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Development of a Greedy Auction-Based Distributed Task Allocation Algorithm for UAV Swarms with Long Range Communication

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Abstract: This study proposes a greedy auction-based distributed task allocation algorithm (GCAA) for swarm unmanned aerial vehicles (UAVs) with long range (LoRa) communication capabilities. Air-to-air (A2A) communication channels are established using LoRa technology to enable inter-agent communication, while air-to-ground (A2G) communication is facilitated through narrowband Internet of Things (NB-IoT) technology. The negotiation phase is conducted over these communication channels. Using LoRa and NB-IoT parameters, a link budget analysis is performed to determine the A2A reference distance, and a k-means clustering algorithm is developed. The proposed algorithm places base stations at cluster centers and prepares a simulation environment. The decentralized algorithm is compared with a greedy optimization algorithm under uninterrupted and interrupted communication scenarios, and the simulation results are presented in MATLAB. The developed distributed task allocation algorithm demonstrates lower system costs and shorter task completion times compared to the conventional greedy optimization algorithm. Additionally, the performance parameters exhibit more excellent stability in cumulative distribution functions.

Keywords: Greedy auction-based distributed task allocation algorithm, A2A/A2G communication, LoRa, NB-IoT.

Uzak Mesafe Haberleşmesine Sahip İHA Sürüleri için Açgözlü Açık Artırma Temelli Dağıtılmış Görev Tahsis Algoritmasının Geliştirilmesi

Özet: Bu çalışmada uzak mesafe (long range, LoRa) iletişimine sahip sürü insansız hava araçlarında (İHA) açgözlü açık artırma temelli dağıtık görev tahsis algoritması (greedy auction-based distributed task allocation algorithm, GCAA) önerilmiştir. Ajanlar arası haberleşmesinin sağlanabilmesi için LoRa teknolojisi kullanılarak havadan havaya (air-to-air, A2A), dar bant nesnelerin interneti (narrowband Internet of Things, NB-IoT) teknolojisi kullanılarak da havadan yere (air-to-ground, A2G) haberleşme kanalları oluşturulmuş ve müzakere aşaması bu haberleşme kanallarından sağlanmıştır. LoRa ve NB-IoT parametreleri kullanılarak hat bütçe analizi ile A2A referans mesafesi ve k-ortalamalı kümeleme algoritması geliştirilmiştir. Geliştirilen algoritma ile küme merkezlerine baz istasyonları yerleştirerek, simülasyon ortamı hazırlanmıştır. Önerilen merkezi olmayan algoritma ile haberleşmenin kesintisiz ve kesintili olduğu ortamda açgözlü optimizasyon algoritması ile karşılaştırılarak, MATLAB ortamında benzetim sonuçları aktarılmıştır. Geliştirilen dağıtık görev tahsis algoritması, geleneksel açgözlü optimizasyon algoritmasına göre sistem maliyetinin ve görev bitirme süresinin daha kısa olduğu gözlenmiştir. Aynı zamanda performans parametrelerinin, birikimsel dağılım fonksiyonlarında daha kararlı olduğu gözlenmiştir.

Anahtar Kelimeler: Açgözlü açık artırma temelli dağıtık görev tahsis algoritması, A2A/A2G haberleşme, LoRa, NB-IoT.

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1 INTRODUCTION

Algorithms used to solve task assignment problems are divided into centralized and distributed decision-making algorithms. In centralized task assignment algorithms, the coordinator manages all task assignments, and thus, conflicts are prevented, and optimum solutions are obtained. In distributed algorithms, there is no coordinator agent, and task sharing is carried out in a distributed manner due to negotiations between agents [1], [2].

Greedy algorithms do not require specific knowledge of the problem they are interested in. They do not require too many control parameters and are suitable for working harmoniously with the operator [3]. In multi-agent systems, the greedy algorithm focuses on the individual benefits of the agents. It aims to maximize the individual return without negotiation between the agents. In [4], the authors have improved the task completion and road coverage in unmanned aerial vehicles (UAVs) using the greedy method. However, since this method is not a negotiation-based algorithm, the UAVs do not share the tasks, and the system performs their optimization. In [5], they developed a distributed task-sharing algorithm by combining the optimization and greedy algorithms. However, the processing load is heavy due to the complex algorithm layout. A decentralized greedy auction-based distributed task allocation algorithm (GCAA) has been proposed in [6]. This study observes an increase in the system cost because more than one agent executes a task. However, communication parameters are not used during task sharing.

