Multi-UAV Network Logistics Task Allocation Algorithm Based on Mean-Field-Type Game

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Abstract. Unmanned aerial vehicles (UAVs) has become the vital driving force of logistics distribution development as an important carrier of advanced productivity. However, it is challenging to efficiently allocate logistics tasks on a large scale with the lowest energy consumption, considering the selfishness of UAVs. To tackle the above problem, we propose a mean field type game (MFTG) based logistics task allocation scheme in the multi-UAV networks. Specifically, we first develop a MFTG framework to fully model the interactions between the UAVs, the influence of aerodynamics and the features of tasks. Then, we propose the consensus-based bundle algorithm (CBBA) to provide a feasible and conflict-free solution to the multi-UAV network task allocation problem under multiple interactions in the dynamic environment. Extensive simulations are finally conducted, and results demonstrate that the proposed scheme can efficiently reduce the energy consumption of the multi-UAV network and provide users with high-quality task transportation service.

Keywords: Unmanned aerial vehicles (UAVs) · Mean-field-type game (MFTG) · Consensus-based bundle algorithm (CBBA) · Logistics task allocation

1 Introduction

With the development of e-commerce, one of the essential ways of logistics distribution in the future relays on unmanned aerial vehicles (UAVs) [1]. UAVs are suitable for remote areas and emergency delivery, which can effectively improve the efficiency of distribution, and achieve the reduction of labor and the transport costs. Therefore, the UAV-based supply delivery is becoming a potential development direction [2]. Realizing the full potential of UAVs may require a complete overhaul of logistics systems so that supply chains can have a chance to evolve from previous, old-fashioned standards to continuous, new fluid supply chains.

I. M. Pires et al. (Eds.): GOODTECHS 2022, LNICST 476, pp. 3–18, 2023.
https://doi.org/10.1007/978-3-031-28813-5_1

However, how to allocate logistics tasks such as the goods people buy online reasonably in a dynamic environment still faces many challenges. Specifically, UAVs have limited payloads and battery life. The number of UAVs in the multi-UAV network is limited, and the selfishness of UAVs have severe effects on the task allocation. Besides, due to the various user needs, UAVs need to tackle a variety of tasks. Therefore, an appropriate task allocation scheme should be devised to tackle the above issues and minimize the energy consumption.

In this paper, we propose a novel mean-field-type game (MFTG) framework with consensus-based bundle algorithm (CBBA) in the multi-UAV network to allocate the tasks and minimize the energy consumption. Specifically, the framework is first proposed to model the interactions between the UAVs in the static environment, which can motivate the participation of the UAVs and determine the optimal task allocation strategy to minimize the energy consumption. Furthermore, for lack of the knowledge on interactions between UAVs in dynamic network scenarios, the CBBA is used to decide the optimal task allocation strategy through trial and error under multiple interactions. The main contributions of this paper are as follows:

(1) We build an air-to-ground task allocation model in the multi-UAVs network for logistics distribution, considering aerodynamic factors, load and data transmission consumption and the time-to-live (TTL) of the tasks.
(2) We model the problem of task allocation as a MFTG framework to fully consider the impact of UAVs' selfishness on task allocation with the state equation.
(3) Without knowing the utility parameters between UAVs, the CBBA is utilized into the MFTG framework to minimize the energy consumption of task allocation while ensuring timely service in the dynamic environment.

The rest of this paper is organized as follows. Section 2 reviews the related work. The system model is introduced in Sect. 3. Section 4 presents the problem formulation and Sect. 5 analyzes the optimal strategy for static mean-field-type game. The consensus-based bundle algorithm based optimal strategy decision is expounded in Sect. 6. Performance evaluation is shown in Sect. 7 and the conclusion is summarized in Sect. 8.

2 Related Work

2.1 Mean-Field-Type Game in UAVs

In recent years, the mean-field-type game theory in UAVs has attracted wide attention from academic research to life application. Chen *et al.* [3] investigated the resource management problem for large-scale UAV communication networks and discussed the potential applications. Li *et al.* [4] formulated the power control problem of the UAVs as a discrete mean-field game and transformed it into a Markov decision process by simulating the interactions among a large number of UAVs to obtain an equilibrium solution. It can be seen that there are few studies in the existing literature on solving the task allocation problem in multi-UAVs networks by using the mean-field-type game theory with the CBBA algorithm.

