that there is perfect communication between agents and that the communication channel has unlimited bandwidth [19]. However, in real life, drone swarms operate in environments where bandwidth is limited. Some studies developing algorithms for agent coordination in multi-agent systems under limited bandwidth are listed as follows. Otte and Correll [20], Kassir et al. [21], Guo et al. [22], Kantaros et al. [23], Best et al. [24], Williams et al. [25], Zhou et al. [26], Vander Hook et al. [27], Li et al. [28].

Lately, there has been a surge of interest in drone swarms, leading to increased focus on research into task allocation within unmanned aerial vehicle (UAV) swarms. The ideal task assignment algorithm for drone swarms can vary depending on specific application needs [29], swarm scale, communication capacities, and environmental conditions [30].

Afghah et al. [31] introduced a novel approach to fire surveillance utilizing a group of UAVs. The objective of this system is to offer rapid response times by employing a decentralized leader-follow coalition algorithm, which reduces the number of drones needed and minimizes energy usage while ensuring comprehensive area coverage within an efficient timeframe.

Oberlin et al. [32] and Kim et al. [33] extend the multi-traveling salesmen problem to encompass multi-UAV path planning tailored for reconnaissance and surveillance applications.

Sujit et al. [34] introduce a team-based method enabling UAVs to make decisions autonomously in scenarios where communication among UAVs is unavailable.

Heuristic algorithms have gained traction in drone task allocation. For instance, L. Huo et al. [35] introduced a simulated annealing algorithm with exchange and judgment mechanisms to enhance the generation of feasible adjacent solutions efficiently. Similarly, S. Gao et al. [36] incorporated a negative feedback mechanism into a group algorithm to accelerate convergence and achieve quicker results.

Some recent studies explores task assignment within drone swarms by combining genetic algorithms and neural network logic. This approach is exemplified in studies such as Changliang et al. [37], Song et al. [38], Wang et al. [39].

Creating a truthful combinatorial auction mechanism is inherently challenging due to the multiple private parameters each UAV possesses. Wu et al. [40] addressed this issue by introducing an anti-strategy auction mechanism tailored for spectrum allocation, employing combinatorial auctions.

This study introduces Harmony DTA, an auction-based distributed task assignment algorithm specifically designed for application in heterogeneous drone swarms. The primary contributions of Harmony DTA include:

• Maximizing the overall system benefit and minimizing task assignment costs through the implementation of a two-stage auction structure.

• Thanks to the developed cost calculation function, it ensures almost equal sharing of the workload among drones.

• Due to the proposed communication protocol, the message sizes transmitted are minimized, consequently reducing the total number of bits utilized for task assignment.

• The effectiveness of most task assignment algorithms in the literature hasn't been scrutinized in settings with communication obstacles. This study's contribution lies in assessing both the suggested algorithm and the CBBA algorithm, prevalent in existing literature, within environments hampered by communication issues.

The structure of this article is as follows: Section II elucidates the task assignment problem and introduces the case studies for task allocation within drone swarms. Section III introduces the proposed distributed decision-making algorithm. Section IV details the simulation results of the proposed algorithm and presents data from performance comparisons with the CBBA algorithm. Section V outlines the conducted field tests. Section VI is the conclusion.

2 Task assignment problem description

This section outlines fundamental definitions pertaining to the task assignment problem within drone swarms, along with the constraints and assumptions associated with it. The drone swarm comprises N drones, each possessing distinct capabilities. Denoted as D, the swarm consists of N heterogeneous drones and can be symbolized as articulated in Equation (1).

$$D = \{1, 2, ..., N\} \tag{1}$$

The system comprises M tasks, all of which are heterogeneous. Each task requires a drone with the appropriate capability to fulfill it. The set T, representing the collection of M tasks, is denoted as depicted in Equation (2).

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

The objective is to allocate assignments to drones in a manner that maximizes the overall benefit of the collective group. This scenario is represented through mathematical expression in Equation (3).

$$\max \sum_{i=1}^{N} \sum_{j=1}^{M} x_{ij} R_{ij} \tag{3}$$

If task j is assigned to agent i, then x_{ij}=1; otherwise, x_{ij}=0. R_{ij} denotes the utility value that agent i will attain if assigned task j. The constraints and assumptions specified for the problem are as follows:

A drone is capable of executing only one task at a time, and its velocity remains constant throughout the duration of the task.