In this study, the GCAA algorithm is developed for UAV swarms that communicate long-distance. In order for agents to communicate with each other in the air, air-to-air (A2A) and when A2A communication distance is not sufficient, air-to-ground (A2G) communication channels are established via the base station (BS). The proposed algorithm aims to provide long-distance communication between agents, minimum agent cost, and average signal-to-noise ratio (SNR) values. In the second section of the study, the performance criteria of A2A and A2G communication channels include the maximum communication distances of agents using long range (LoRa) and narrowband Internet of Things (NB-IoT) communication technologies. In the third section of this study, the developed GCAA algorithm is presented. The proposed algorithm consists of four functions. The first function determines the BS locations depending on the tasks using the k-means clustering method. The second function controls the best task selections of the agents. The third function realizes the communication channels for the agents' communication and the primary task sharing. Finally, the last function completes the algorithm by performing the secondary task sharing of the agents. The advantages and disadvantages of the proposed distributed decision-making algorithm and the simulation results with the traditional greedy optimization algorithm are given in section 4. In the last section, the obtained results are evaluated.

2 DISTANCE ANALYSIS in A2A and A2G for UAVs

This section investigates distance analysis in A2A and A2G communication systems, focusing on signal power calculations, path loss models, and key performance metrics used in UAV networks, including determining the maximum communication range.

2.1 A2A Communication

A2A communication refers to the communication between two or more vehicles in the air. In A2A communication, performance metrics are determined using the two-ray path loss model. In the communication system, the signal power reaching the receiver from the transmitter is shown in (1). Here are wavelength (λ), communication distance (d), transmitter power (P_t), transmitter antenna gain (G_t), receiver antenna gain (G_r), transmitter antenna height (h_t), and receiver antenna height (h_r) [7]–[13],

$$P_r(w) = \frac{\lambda^2}{(4\pi d)^2} 4\sin^2\left(\frac{2\pi h_r h_t}{\lambda d}\right) G_r G_t P_t. \tag{1}$$

If the condition of $d\lambda \gg 4h_r h_t$ and $\sin(x) \approx x$ approximation is applied, (1) can be re-written as (2)

$$P_r(w) = P_t G_t G_r \frac{h_r^2 h_t^2}{d^4}. \tag{2}$$

2.2 A2G Communication

A2G communication is used in cases where air vehicles can communicate with targets on the ground or with systems controlled from the ground station [14]–[17]. In A2G communication, performance measurements were determined using the Okumura-Hata model. The Okumura-Hata model is a modified version of the Okumura model that operates in the frequency range of 150 MHz to 1.5 GHz and a distance of 1-100 km. The BS height (h_b) is 30 m to 100 m, while the mobile station height (h_m) is 1 m to 10 m. The path loss for urban areas is given in (3). The operating frequency (f_c) unit is defined in MHz, while (d) is in km, (h_b) and (h_m) are in meters [18]–[20],

$$\begin{aligned} L_P(\text{urban}) &= 69.55 + 26.16\log(f_c) - 13.82\log(h_b) \\ &\quad - a(h_m) + [44.9 - 6.55\log(h_b)]\log(d). \end{aligned} \tag{3}$$

For smaller cities, $a(h_m)$ can be expressed as in (4)

$$a(h_m) = (1.1\log(f_c) - 0.7)h_m - (1.56\log(f_c) - 0.8). \tag{4}$$

In rural or open areas, (3) can be expressed as in (5),

$$L_P(\text{rural}) = L_P(\text{urban}) - 4.78[\log(f_c)]^2 + 18\log(f_c) - 40.94. \quad (5)$$

The received signal power can be concluded as follows

$$P_r(\text{dBm}) = P_t(\text{dBm}) + G_t + G_r - L_P(\text{rural}). \quad (6)$$

SNR is a widely used metric for measuring signal quality in a communication system, as shown by (7). $P_r(w)$ represents the power received by the receiver, and σ^2 represents the thermal noise power,

$$\text{SNR}(w) = \frac{P_r(w)}{\sigma^2(w)}. \quad (7)$$

2.3 Communication Range

Receiver sensitivity is the minimum power level at which the receiver can demodulate and extract the transmitted information from the received weak signal. Due to the innovative modulation scheme, LoRa and NB-IoT systems have low receiver sensitivity. Receiver sensitivity depends on the bandwidth (BW), SNR, and receiver noise factor (NF). At room temperature, it is shown as (8) [17], [19]–[22],

$$R_{sens}(\text{dBm}) = -174 + 10\log(\text{BW}) + \text{NF} + \text{SNR}. \quad (8)$$

The link margin between the received power and receiver sensitivity is given in (9) to ensure secure communication,

$$LinkMargin(\text{dB}) = P_r - R_{sens}. \quad (9)$$

The noise factor as $\text{NF(dB)} = 10\log(F_{total})$, is the total amount of power added by the radio frequency (RF) front end at the receiver to the thermal noise power at the input where

$$F_{total} = F_1 + \frac{F_2 - 1}{G_1} + \frac{F_3 - 1}{G_1 G_2} + \cdots + \frac{F_N - 1}{G_1 G_2 \ldots G_{N-1}}. \quad (10)$$

Here, $F_{1,\ldots,N}$ represents the linear noise factor of the RF stages, and $G_{1,\ldots,N-1}$ represents the linear gain of these stages.