2.2 Incentives with Consensus-Based Bundle Algorithm

With the development of distributed algorithms, the CBBA has been studied extensively. Zitouni *et al.* [5] devised a distributed approach to multi-robot task assignment by combining CBBA with ant colony algorithm. To solve the potential problems of information transmission quality and energy consumption in wireless sensor network, Chen *et al.* [6] adopted the consensus-based bundle algorithm to generate corresponding task assignment schedules. However, the considerations of the UAVs' interactions and the network state update in the multi-UAVs networks are still insufficient.

Different from existing works, the proposed scheme studies the task allocation in the multi-UAVs network. The internal (e.g., selfishness and the battery life of UAVs) and external(e.g., aerodynamics and the TTL of tasks) factors of the network are jointly considered in the dynamic environment to improve the efficiency of delivery. In addition, the CBBA is employed to acquire the optimal tasks allocation strategy of UAVs in the dynamic MFTG.

3 System Model

In this section, we introduce the system model including network model, task model, motion model and communication model.

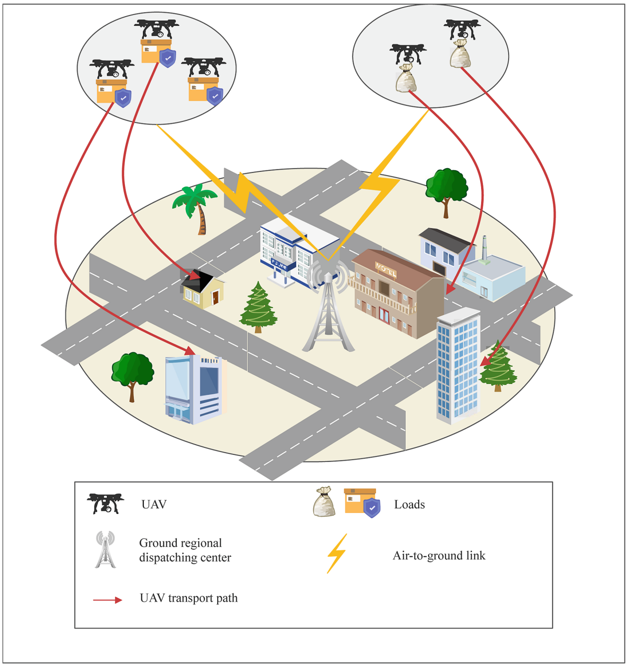

Fig. 1. System model.

3.1 Network Model

In this paper, we consider an intelligent logistics model, as shown in Fig. 1, which includes a ground dispatching center, multiple UAVs, and some users.

Ground Dispatching Center. The ground dispatching center collects information such as geographical location, the demand and TTL of distribution tasks, and publishes them to the multi-UAV network.

UAVs. UAVs submit the latest location information to the ground dispatching center, and obtain the released task information through the dispatching center. The set of UAVs is denoted as $\mathcal{U} = \{1, 2, ..., u, ..., U\}$. UAVs are equipped with various types of sensors to collect sensing data from users on the ground. Let $\mathcal{L} = \{L_1, L_2, ..., L_U\}$ denote the maximum load constraint of different UAVs. Define the state of UAV u at time t as $\mathbf{x}_u = \{q_u(t), E_{u,remain}(t)\}$, where $q_u(t)$ and $E_{u,remain}(t)$ are the position coordinates and the remaining energy of UAV u at time t, respectively.

Users. Users submit their geographical location and task information to the ground dispatching center. The set of users is denoted as $\mathcal{I} = \{1, 2, ..., i, ..., I\}$. Let $\mathcal{R} = \{R_1, R_2, ..., R_I\}$ denote the load requirement of different users, which represent the weight of each task.

3.2 Task Model

Defined the task allocation strategy of the ground dispatching center to UAV u at time t is $\mathbf{s}_u$, i.e., the allocation strategy selects k tasks in the task set $\mathcal{M}$ are selected and are assigned them to UAV u.