Each task necessitates the assignment of a single drone, as indicated in Equation (4). This condition ensures that the algorithm proposed is devoid of conflicts.

$$\sum_{i=1}^{N} x_{ij} = 1, j \in T \tag{4}$$

The task initiation must occur within the predefined timeframe as indicated in Equation (5).

$$t_{start_j} \leq t_{d_{ij}} \leq t_{finish_j} \tag{5}$$

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 drones should be balanced, aiming to distribute the workload evenly among the drones. This constraint is articulated in Equation (6).

$$|s_i| - |s_k| \leq B, i \neq k \tag{6}$$

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

2.1 Case studies for UAV task assignment problem

This subsection presents two case studies for investigating the task assignment challenge within drone swarms.

Within the case studies, drones and tasks were randomly dispersed across an area measuring 25×25 meters. The heterogeneous drone swarm consists of two different types of drones: reconnaissance and payload drones. Tasks are categorized into two types: intelligence gathering (IG) and delivery (DL), each with a defined time window. It's imperative that tasks commence within this time period; otherwise, the task cannot be executed. Reconnaissance drones are limited to performing intelligence gathering tasks, whereas payload drones are capable of executing delivery tasks.

Drones possess comprehensive information about the tasks, and the tasks remain static, implying they do not change over time nor are new tasks added. A complete communication structure is established among drones, enabling all drones to communicate with each other effectively.

In the first case study, where algorithm performances are compared, there are 3 drones and 9 tasks. Drone 1 is of reconnaissance type, while Drone 2 and Drone 3 are payload type drones. Tasks 1, 2, 3 and 4 are intelligence gathering type tasks, while Tasks 5, 6, 7, 8 and 9 are delivery type tasks. The drone parameters for the first case study are given in Table 1, and the task parameters are given in Table 2.

In the Table 2, IG denotes the intelligence gathering task type, DL denotes the delivery task type, and t represents the duration of the task.

Table 1. Drone parameters for first case study

Parameter	Value
The number of drones	3
Type of Drone 1	Reconnaissance
Type of Drone 2	Payload
Type of Drone 3	Payload
Initial position of Drone 1	[-0.65,2.80,0]
Initial position of Drone 2	[3.72,6.97,0]
Initial position of Drone 3	[5.76,-6.33,0]

Table 2. Task parameters for first case study

ID	The coordinates of task (x,y,z)	Type	Time window of task validity (s)	t(s)
1	[7.25,5.99,1.07]	IG	[23.90,28.90]	5
2	[-5.28,0.11,1.19]	IG	[69.04,74.04]	5
3	[-2.66,2.05,1.19]	IG	[47.79,52.79]	5
4	[2.38,2.85,1.97]	IG	[99.35,104.35]	5
5	[6.92,4.75,1.95]	DL	[83.26,98.26]	15
6	[-4.35,1.08,0.36]	DL	[10.22,25.22]	15
7	[-2.48,0.16,1.71]	DL	[67.12,82.18]	15
8	[5.21,1.73,1.18]	DL	[20.89,35.89]	15
9	[-2.04,-2.73,0.59]	DL	[49.70,64.70]	15

In the second case study, where algorithm performances are compared, there are 5 drones and 20 tasks. Drone 1 and Drone 2 are reconnaissance type drones, while Drone 3, Drone 4, and Drone 5 are payload type drones. Tasks 1 to 10 are intelligence gathering type tasks, and Tasks 11 to 20 are delivery type tasks. The drone parameters for the second case study are given in Table 3, and the task parameters are given in Table 4.

Table 3. Drone parameters for second case study

Parameter	Value
The number of drones	5
Type of Drone 1	Reconnaissance
Type of Drone 2	Reconnaissance
Type of Drone 3	Payload
Type of Drone 4	Payload
Type of Drone 5	Payload
Initial coordinate of Drone 1	[-0.87,3.73,0]
Initial coordinate of Drone 2	[4.96,9.30,0]
Initial coordinate of Drone 3	[7.69,-8.44,0]
Initial coordinate of Drone 4	[-5.21,9.66,0]
Initial coordinate of Drone 5	[7.99,0.74,0]