Table 1 LoRa and NB-IoT parameters

Parameters	LoRa	NB-IoT
Frequency (MHz)	868	800
Bandwidth (kHz)	125	180
Rx sensitivity (dBm)	-139.5	-129
Transmitted power, P_t (dBm)	14	23
Thermal noise power, σ^2	5.01×10^{-23}	3.98×10^{-21}
Receiver antenna gain, G_r	1	1
Transmitter antenna gain, G_t	1	1
Link margin (dB)	10	10
Agent speed (m/s)	1	1
Agent height (h_t, h_m, h_r) (m)	10	10
Base station height, h_b (m)	30	30

In this study, LoRa is used by UAVs, and BSs use NB-IoT. SX1301 parameters are taken as LoRa gateway, and Quectel BC95-G parameters are taken as NB-IoT references. The spreading factor (SF) is assumed to be 12 for long-distance communication. LoRa, NB-IoT, and UAV parameters are presented in Table 1 [22], [23].

3 GREEDY AUCTION-BASED DISTRIBUTED TASK ALLOCATION ALGORITHM

The k-means algorithm is centralized. This method starts with random 'k' cluster centers. Starting points affect the clustering process and results. Euclidean and similar distance functions measure object similarity [24], [25].

The clusters and centers of the tasks are determined with the proposed k-means algorithm (Algorithm 1). The d_{min} and d_{max} explained in Algorithm 1 represent the minimum and maximum communication distance. The minimum reference distance is the maximum communication range between agents, as shown in (11). The maximum reference distance is the maximum range agents communicate with the BS and is given in (12).

$$\log(d_{min}) = \frac{L_P + 10\log(G_t G_r) + 20\log(h_t h_r)}{40}, \quad (11)$$

$$log(d_{max}) = \frac{A + B}{44.9 - 6.55\log(h_b)} \quad (12)$$

where $A = L_P(\text{rural}) - 27.81 - 46.05\log(f_c) + 13.82\log(h_b)$ and $B = (1.1\log(f_c) - 0.7)h_m + 4.78(\log(f_c))^2$.

Algorithm 1 k-means Clustering Algorithm

function CLUSTERING($T, k = 10, d_{\min}, d_{\max}$)
  $T = \{t_1, t_2, \ldots, t_n\}, \quad t_i = (x_i, y_i)$ ▷ Randomly initialize task points
  $C = \{c_1, c_2, \ldots, c_k\}, \quad c_i = (x_i, y_i)$ ▷ Randomly initialize cluster centers
  $\text{idx}_c(i) \leftarrow \arg\min d(t_i, c_j), \quad \forall t_i \in T$ ▷ Find the nearest cluster center for each task
  while true **do**
    for $i \in [1, k]$ **do**
      if cluster_element is not empty **then**
        $C_j = \frac{1}{|S_j|} \sum_{t_i \in S_j} t_i, \quad S_j = \{t_i \mid \text{idx}_C(i) = j\}$ ▷ Update cluster centers
      else
        Select a random cluster center
      end if
    end for
    for $i \in [1, T]$ **do** ▷ Check the distance between tasks and cluster centers
      if $d(t_i, c_{\text{idx}_c}(i)) < d_{\min}$ **then**
        Search for another cluster center
      else if $d_{\min} \le d(t_i, c_j) \le d_{\max}$ **then**
        Assign the task to this cluster
      else
        $k = k + 1, \; C = C \cup \{c_{\text{new}}\}$ ▷ Add a new cluster
      end if
    end for
    if $d_{\min} \le d(c_i, c_j) \le d_{\max}$ **then** ▷ Check the distance between cluster centers
      break
    else
      $k = k - 1$ ▷ Remove unnecessary clusters
    end if
  end while
end function

Algorithm 2 Greedy Auction-Based Task Allocation Algorithm

function TaskAllocation(Clustering(), BestTask(), CommunicationChannel(), SecondaryTask())
$\tau = 1$ ▷ Iteration counter
Clustering($T = 30, 50$)
BestTask(0) = 0
CommunicationChannel(0) = 0
SecondaryTask(0) = 0
while not empty(T) or not empty(u_{xy}) **do**
BestTask(τ)
CommunicationChannel(τ)
SecondaryTask(τ)
$\tau \leftarrow \tau + 1$
end while
end function