Assuming that the ground dispatching center randomly releases M tasks at time t_0, where the set of tasks is denoted as $\mathcal{M} = \{1, 2, ..., m, ..., M\}$. The time-to-live (TTL) of task m is denoted by t_m, indicating that the task should be executed before its deadline [7]. When the TTL of task m is smaller, it indicates that the urgency of the task is higher. It should be assigned to the UAV as soon as possible and the UAV should execute the task at a faster speed. Otherwise, the UAV will fly at a constant initial speed v_0. Set the UAV to complete the task at time t, so the speed of the UAV when it executes task m with TTL of t_m is

$$v_m = \frac{t_m - t_0}{t - t_0} v_0 \tag{1}$$

Define the quadruple of task m as $\{q_i(t), R_m, i, t_m\}$, where $q_i(t)$ indicates the target position coordinates of task m. R_m is the weight of task m. i is the user corresponding to task m. t_m is the TTL of task m.

3.3 Motion Model

We consider that UAVs fly at a constant altitude, and the position coordinates of UAV u is $q_u(t) = [x_u(t), y_u(t), H]$, where $x_u(t)$ and $y_u(t)$ are the horizontal and vertical coordinates of UAV u, and H is the altitude of UAV u. The position coordinates of user i is $q_i(t) = [x_i(t), y_i(t), 0]$. Therefore, the distance between UAV u and user i is

$$d_{u,i} = \sqrt{[x_u(t) - x_i(t)^2] + [y_u(t) - y_i(t)^2] + H^2} \tag{2}$$

Assuming that UAVs fly at a constant speed, the flight time of the UAV u for executing task m is

$$t_m^u = \frac{\sqrt{[x_u(t) - x_i(t)^2] + [y_u(t) - y_i(t)^2] + H^2}}{v_m} \tag{3}$$

and the position change trend of UAV u at time t is expressed by state dynamic equation $\mathbf{x}'(t)$ [14].

$$\mathbf{x}'_u(t) = \theta \mathbf{x_u}(t) + \sum_{u=1}^{U} \lambda_u \mathbf{s}_u(t) \tag{4}$$

where θ and λ_u indicate the impact of the environment in the current state and the speed of UAV u relative to other UAVs, respectively.

3.4 Communication Model

The LoS channel model provides a practical approximation for the air-to-ground (A2G) channel transmission [8]. Therefore, the channel gain between UAV u and user i is

$$g_{ui}(t) = \frac{g_0}{[(x_u(t) - x_i(t)]^2 + [y_u(t) - y_i(t)]^2 + H^2} \tag{5}$$

where g_0 represents the channel gain per unit distance.

In the process of logistics delivery, information such as distribution status, geographical location and expected arrival time is continuously communicated with users, so the signal-to-noise ratio between UAV u and user i [8] is

$$\varphi_{ui} = \frac{g_{ui}(t) p_u}{\sum_{u' \in \mathcal{U} \setminus u} g_{u'i}(t) p_{u'} + \sigma^2} \tag{6}$$

where p_u is the downlink transmission power of UAV u. $\sum_{u' \in \mathcal{U} \setminus u} g_{u'i}(t) p_{u'}$ is the interference power from all UAVs except UAV u. σ^2 denotes the Gaussian noise.

The data transmission rate is characterized as

$$r_{ui} = \omega \log_2 (1 + \varphi_{ui}) \tag{7}$$

where ω is the bandwidth allocated to UAV u.

4 Problem Formulation

4.1 Utility Function

The energy consumption of UAVs is determined by three parts, including the fight energy consumption, the data transmission consumption and the load consumption. We use the cost function of energy consumption to represent the utility function, and achieve the lowest energy consumption by minimizing the utility function.

Flight Energy Consumption. [9]

$$c_{1,u} = \int_0^{t_m^u} [a_1(1 + a_2 v_m^2) + a_3(\sqrt{1 + \frac{v_m^4}{4a_4^2}} - \frac{v_m^2}{2a_4})^{\frac{1}{2}}]dt \tag{8}$$

where a_1 and a_2 are the parameters based on the UAV weight and air density. a_3 is the UAV rotor parameters and a_4 is the coefficient of air resistance.