Table 4. Task parameters for second case study

ID	The coordinates of task [x,y,z]	Type	Time window of task validity (s)	t(s)
1	[-7.05,0.15,1.19]	IG	[69.04,74.04]	5
2	[-3.55,2.74,1.19]	IG	[47.79,52.79]	5
3	[3.18, 3.80, 1.97]	IG	[99.35,104.35]	5
4	[9.22, 6.33, 1.95]	IG	[83.26,88.26]	5
5	[-5.80,1.44,0.36]	IG	[10.22,15.22]	5
6	[-3.30,0.21,1.72]	IG	[67.12,72.12]	5
7	[6.95,2.31,1.18]	IG	[20.89,25.89]	5
8	[-2.72,-3.65,0.59]	IG	[49.70,54.70]	5
9	[1.60,-8.82,0.65]	IG	[15.12,20.12]	5
10	[3.74,6.80,0.63]	IG	[45.50,50.50]	5
11	[6.47,-3.67,1.86]	DL	[66.45,81.45]	15
12	[-9.19,-8.67,1.85]	DL	[86.77,101.77]	15
13	[-7.84,-4.44,0.43]	DL	[14.88,29.88]	15
14	[-7.15,2.30,0.76]	DL	[75.51,90.51]	15
15	[-9.56,3.09,1.39]	DL	[9.90,24.90]	15
16	[-2.23,1.78,1.13]	DL	[81.27,96.27]	15
17	[-8.90,-5.10,1.75]	DL	[33.27,48.27]	15
18	[-7.89,6.74,0.03]	DL	[92.49,107.49]	15
19	[8.49,1.13,0.02]	DL	[72.48,87.48]	15
20	[-6.96,5.81,0.30]	DL	[90.87,105.87]	15

3 Harmony Drone Task Allocation (DTA) algorithm

The Harmony DTA algorithm is an auction-based approach for dynamic task assignment within heterogeneous drone swarms.

The concept behind Harmony DTA draws from the management principle applied to large-scale projects, emphasizing the potential synergy between closely interrelated tasks within such projects. It suggests that by strategically designing or executing one task, it can positively influence the outcomes or processes of another, thus maximizing overall efficiency. In line with this principle, Harmony DTA offers a method to enhance the overall system benefits by leveraging the synergy between associated tasks, rather than assigning tasks individually to agents in each iteration.

The Harmony approach employs a two-stage auction process. Notably, the algorithm's auction mechanism consists of two distinct stages. Here, agents aim not only to win the task offering the highest individual benefit but also strive to acquire the task providing the second-highest benefit, commonly referred to as the synergy task. This dual-stage process distinguishes Harmony from existing task assignment algorithms found in the literature, where typically one stage involves an auction while the other entails reaching a consensus.

An example scenario where the proposed algorithm can be applied is shown in Figure 1. Here, there are 12 tasks categorized into 4 different types, alongside a total of 7 drones, each belonging to one of 3 distinct types. Notably, the scout drone's role revolves around patrolling to identify new tasks; upon detection, it relays this information to other drones without executing tasks itself. At time t_0, a predefined list of tasks necessitates assignment, with the potential for new tasks to emerge dynamically from either the Ground Control Unit (GCU) or the Scout drone. Drones of type 1 are capable of executing tasks categorized as types 1 and 2, whereas type 2 drones are suited for tasks classified as types 3 and 4. Each task is associated with a defined timeframe and duration for completion. Additionally, should a drone's charge level fall below a critical threshold, it must promptly return to the nearest GCU for recharging.

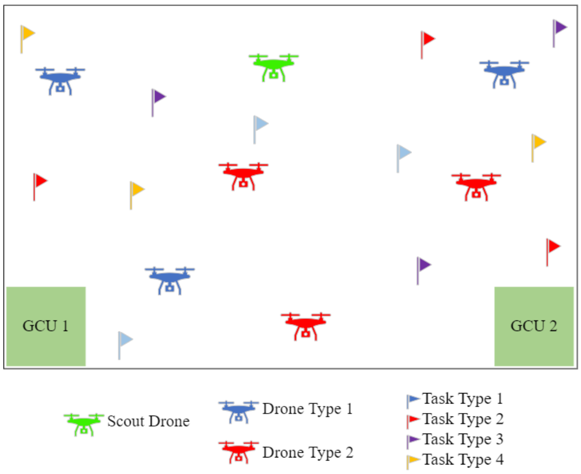

Figure 1. Sample scenario

Harmony DTA comprises three main modules: States and Modes, Logic, and CLAW. These modules are illustrated in Figure 2.