Algorithm 3 Selecting the Best Task

function BestTask(T)
for $i \in [1, u_n]$ **do**
$t = \frac{dt}{v}$
$dt = \sqrt{(u_x(t) - T_x(t))^2 + (u_y(t) - T_y(t))^2}$
$E_i = \frac{1}{2} C_D \rho v^3 S_t$ ▷ Drag energy
$H_t = (P_{D0} - E_i)$
$b_i(t) \leftarrow \max(H_t)$
idx$_A(t) \leftarrow \arg\max(H_t)$
end for
end function

The greedy auction-based distributed task allocation algorithm (Algorithm 2) is a negotiation algorithm that tries to make the best short-term decision that maximizes the individual benefits of the agents. The auction process is the first stage of the algorithm. Each agent calculates its costs for all tasks with the published task coordinates. The calculated cost values are subtracted from the agent's utility value P_{D0} to determine individual benefits (remaining energy). The b_i set of the relevant agent is updated by taking the maximum value of the determined benefits. This set also represents the agent's utility for the task it requests. The idx_A value defines the task number the agent requests. The auction stage of the agents and the best task selection are presented in Algorithm 3.

Agents calculate the distance between the starting point and the desired task and create a return E_b cost matrix. If the remaining energy value of the agents is less than the return energy, the agent is disabled and returns to the starting position. If the remaining energy value of the agents is more than the return energy, the agent broadcasts a Y_A message. When the agents broadcast the same task and, therefore, the same Y_A value, the negotiation process begins. During the negotiation process, agents first broadcast their locations. Agents calculate the distance between them according to the broadcasted location values. Agents within the d_{min} reference distance perform A2A communication among themselves and share tasks due to the negotiation process. The negotiation process with A2G communication through the defined BS to prevent interruption of communication and increase in system cost is presented in Algorithm 4.

Algorithm 4 Communication Channels and Primary Task Sharing

function CommunicationChannel($idx_A(\tau), b_i(\tau)$)
$d_B = \sqrt{(x_{B_i} - idx_{A x_i})^2 + (y_{B_j} - idx_{A y_j})^2}$
$t_b = R_B / v$
$E_b = \frac{1}{2} C_D \rho v^3 S_{tb}$
if $b_i > E_b$ **then**
$Y_A(t) = idx_{A i}$
else
Broadcast the number of the disabled agent
end if
if $Y_{A_i}(t) == Y_{A_j}(t)$ **then**
$d_k = \sqrt{(u_{x_i}(t) - u_{x_j}(t))^2 + (u_{y_i}(t) - u_{y_j}(t))^2}$
if $d_k < d_{\min}$ **then**
comA2A(τ) $= [u_i, u_j]$
Broadcast numbers of agents communicating via A2A
else
comA2G(τ) $= [u_i, u_j]$
Broadcast numbers of agents communicating via A2G
end if
if agents communicate only via A2A **then**
for $i \in [1,$ comA2A$_n]$ **do**
if $d_k \lambda \gg 4 h_t h_r$ **then**
Equation (1), Equation (7)
else
Equation (2), Equation (7)
end if
Broadcast b_i values of agents participating in bilateral negotiations
Broadcast the numbers of winning and losing agents
if comA2A$_W \cup$ comA2A$_L$ **then**
The agent cannot receive a task
else
The agent whose task assignment is finalized in bilateral negotiations broadcasts its number
$P_{D0i} = b_i($comA2A$_W), u_{xy}(t) = T(idx_A)$
Broadcast the number of the agent who lost the bilateral negotiation ($P_{D0i} = 0$)
end if
end for
else if agents communicate via both A2A and A2G **then**
for $i \in [1,$ comA2A$_n$ and comA2G$_n]$ **do**
if comA2A$_n$ **then**
if $d_k \lambda \gg 4 h_t h_r$ **then**
Equation (1), Equation (7)
else
Equation (1), Equation (7)
end if
else
if comA2G$_n$ **then**
$P_r(w) = 10^{(P_r(\text{dBm})/10)-3}$
Equation (7)
end if
end if
end for
Broadcast the number of the agent who won the task in A2A comm.
Broadcast the number of the agent who won the task in A2G comm.
The common winner in A2A and A2G communication wins the task and broadcasts its number
$P_{D0i} = b_i($comA2A$_W \cap$ comA2G$_W), u_{xy}(t) = T(idx_A)$
$P_{D0i} = 0$
else if agents communicate only via A2G **then**
for $i \in [1,$ comA2G$_n]$ **do**
if comA2G$_n$ **then**
$P_r(w) = 10^{(P_r(\text{dBm})/10)-3}$
Equation (7)
end if
Broadcast b_i values of agents participating in bilateral negotiations
Broadcast the numbers of winning and losing agents
if comA2G$_W \cup$ comA2G$_L$ **then**
The agent cannot receive a task
else
The agent whose task assignment is finalized in bilateral negotiations broadcasts its number
$P_{D0i} = b_i($comA2G$_W), u_{xy}(t) = T($idx$_A)$
Broadcast the number of the agent who lost the bilateral negotiation ($P_{D0i} = 0$)
end if
end for
end if
end if
end function