Data Transmission Consumption. In the process of executing tasks, each UAV must ensure the communication quality. Meanwhile, data transmission also consumes a significant amount of energy. As such, the data transmission consumption of UAV u is given by

$$c_{2,u} = p_u \frac{D}{r_{ui}} \tag{9}$$

where D is the size of the transmitted data.

Load Cost. The UAV performing the task needs to meet the weight required of the task. And the load cost of UAV u performing task m is

$$c_{3,u} = P_m t_m^u \tag{10}$$

where P_m is the load power of UAV for task m.

Combining (8), (9) and (10), the cost function of UAV u is expressed as

$$c_u = \sum_{m=1}^{M} Z_{u,m}(\omega_1 c_{1,u} + \omega_2 c_{2,u} + \omega_3 c_{3,u}) \tag{11}$$

where $Z_{u,m}$ is a binary variable. When $Z_{u,m} = 1$, it indicates that task m is allocated to UAV u; otherwise, $Z_{u,m} = 0$. $\omega_1, \omega_2, \omega_3$ are the weighting parameter.

Therefore, the utility function of UAV u is

$$\begin{aligned}
U_u(\mathbf{x}_u,\mathbf{s}_u) = c_u &= \sum_{m=1}^{M} Z_{u,m}(\omega_1 c_{1,u} + \omega_2 c_{2,u} + \omega_3 c_{3,u}) \\
&= \sum_{m=1}^{M} Z_{u,m}(\omega_1 \int_0^{t_m^u} [a_1(1+a_2 v_m^2) \\
&+ a_3(\sqrt{1+\frac{v_m^4}{4a_4^2}} - \frac{v_m^2}{2a_4})^{\frac{1}{2}}]dt + \omega_2 p_u \frac{D}{r_{ui}} + \omega_3 P_m t_m^u) \\
&= \sum_{m=1}^{M} Z_{u,m}(\omega_1 \int_0^{\frac{\sqrt{[x_u(t)-x_i(t)^2]+[y_u(t)-y_i(t)^2]+H^2}}{v_m}} [a_1(1+a_2 v_m^2) \\
&\quad + a_3(\sqrt{1+\frac{v_m^4}{4a_4^2}} - \frac{v_m^2}{2a_4})^{\frac{1}{2}}]dt + \omega_2 p_u \frac{D}{r_{ui}} \\
&\quad + \omega_3 P_m \frac{\sqrt{[x_u(t)-x_i(t)^2]+[y_u(t)-y_i(t)^2]+H^2}}{v_m})
\end{aligned} \tag{12}$$

4.2 Optimization Problem

With the above description, a task allocation strategy to achieve the lowest energy consumption is obtained by minimizing the utility function. As such, the optimization problem is introduced.

Problem 1: The optimization problem for minimizing the energy consumption of the UAV can be formulated as

$$\begin{aligned}
min \quad & U_u(\mathbf{x}_u,\mathbf{s}_u), \\
s.t. \quad & t_0 \le t < t_m. \quad \forall m \in \mathcal{M} \\
& c_u \le E_{u,remain}(t). \quad \forall u \in \mathcal{U} \\
& \sum_{u=1}^{U} Z_{u,m} \le 1. \quad \forall u \in \mathcal{U} \\
& \sum_{m=1}^{M} Z_{u,m} \le L_u. \quad \forall u \in \mathcal{U}, \forall m \in \mathcal{M}
\end{aligned} \tag{13}$$

The proposed optimization problem is a NP-hard problem, which uses the MFTG to decompose the problem into the minimization problem of each UAV to realize the overall minimization. Considering the interactions between UAV's in the game, a new utility function is constructed by means of the mean-field value.