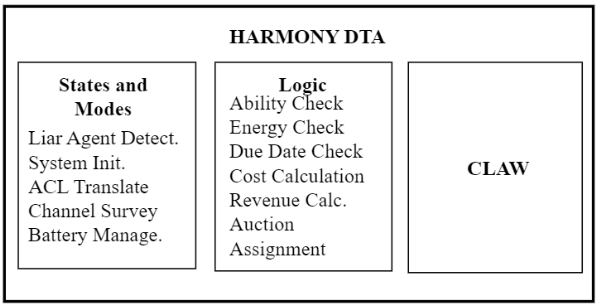

Figure 2. Modules of Harmony DTA

The States and Modes submodule is responsible for several tasks including detecting traitor agents, interpreting received messages and directing them to relevant subsystems, managing communication links, and monitoring drone battery levels. In essence, this submodule handles fundamental level controls for both individual agents and the entire swarm.

The Logic module acts as the central component where the task assignment algorithm functions. This section carries out various functions, including cost and reward calculations, auction processes, and task assignments. Task assignment takes place within the Logic module, utilizing a two-stage auction process called pre-auction and synergy-auction. This iterative process continues until all tasks are assigned.

Within the CLAW module, essential control loops and route planning operations are executed to enable the drone to fulfill its assigned task effectively.

In this study, the evaluation of the proposed algorithm's assignment performance was limited to static tasks, and detailed discussions on all its modules were not included within the scope of the study.

Table 5 presents the message package structure and corresponding values utilized by Harmony DTA for agent communication language.

Table 5. Message package structure

Agent Message Package Structure	
Package	***Description***
Receiving Address (8 Bit)	Specifies the receiving agent ID number. For broadcast messages, this value is "0xFF".
Sender Adress (8 Bit)	Specifies the ID number of the agent sending the message. The address of the central computer sharing the tasks is "0x00".
Message Type (8 Bit)	Indicates the type of message sent. This field can take up to 8 different values. 0x01: Sharing task locations 0x02: Pre-Auction 0x04: Pre-Auction Result 0x08: Bidding 0x10: Synergy-Auction Result 0x20: Dron Trust Calculation 0x04: Task completion notification 0x80: Ping message
Task Number (8 Bit)	Indicates the number of the task.
MaxReward (32 Bit)	Indicates the reward value of the best task.
MaxTaskInc (32 Bit)	Indicates the δ value.
SynergyTaskInc (32 Bit)	Indicates the γ value.
Auction (1 Bit)	Indicates that the agent is in the process of auction for the task.
longitude (64 Bit)	Longitude value of location information from GPS.
Latitude (64 Bit)	Latitude value of location information from GPS.
Agent Number (8 Bit)	It is the area where the ID numbers of the relevant agent are kept in the message packets of the traitor and disabled agents.
Time Information (64 Bit)	It is the field that is sent periodically to measure the quality of the communication channel and indicates the time elapsed since the start of the task.

3.1 Cost function design

The cost function is used to calculate the task costs of the drone, it consists of two components: balance cost and distance cost. The cost of task *j* for agent *i*, denoted as C_{ij}, is computed using Equation (7). w_1 and w_2 are the distance and balance cost coefficients, respectively.

$$C_{ij} = w_1 C_{ij}^D + w_2 C_{ij}^B \tag{7}$$

The balance cost $\left(C_{ij}^B\right)$ for drone *i* performing task *j* is determined using Equation (8), which takes into account the task load of the drone.

$$C_{ij}^B = \frac{|b_i|}{MT_i} \tag{8}$$

where $|b_i|$ represents the number of elements in the task list of drone *i* and MT_i denotes the maximum number of tasks that drone *i* can add to its task list.

The distance cost $\left(C_{ij}^D\right)$ of drone *i* for task *j* is determined by Equation (9), which considers the distance of the drone to the task location.

$$C_{ij}^D = \frac{d_{ij}}{MFD_i} \tag{9}$$

where MFD_i represents the distance of drone *i* to the farthest task, while d_{ij} denotes the distance between drone *i* and task *j*. The cost matrix for agent *i* is expressed as depicted in Equation (10).

$$C_i = [C_{i1} \quad C_{i2} \quad \dots \quad C_{iM}] \tag{10}$$

Employing the defined cost function, the local utility value is computed according to Equation (11), where R_{ij} represents the utility value for agent *i* of task *j*.

$$R_{ij} = V_j e^{-\tau*(tc_{start}-(tp_{start}+tp_{duration}))} - C_{ij} \tag{11}$$

In this context, 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* is able to 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 the calculation of 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 (11). The utilization of the synergy income 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.