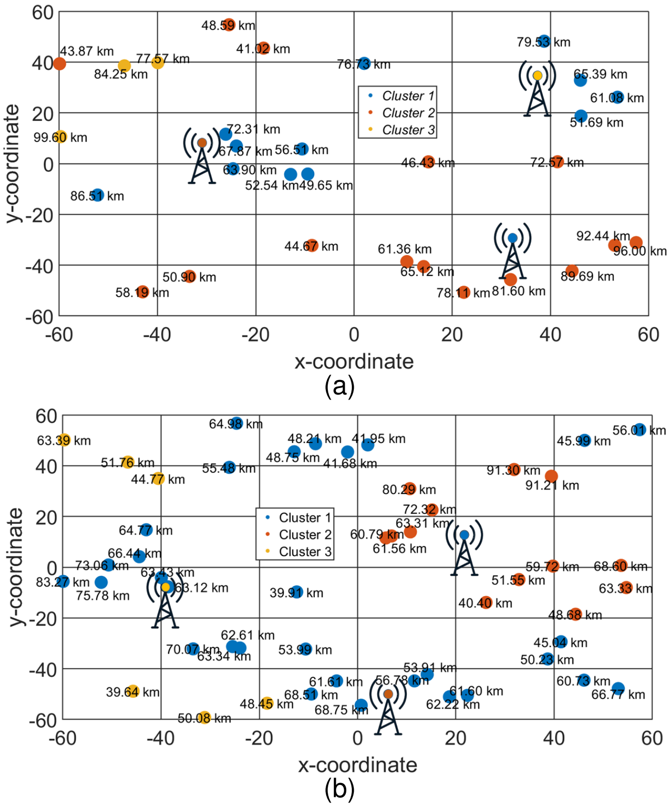

Fig. 1 BS and task positions a) 30 tasks, b) 50 tasks.

In the first stage of task sharing, the agents that lost due to the negotiation publish their numbers. In the first negotiation stage, the losing agents are subjected to the second negotiation process to not fall behind the other agents in the swarm and maximize individual benefit. In this stage, only the losing agents share the remaining tasks while the others wait to execute the tasks they won. The second stage of negotiation is presented in Algorithm 5. The BS and task sets determined in Algorithm 1 are presented in Fig. 1.

4 NUMERICAL RESULTS

The simulation results of the designed algorithm in MATLAB environment are presented on a Windows 11 operating system computer with an Intel Core i7-12700H processor, NVIDIA GeForce RTX 3050 graphics card, and 16 GB RAM hardware. The system cost, SNR values of communication channels, and agent task completion times are taken as reference for the developed algorithm. The performance metrics taken as reference for the developed algorithm are compared with the greedy optimization algorithm in the uninterrupted communication environment and the environment without A2G communication.

For agents to be able to communicate A2A and A2G, the maximum reference distances were calculated as d_{min} = 38.681 km and d_{max} = 145.02 km using (11) and (12). However, since the Okumura-Hata model works 0-100 km, the simulation was run at a reference distance of d_{max} 100 km.

Algorithm 5 Secondary Task Assignment

function SECONDARYTASK($P_{D0i} = 0$, CommunicationChannel())
  $P_{D0i} = []$, $u_{xy} = []$, $T = []$
  while any($P_{D0i} == 0$) **do**
    BestTask($P_{D0i} = 0$)
    CommunicationChannel($P_{D0i} = 0$)
  end while
end function

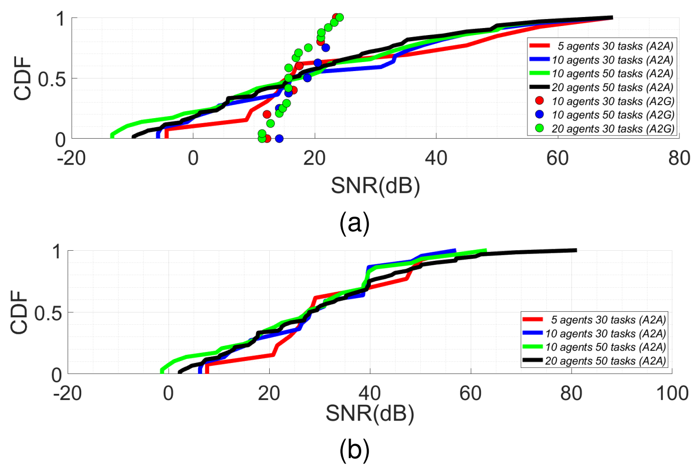

Fig. 2 Cumulative distribution function (CDF) of the communication channel during bilateral negotiation a) A2A-A2G environment b) Only A2A environment.