5 Static Mean-Field-Type Game Analysis

In this section, we construct the MFTG framework and obtain the equilibrium solution. The framework allows UAVs, as the multi-agents, to perform heterogeneous behaviors. The selfish behavior of any UAV in the network will affect the cost of other agents in the game. We analyze the optimal strategy of UAVs with the static MTFG, where the parameters of the game are public knowledge to all UAVs. The mean-field value of state and the mean-field value of strategy are shown in (14), (15), respectively.

$$\bar{\mathbf{x}}(t) = \frac{\sum_{u=1}^{U} \mathbf{x}_u(t)}{U} \tag{14}$$

$$\bar{\mathbf{s}}(t) = \frac{\sum_{u=1}^{U} \mathbf{s}_u(t)}{U} \tag{15}$$

At the final time $t = t_m^u$, considering the state of the UAV u, the terminal cost function can be expressed as

$$\Phi_u(\mathbf{x}(t_m^u), t_m^u) = \omega_4 E_{u,remain}^2(t_m^u) \tag{16}$$

The terminal function can be rewritten as

$$\Phi_u(\mathbf{x}_u, \bar{\mathbf{x}}, t_m^u) = \omega_4[\mathbf{x}_u^2(t_m^u) + \bar{\mathbf{x}}^2(t_m^u)] \tag{17}$$

According to the mean-field values, the utility function can be rewritten as

$$\begin{aligned}
\widetilde{U}_u(\mathbf{s}) &= U_u(\mathbf{x}_u, \bar{\mathbf{x}}, \mathbf{s}_u, \bar{\mathbf{s}}, t) + \Phi_u(\mathbf{x}(t_m^u), t_m^u) \\
&= \sum_{m=1}^{M} Z_{u,m}\{\omega_1[(c_{1,u}(\mathbf{x}_u, \mathbf{s}_u, t) + c_{1,u}(\mathbf{x}_u, \bar{\mathbf{x}}, \mathbf{s}_u, \bar{\mathbf{s}}, t)] \\
&+ \omega_2[c_{2,u}(\mathbf{x}_u, \mathbf{s}_u, t) + (c_{2,u}(\mathbf{x}_u, \bar{\mathbf{x}}, \mathbf{s}_u, \bar{\mathbf{s}}, t)] \\
&+ \omega_3[c_{3,u}(\mathbf{x}_u, \mathbf{s}_u, t) + (c_{3,u}(\mathbf{x}_u, \bar{\mathbf{x}}, \mathbf{s}_u, \bar{\mathbf{s}}, t)] + \Phi_u(\mathbf{x}(t_m^u), t_m^u)\}
\end{aligned} \tag{18}$$

Meanwhile, according to the MFTG model, the state dynamics equation can be rewritten as

$$d\mathbf{x}(t) = \theta\mathbf{x}(t) + \sum_{u=1}^{U} \lambda_u \mathbf{s}_u(t) + \bar{\theta}\bar{\mathbf{x}}(t) + \sum_{u=1}^{U} \bar{\lambda}_u \bar{\mathbf{s}_u}(t))dt + \mu dB(t) \tag{19}$$

where $B(t)$ represents a random Brownian process. μ is a parameter to measure Brownian process. $\bar{\theta}$ and $\bar{\lambda_u}$ respectively represent the mean of environmental impact factors and the mean of relative speed.

Hence, the MFTG problem is formulated in Problem 2.

Problem 2 (MFTG Problem): Consider the following problem:

$$\begin{cases} \inf_{\mathbf{s}_u \in \mathbf{S}_u} \mathbb{E}[\widetilde{U}_u(\mathbf{s})] = \inf_{\mathbf{s}_u \in \mathbf{S}_u} \mathbb{E}[\int_0^{t_u^m} U_u(\mathbf{x}_u, \bar{\mathbf{x}}, \mathbf{s}_u, \bar{\mathbf{s}}, t)dt + \Phi_u(\mathbf{x}_u, \bar{\mathbf{x}}, t_m^u)] \\ dx(t) = \theta x(t) + \sum_{u=1}^{U} \lambda_u \mathbf{s}_u(t) + \bar{\theta}\bar{\mathbf{x}}(t) + \sum_{u=1}^{U} \bar{\lambda}_u \bar{\mathbf{s}}(t))dt + \mu dB(t) \end{cases} \tag{20}$$

Definition 1. (*MFTG Best Response*): Any feasible strategy $\mathbf{s}_u^* \in \mathbf{S}_u$ satisfying the infimum in (20) is the best response strategy of decision maker $u \in \mathcal{U}$ against the others decision makers strategies $\mathbf{s}_{-u} \in \prod_{u' \in \mathcal{U}\setminus\{u\}} \mathbf{S}_u$. The set of strategies is given by $BR_u : \mathbf{u}_{-u} \prod_{u' \in \mathcal{U}\setminus\{u\}} \mathbf{S}_u \to 2^{\mathbf{S}_u}$, where $2^{\mathbf{S}_u}$ is the power set of all the possible subsets of $\mathbf{S}_u$.