3.2 Pre-auction phase

The first stage of the Harmony DTA algorithm. During this stage, the drone conducts an initial check to determine if its task list has reached maximum capacity. If the task list is already full, the drone is excluded from the auction and subsequent task assignment processes. If there is available space for a new task in the task list, the drone 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 (12), where s_i represents the utility value of the agent's second-best task.

$$\begin{aligned} \delta_i &= f_i - s_i \\ j_i &= \arg \max_{j=1,\dots,n} \{R_{ij}^N\} \\ f_i &= \max_j \{R_{ij}^N\} \\ s_i &= \max_{j \neq j_i} \{R_{ij}^N\} \end{aligned} \tag{12}$$

After receiving auction messages from all agents, the drone checks whether other drones have initiated an auction for the same task. If multiple drones have started an auction for a task, the drone with the highest reward value wins the task. In cases where income values are equal, the drone with the smaller ID wins the task. This process is referred to as the pre-auction. The winning drone announces its success to other agents in the swarm with a Pre-Auction Result message.

The winning drone in the pre-auction can also bid for the synergy task in the second stage. The drone that loses the preliminary auction cannot bid on the synergy task either.

3.3 Synergy-auction phase

This stage involves making bids for synergy tasks. If an agent wins a task during the pre-auction phase, synergy task bids are extended for synergy task during the synergy-auction phase. If the drone receives a Pre-Auction Result message from another drone regarding the task with the highest value in the synergy revenue matrix, it then forwards its bid for the relevant task to the winning drone. When computing the bid for the synergy task, the drone determines it using the synergy revenue matrix, as outlined in Equation (13).

$$\begin{aligned} \gamma_i &= g_i - h_i \\ j_i &= \arg \max_{j=1,\dots,n} \{R_{ij}^S\} \\ g_i &= \max_j \{R_{ij}^S\} \\ h_i &= \max_{j \neq j_i} \{R_{ij}^S\} \end{aligned} \tag{13}$$

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.

At the conclusion of the synergy-auction phase, all agents announce the tasks they have won using the Synergy-Auction Result message. Agents unable to win a task set the task ID to 0 and broadcast the message accordingly. Agents receiving the message then remove the corresponding task from the unassigned task list. This measure helps prevent disagreements between agents and maintains an accurate record of unassigned tasks.

4 Simulation experiments

In this section, simulation studies to evaluate the performance of Harmony DTA are presented first. Additionally, to compare the algorithm's performance with existing approaches, the CBBA algorithm proposed by Choi et al. [18] was also implemented, and the performance comparison results obtained were subsequently shared.

The primary rationale behind selecting the CBBA algorithm for comparison with the proposed algorithm is its auction-based nature, which mirrors that of the proposed algorithm. This characteristic lends itself well to heterogeneous drone swarms operating in dynamic environments, making CBBA a suitable benchmark. Furthermore, the authors' familiarity and expertise with CBBA reinforced this decision. CBBA is recognized for its effectiveness in mitigating and streamlining the complexity of contemporary challenges, and its widespread use in various applications, including coordination and task allocation within UAV swarms, underscores its relevance and applicability.

Numerous studies have investigated the effectiveness and efficiency of traditional CBBA and its enhanced iterations within the realm of drone swarms. This prevalence of research served as a key motivation for evaluating the proposed algorithm against CBBA. Chen et al. [41] present a variation of CBBA known as CBBA with local replanning (CBBA-LR), designed to swiftly generate dependable task replanning solutions in response to new tasks. CBBA-LR employs a capable matrix to signify the capable relationship between UAVs and tasks, ensuring that only capable UAVs for the new task are incorporated in the task replanning process. Choi et al. [42] propose an extension to the Consensus Based Bundle Algorithm (CBBA) in two notable ways. Firstly, CBBA has been enhanced to enable safe routing of UAVs around ground environment obstacles. Secondly, CBBA now addresses the issue of churning in UAV flight paths caused by uncertainty in target situational awareness. [43-45] have refined the traditional CBBA algorithm, focusing particularly on enhancing task bundle construction methodologies. [46, 47] have enhanced the classical CBBA algorithm by addressing various aspects such as information interaction modes, efficiency, and task types. [48, 49] have advanced the classical CBBA algorithm by concentrating on enhancing its structural framework. Yan et al. [50] propose three enhancements to the classic CBBA algorithm. Firstly, they augment the information exchange between humans and machines. Secondly, they integrate task time windows to cater to the demands of close combat scenarios. Thirdly, they introduce task-time indicators to prioritize tasks that are geographically closer to the UAVs themselves.