The cumulative distribution function of the communication channel during bilateral negotiation is shown in Fig. 2. In all simulation environments, the distributed decision-making algorithm, including A2G and A2A communication, observed an average SNR value of 22.427 dB in A2A communication and an average SNR value of 18.083 dB in A2G communication. The distributed decision-making algorithm, including only A2A communication, observed an average SNR value of 28.481 dB.

The number of bilateral negotiations varies according to the communication environments where the agents are located. In the 5-agent 30-task system, it was observed that the number of bilateral negotiations was equal in the environment containing A2A and A2G communication and in the environment containing only A2A communication, and the negotiations contained only A2A communication. It was observed that the algorithm containing only an A2A communication medium showed lower density at lower costs compared to the greedy optimization algorithm. It was observed that the algorithm containing an A2A-A2G communication medium could reach the same density level at a lower cost than the greedy optimization algorithm. When we look at the general cost, the distributed task allocation algorithm containing the uninterrupted communication medium reached the saturation level with a lower cost than the other two algorithms, as presented in Fig. 3.

Table 2 Algorithms' performances for different scenarios

	5 Agents 30 Tasks			10 Agents 30 Tasks			10 Agents 50 Tasks			20 Agents 50 Tasks		
	Greedy Algorithm	**GCAA (A2A-A2G)**	**GCAA (A2A)**	**Greedy Algorithm**	**GCAA (A2A-A2G)**	**GCAA (A2A)**	**Greedy Algorithm**	**GCAA (A2A-A2G)**	**GCAA (A2A)**	**Greedy Algorithm**	**GCAA (A2A-A2G)**	**GCAA (A2A)**
Iterations	8	9	9	4	3	4	6	6	6	3	3	3
Tasks	28	30	30	30	30	30	50	50	50	50	50	50
Messages	78	151	151	146	428	425	201	486	470	320	1989	1918
Cost (J)	4.535×10^4	3.878×10^4	3.878×10^4	6.232×10^4	5.898×10^4	6.628×10^4	8.175×10^4	7.105×10^4	7.223×10^4	8.175×10^4	7.105×10^4	7.223×10^4
Time (s)	7.242×10^5	6.26×10^5	6.26×10^5	3.712×10^5	3.238×10^5	4.184×10^5	5.483×10^5	4.548×10^5	5.389×10^5	2.019×10^5	2.283×10^5	2.34×10^5
Active Agents	0	1	1	4	3	4	5	5	5	20	20	20
Same Task Preference	0	0	0	0	0	3	0	0	3	0	0	6
Pairwise Negotiations	-	13	13	-	27	22	-	37	29	-	84	60
A2A Average SNR (dB)	-	26.481	26.481	-	23.456	29.568	-	20.104	27.652	-	19.667	30.224
A2G Average SNR (dB)	-	-	-	-	18.116	-	-	19.154	-	-	16.980	-

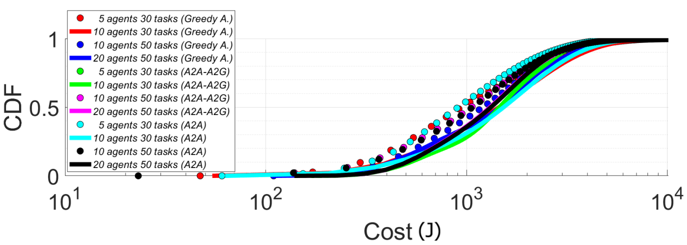

Fig. 3 Cumulative distribution function for task cost.

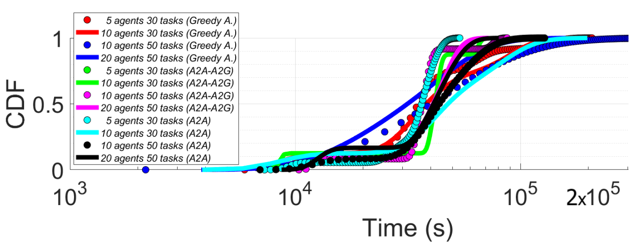

Fig. 4 Cumulative distribution function for task completion time.