Definition 2. (*MFTG Nash Equilibrium*): The profile of any feasible strategy $[\mathbf{s}_u^*, ..., \mathbf{s}_U^*] \in \prod_{u' \in \mathcal{U}} \mathbf{S}_u$ that optimizes $\mathbf{s}_u^* \in BR_u(\mathbf{s}_{-u}^*)$ for every $\mathbb{E}[\mathbf{x}^*(t)]$ is a mean-field-type Nash equilibrium of the MFTG, as Eq. (21) shows

$$\widetilde{U}_u(\mathbf{s}_u^*, \mathbf{s}_{-u}^*) \leq \widetilde{U}_u(\mathbf{s}_u, \mathbf{u}_{-u}^*) \tag{21}$$

The mean-field-type game problem of interest in this section is achieve that u is the best response to problem 3.2 for every UAV by finding and representing processes such as $[\mathbf{x}^*, \mathbf{s}^*, \mathbb{E}[\mathbf{x}^*], \mathbb{E}[\mathbf{s}^*]]$. It suggests that the Nash equilibrium is a fixed point for the best response $[BR = (BR_1, BR_2, ..., BR_U)]$, where each BR_U is the best response corresponding to UAV u.

Proposition 1. The optimal strategy is given by:

$$\mathbf{s}_u^* = -\beta_u \frac{(b_u + \bar{b}_u)}{(r_u + \bar{r}_u)} \mathbb{E}[\mathbf{x}] - \alpha_u \frac{b_u}{r_u} (\mathbf{x} - \mathbb{E}[\mathbf{x}]) \tag{22}$$

Proof: This proof is presented in [10].

6 Consensus-Based Bundle Algorithm Based Optimal Strategy Decision for Dynamic MFTG

In this section, we analyze the dynamic MFTG in the multi-UAVs, where the interactions between UAVs are repeatedly conducted over time. In the dynamic MFTG game, the utility parameters between UAVs are private in reality and cannot be fully understood by all UAVs. The UAVs interact with each other several times, to find the optimal strategy through trial and error. CBBA can model the UAVs under multiple interactions.

6.1 Score Function

The interactions between UAVs of the task allocation problem is simplified into mean-field value interaction by the MFTG theory. Therefore, the utility function is updated to score function to measure the effect of task allocation strategy in dynamic MTFG. The score function should be modified as

$$\hat{U}_u(\mathbf{x}_u, \mathbf{s}_u, \mathbf{p}_u) = U_u(\mathbf{x}_u, \bar{\mathbf{x}}, \mathbf{s}_u, \bar{\mathbf{x}}, t) + F_0 + e^{-\mu_u(t_u - t_0)}(F - F_0)X_{tw} \tag{23}$$

where F_0 is the fixed reward to ensure the total score is non-negative and $(F - F_0)$ is the discount reward of the task. μ_u is the discount factor. X_{tw} is the binary variable that indicates if the task plan satisfies the TTL constrain.

6.2 Task Allocation Model

The objective of CBBA is to obtain feasible and conflict-free task allocation solution when maximizes the score function [11]. The problem is expressed as follows:

$$\begin{aligned} max \quad & \hat{U}_u(\mathbf{x}_u, \mathbf{s}_u, \mathbf{p}_u) Z_{u,m}, \\ s.t. \quad & t_0 \leq t < t_0 + t_m. \quad \forall m \in \mathcal{M} \\ & c_u \leq E_{u,remain}(t). \quad \forall u \in \mathcal{U} \\ & \sum_{u=1}^{U} Z_{u,m} \leq 1. \quad \forall u \in \mathcal{U} \\ \sum_{m=1}^{M} Z_{u,m} \leq L_u. \quad & \forall u \in \mathcal{U}, \forall m \in \mathcal{M} \\ \sum_{u=1}^{U} \sum_{m=1}^{M} Z_{u,m} & = min\{\mathcal{U}, \mathcal{M}, R_m\}. \end{aligned} \tag{24}$$

where $\mathbf{p}_u$ is the order in which the UAV u executes the assigned tasks.