In simulation and field tests, w_1= 0.7, w_2= 0.3 and τ = 0.1. These constants can be changed by the user depending on the task and swarm type.

Matlab software was used for simulations. The personal computer utilized for these simulations features a 2.53GHz

Intel processor, 12GB of memory, and operates on the Windows 10 operating system.

4.1 Assignment results for case studies

The drone routes resulting from the assignment of 9 tasks to 3 drones using Harmony DTA for the first case study, as outlined in the third section, are illustrated in Figure 3. Within the figure, the x and y axes denote the longitudinal and lateral positions of the aircraft, respectively, while the z axis signifies the time constraints linked to the tasks.

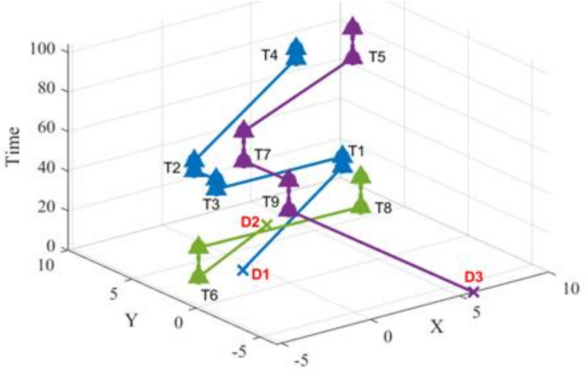

Figure 3. Agent routes for first case study

As illustrated in Figure 3, Harmony DTA has effectively completed the task assignment process for the defined scenario without encountering any conflicts. Tasks were assigned to appropriate drones based on their types and time frames and were integrated into their paths. Specifically, drone 1 will execute tasks 1, 3, 2, and 4 sequentially, drone 2 will execute tasks 6 and 8, and drone 3 will undertake tasks 9, 7, and 5 respectively.

The drone routes resulting from the assignment of 20 tasks to 5 drones using Harmony DTA for the second case study, as outlined in the third section, are illustrated in Figure 4. Drone 1 will execute tasks 5, 9, 7, and 8 sequentially, drone 2 will execute tasks 10, 2, 6, 1, 4 and 3 sequentially, drone 3 will execute tasks 11 and 20 respectively, drone 4 will execute tasks 15, 13, 17, 14, 16 and 18 respectively, drone 5 will execute tasks 19 and 12 respectively.

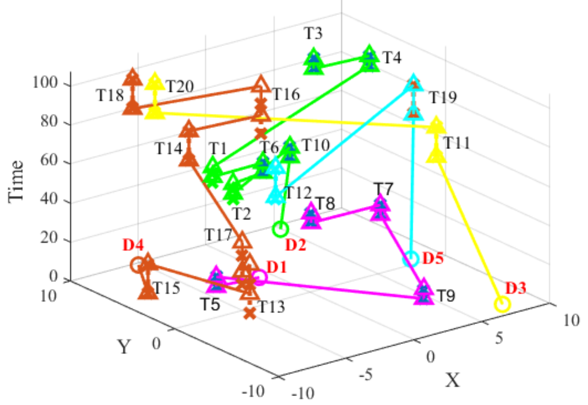

Figure 4. Agent routes for second case study

4.2 Comparison with CBBA

The results and comparisons regarding the assignments obtained with Harmony DTA and CBBA for the first case study are provided in Table 6 and Table 7. In the comparison result tables, total travel distance represents the cumulative distance travelled by all agents upon completion of the assignment. Total message number indicates the overall count of messages exchanged between agents during problem-solving. Number of unassigned tasks signifies the quantity of tasks that the algorithm fails to assign to any agent. Total message size corresponds to the aggregate size, in bits, of all messages transmitted between agents during the problem-solving process. In the assignment result tables, "Harmony DTA path" denotes the route formulated for the respective agent when a task is assigned using Harmony, while "CBBA path" signifies the route devised for the relevant agent when a task is assigned using CBBA. "Harmony travel distance" represents the distance in meters that the relevant agent will traverse when a task is assigned using Harmony, while "CBBA travel distance" indicates the distance in meters that the relevant agent will cover when task assignment is made using CBBA.