It is observed that the greedy optimization algorithm shows changes in time performance with the increase in the number of tasks. The algorithm that only includes A2A communication is observed to have the longest completion time in the 50-task system. It is observed that the A2G-A2A algorithm offers a more stable completion time compared to the other two algorithms. The curves show a more controlled and steep increase, and the task completion speed increases after a certain period, whereas the curve shifts to the right more as the number of tasks increases (50 tasks), as observed in Fig. 4. The performance values of the greedy optimization and auction-based distributed task allocation algorithms are presented in Table 2.

5 CONCLUSION

This study proposes a distributed task allocation algorithm solution for swarm UAVs with long-distance communication. Simulation results for the proposed algorithm are evaluated through the parameters of the number of agents, number of tasks, task location, BS locations, A2A reference distance, and initial energy of the agents. When the distributed decision-making algorithm tested in MATLAB environment is compared with the optimization algorithm, it is seen that the system cost, the number of disabled agents, and the task duration are less depending on the system parameters. At the same time, while the greedy optimization algorithm is a faster and more effective method for small and medium-sized tasks, it is observed that the developed distributed decision-making algorithm provides more balanced performance in variable task sets. It is observed that the optimization algorithm performs better in the number of messages broadcasted. In the distributed decision-making algorithm where communication is limited, it is concluded that some agents choose the same task, and the performance values are lower than the A2G-A2A distributed algorithm. It is observed from the simulation results that the active agents complete the tasks that the disabled agents cannot complete.

AUTHOR CONTRIBUTIONS

The authors Erdem Can contributed to the writing, investigation, and software; Mustafa Namdar and Arif Basgumus contributed to the methodology, validation, and editing.

REFERENCES

[1] E. Can, B. I. Kirklar, M. Namdar, and A. Basgumus, "Deep learning based target tracking and diving algorithm in kamikaze UAVs," in *Innovations in Intelligent Systems and App. Conf. (ASYU)*, 2024, pp. 1–6. DOI: 10.1109/ASYU62119.2024.10757004.

[2] E. Can, Z. Yildirim, Y. Kaya, M. Eser, M. Namdar, and A. Basgumus, "Development of greedy auction-based distributed decision-making algorithm and agent communication language in swarm unmanned aerial vehicles," in *IEEE National Conf. on Electrical and Electronics Eng. (ELECO)*, 2024, pp. 1–5. DOI: 10.1109/ELECO64362.2024.10847247.

[3] Y. Demir, "Tekrarli acgozlu algoritma uzerine kapsamli bir analiz," *Journal of the Institute of Science and Technology*, vol. 11, no. 4, pp. 2716–2728, 2021. DOI: 10.21597/jist.935652.

[4] Y. Jia, S. Zhou, Q. Zeng, *et al.*, "The UAV path coverage algorithm based on the greedy strategy and ant colony optimization," *Electronics*, vol. 11, no. 17, p. 2667, 2022. DOI: 10.3390/electronics11172667.

[5] J. Zhou, X. Zhao, X. Zhang, D. Zhao, and H. Li, "Task allocation for multi-agent systems based on distributed many-objective evolutionary algorithm and greedy algorithm," *IEEE Access*, vol. 8, pp. 19 306–19 318, 2020. DOI: 10.1109/ACCESS.2020.2967061.

[6] M. Braquet and E. Bakolas, "Greedy decentralized auction-based task allocation for multi-agent systems," *IFAC-PapersOnLine*, vol. 54, no. 20, pp. 675–680, 2021. DOI: 10.1016/j.ifacol.2021.11.249.

[7] C. Sommer, S. Joerer, and F. Dressler, "On the applicability of two-ray path loss models for vehicular network simulation," in *IEEE Vehicular Netw. Conf.*, 2012, pp. 64–69. DOI: 10.1109/VNC.2012.6407446.

[8] E. Zöchmann, K. Guan, and M. Rupp, "Two-ray models in mmWave communications," in *IEEE Int. Workshop on Signal Proc. Adv. in Wireless Comm.*, 2017, pp. 1–5. DOI: 10.1109/SPAWC.2017.8227681.

[9] K. Uchida, J. Honda, T. Tamaki, and M. Takematsu, "Handover simulation based on a two-rays ground reflection model," in *IEEE Int. Conf. on Complex, Intelligent, and Software Intensive Systems*, 2011, pp. 414–419. DOI: 10.1109/CISIS.2011.119.