Table 6. Comparison results of case study 1

Method	Total Travel Distance (m)	Total Message Number	Number of unassigned tasks	Total message size (bit)
Harmony	16.35	27	0	585
CBBA	17.11	15	1	6600

Table 7. Assignment results of case study 1

Agent ID	Harmony DTA Path	Harmony Travel Dist. (m)	CBBA Path	CBBA Travel Dist.(m)
1	1,3,2,4	7,70	1,3,2	7,70
2	6,8	4,03	6,5,4	9,41
3	9,7,5	4,61	9,7	0

In the first case study, Harmony DTA successfully solved the assignment problem with a lower total cost compared to CBBA. Furthermore, while CBBA failed to assign a task to any agent, Harmony DTA appropriately assigned all tasks to drones. In CBBA, agents employ a greedy strategy to form a route in each cycle, appending the task that yields the highest benefit to the route. However, this approach may result in the failure to assign certain tasks, as evidenced by the unassigned task in case study 1. Conversely, Harmony DTA achieves full task assignment by considering synergies, such as proximity relations among tasks, facilitated by its two-stage auction process. When comparing the total message sizes, the CBBA algorithm requires larger message sizes due to its necessity for all agents to share the y, z, and s vectors in the conflict resolution phase, resulting in a solution using 6600 bits. In contrast, Harmony DTA, thanks to its two-stage auction mechanism, achieved much smaller message sizes, solving the problem with only 585 bits. Although the total number of messages transmitted between drones to solve the problem is higher for Harmony DTA due to its two-stage auction process.

The results and comparisons regarding the assignments obtained with Harmony DTA and CBBA for the second case study are provided in Table 8 and Table 9.

Table 8. Comparison results of case study 2

Method	Total Travel Dist.(m)	Total Message Number	Number of unassigned tasks	Total message size (bit)
Harmony	50.39	103	0	2273
CBBA	53.79	40	1	57920

Table 9. Assignment results of case study 2

Agent ID	Harmony DTA Path	Harmony Travel Dist.(m)	CBBA Path	CBBA Travel Dist.(m)
1	5,9,7,8	12.58	5,7,2,6,3	9.76
2	10,2,6,1,4,3	11.32	9,10,8,1,4	21.93
3	11,20	7.27	13,17,11,12	12.59
4	15,13,17,14,16,18	13.46	15,14,18	5.46
5	19,12	5.74	19,20	4.03

In second case study, Harmony DTA outperforms CBBA in task assignment, achieving lower total travel distance and message size thanks to the proposed message structure and two-stage auction process. In addition, similar to the first case study, CBBA could not assign a task to any agent due to its greedy approach.

In order to express the contribution of the proposed algorithm more clearly, in the subsequent phase of simulations, the performances of the proposed algorithm, as well as the CBBA algorithm, 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 (measured in meters) and total message size (measured in bits) 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 5. 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.

The CDF graph in Figure 6 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.

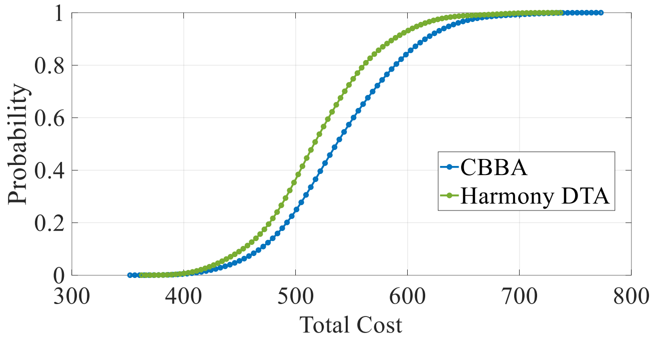

Figure 5. CDF of the total mission cost

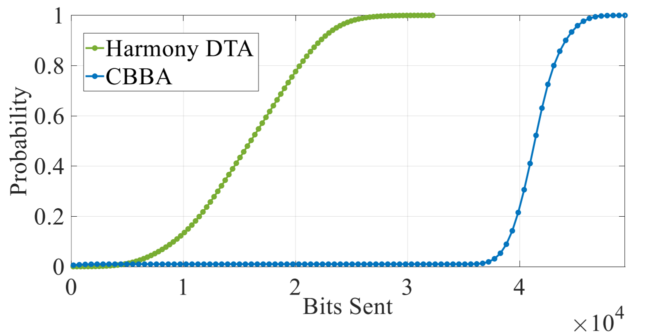

Figure 6. CDF graph of total bits sent

4.3 Comparison with CBBA under limited communication

In this section, the proposed algorithm is evaluated against the CBBA under the scenario 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 7 displays the outcomes of simulating the allocation of 10 tasks among 5 agents under conditions of limited communication. 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.

When communication issues arise and messages fail to transmit, the harmony DTA 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.

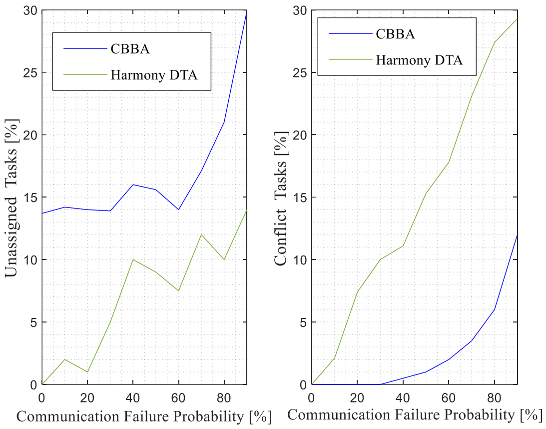

Figure 7. Assigning 10 tasks to 5 agents under limited communication

5 Field experiments

To demonstrate the practical applicability of Harmony DTA in real-world scenarios, the algorithm was implemented on a swarm of two drones, and field tests were conducted at Ankara University Campus on 15.12.2023.

The drones utilized for the field tests are the Ryze Tello models produced by DJI. A custom hardware setup has been designed for the drones to acquire location information and facilitate communication between them. This hardware primarily comprises a LoRa module, a GPS module, and a microcontroller. The developed system architecture is illustrated in Figure 8.

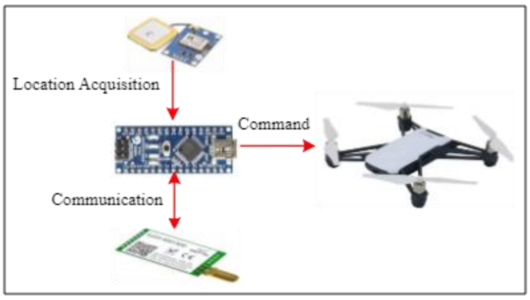

Figure 8. System architecture

A photo of the drone swarm used in field tests is given in Figure 9.

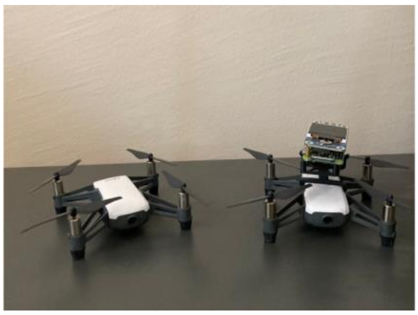

Figure 9. Equipment used in the field experiment

In the field test scenario, two heterogeneous drones and three tasks were defined. The location and other parameters of the drones and tasks are provided in Table 10 and Table 11, respectively. The tasks were transmitted to the drones by the ground station, with a laptop serving as the ground station. Messages exchanged between the agents were monitored and recorded by the ground station to validate that the algorithm was functioning correctly.

Table 10. Drone parameters used in field tests

Drone ID	The coordinates of drone [x,y,z]	Drone Type
1	39.9628,32.78125	Reconnaissance
2	39.96235,32.78115	Payload
GS	39.96235,32.781414	Ground Station

Table 11. Task parameters used in field tests

Task No	The coordinates of task [x,y,z]	Type	Window of task validity	t (s)
1	39.96265,32.78115	IG	[25.00,31.00]	5
2	39.96269,32.78189	IG	[34.00,40.00]	5
3	39.9623,32.781	PL	[10.00,20.00]	15

In the field tests, tasks were efficiently distributed among the drones using Harmony DTA. Drone 1 was assigned routes for Tasks 1 and 2, while Drone 2 was designated routes for Task 3. The satellite image of the movement of drones is given in Figure 10.

Figure 10. Satellite image for field test

The field tests have concluded successfully, demonstrating the applicability of the proposed algorithm in real-world scenarios. This confirms the efficacy observed during simulation.

6 Conclusion

This study proposed the auction-based Harmony DTA algorithm developed for distributed task assignment in drone swarms. 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. 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.

Conflict of interest

The author declares that there is no conflict of interest.

Similarity rate (iThenticate): 7%

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