[10] R. He, Z. Zhong, B. Ai, J. Ding, and K. Guan, "Analysis of the relation between fresnel zone and path loss exponent based on two-ray model," *IEEE Antennas and Wireless Propagation Letters*, vol. 11, pp. 208–211, 2012. DOI: 10.1109/LAWP.2012.2187270.

[11] S. Kurt and B. Tavli, "Path-loss modeling for wireless sensor networks: A review of models and comparative evaluations," *IEEE Antennas Propag. Mag.*, vol. 59, no. 1, pp. 18–37, 2017. DOI: 10.1109/MAP.2016.2630035.

[12] J. Walfisch and H. L. Bertoni, "A theoretical model of uhf propagation in urban environments," *IEEE Trans. Antennas Propag.*, vol. 36, no. 12, pp. 1788–1796, 1988. DOI: 10.1109/8.14401.

[13] S. Duangsuwan and P. Jamjareegulgarn, "Exploring ground reflection effects on received signal strength indicator and path loss in far-field air-to-air for unmanned aerial vehicle-enabled wireless communication," *Drones*, vol. 8, no. 11, p. 677, 2024. DOI: 10.3390/drones8110677.

[14] J. Lee, S. Lee, S. H. Chae, and H. Lee, "Performance analysis of cooperative dynamic framed slotted-ALOHA with random transmit power control in A2G communication networks," *IEEE Access*, vol. 10, pp. 106 699–106 707, 2022. DOI: 10.1109/ACCESS.2022.3211943.

[15] S. Lee, H. Yu, and H. Lee, "Multiagent Q-learning-based multi-UAV wireless networks for maximizing energy efficiency: Deployment and power control strategy design," *IEEE Internet of Things Journal*, vol. 9, no. 9, pp. 6434–6442, 2021. DOI: 10.1109/JIOT.2021.3113128.

[16] S. Lee, S. Lim, S. H. Chae, B. C. Jung, C. Y. Park, and H. Lee, "Optimal frequency reuse and power control in multi-UAV wireless networks: Hierarchical multi-agent reinforcement learning perspective," *IEEE Access*, vol. 10, pp. 39 555–39 565, 2022. DOI: 10.1109/ACCESS.2022.3166179.

[17] A. Almarhabi, A. J. Aljohani, and M. Moinuddin, "Lora and high-altitude platforms: Path loss, link budget and optimum altitude," in *IEEE Int. Conf. Intell. Adv. Syst.*, 2021, pp. 1–6. DOI: 10.1109/ICIAS49414.2021.9642705.

[18] A. Goldsmith, *Wireless communications*. Cambridge university press, 2005, ISBN: 978-0-521-83716-3.

[19] K. Akpado, O. Oguejiofor, A. Adewale, and A. Ejiofor, "Pathloss prediction for a typical mobile communication system in nigeria using empirical models," *IRACST-Int. J. Comput. Netw. Wirel. Commun.*, vol. 3, no. 2, pp. 207–211, 2013, ISSN: 2250-3501.

[20] M. Al Rashdi, Z. Nadir, and H. Al-Lawati, "Applicability of okumura–hata model for wireless communication systems in Oman," in *IEEE Int. IOT, Electronics and Mechatronics Conf. (IEMTRONICS)*, 2020, pp. 1–6. DOI: 10.1109/IEMTRONICS51293.2020.9216441.

[21] Z. K. Adeyemo, O. K. Ogunremi, and I. A. Ojedokun, "Optimization of okumura-hata model for long term evolution network deployment in Lagos, Nigeria," *terrain*, vol. 4, no. 7, p. 14, 2016. DOI: 10.15866/irecap.v6i3.9012.

[22] K. L. B. Ponce, S. Inca, D. Díaz, and M. Núñez, "Towards adaptive lora wireless sensor networks: Link budget and energy consumption analysis," in *IEEE Int. Conf. Electron. Electr. Eng. Comput.*, 2021, pp. 1–4. DOI: 10.1109/INTERCON52678.2021.9532685.

[23] H. Soy, "Coverage analysis of LoRa and NB-IoT technologies on LPWAN-based agricultural vehicle tracking application," *Sensors*, vol. 23, no. 21, p. 8859, 2023. DOI: 10.3390/s23218859.

[24] M. Mardi and M. R. Keyvanpour, "GBKM: A new genetic based k-means clustering algorithm," in *IEEE Int. Conf. on Web Research (ICWR)*, 2021, pp. 222–226. DOI: 10.1109/ICWR51868.2021.9443113.

[25] S. Kapil, M. Chawla, and M. D. Ansari, "On K-means data clustering algorithm with genetic algorithm," in *IEEE Int. Conf. Parallel Distrib. Grid Comput.*, 2016, pp. 202–206. DOI: 10.1109/PDGC.2016.7913145.