6.3 Consensus-Based Bundle Algorithm

The process of consensus-based bundle algorithm (CBBA) solving the multi-tasks allocation problem is divided into two phases: bundle construction and conflict resolution phases [12].

Bundle Construction. In the process of task allocation, the UAV u needs to store and update the following information structure:

- Bundle list $\mathbf{b}_u \in (\mathcal{M} \cup \{\emptyset\})^{L_u}$: indicates that tasks are sorted in the order in which they are added to packages.
- Path list $\mathbf{p}_u \in (\mathcal{M} \cup \{\emptyset\})^{L_u}$: refers to the optimal task execution sequence.
- Winner list $\mathbf{z}_u \in (\mathcal{U} \cup \{\emptyset\})^{\mathcal{M}}$: means the highest bid for task m of corresponding UAV in local information.
- Winning bid list $y_u \in (R_+)^{\mathcal{M}}$: represents the highest bid the UAV u considering task m.
- Time stamp $\mathbf{t}_u \in (R)^{\mathcal{U}}$: is the update time of information received by the UAV u from the other members of the network.

We adopt a diminishing marginal gain function to make the CBBA converge [13]. $S_u^{\mathbf{p}_i \bigoplus_n m}$ represents the reward value of the UAV u executing the task m which is inserted into the nth position.

$$c_{um} = max S_u^{\mathbf{p}_u \bigoplus_n m} - S_u^{\mathbf{p}_u}, \quad u \notin \mathbf{p}_u \tag{25}$$

$$c_{um}(\mathbf{b}_u) \geq c_{um}(\mathbf{b}_u \bigoplus_{end} \mathbf{b}) \tag{26}$$

The bundle construction of UAV u is implemented by Algorithm 1. $S_u^{\mathbf{p}_u}$ represents the total reward value of the UAV u executing the task along its path $\mathbf{p}_u$, where its initial value is 0.

Algorithm 1. CBBA phase 1 for UAV u at iteration t

Input: $\mathbf{b}_u(t-1), \mathbf{p}_u(t-1), \mathbf{z}_u(t-1), \mathbf{y}_u(t-1)$
Output: $\mathbf{b}_u(t), \mathbf{p}_u(t), \mathbf{z}_u(t), \mathbf{y}_u(t)$

```
b_u(t) = b_u(t-1), p_u(t) = p_u(t-1)
z_u(t) = z_u(t-1), y_u(t) = y_u(t-1)
while |b_u(t)| < R_m do
    c_um = max_{u ≤ |p_u|} S_u^{p_u ⊕_n m} - S_u^{p_u},   m ∉ p_u
    h_um = II(c_um > y_um)
    M_u = argmax_u (c_um(b_u) × h_um)
    n_{u,M_u} = argmax_u S_u^{p_u ⊕_n M_u}
    b_u = b_u ⊕_end {M_u}
    b_u = b_u ⊕_{n_{u,M_u}} {M_u}
     y_{u,M_u}(t) = c_{u,M_u}, z_{u,M_u} = u
end while
```

The process of bundle construction continues among the tasks until the construction of the task bundle list is completed, that is, the number of tasks in the bundle list reaches the upper limit of the number of tasks that UAVs can handle, or reaches the number of all tasks that need to be handled.

Conflict Resolution. After the task bundle construction process is completed, the UAV shares the bundle list and other information with the adjacent UAVs, and the corresponding task information is updated according to certain action rules to obtain the conflict-free task allocation. UAV u can take the following three actions on task m after receiving the message assigned by neighboring UAV j:

– Update: $y_{um} = y_{jm}, z_{um} = z_{jm}$;
– Reset: $y_{um} = 0, z_{um} = \emptyset$;
– Leave: $y_{um} = y_{um}, z_{um} = z_{um}$.

The conflict resolution of UAV u is implemented by Algorithm 2. After the multiple rounds of communications and negotiations through the conflict resolution, the winner list and the winning bid list will achieve a consensus [12].

7 Performance Evaluation

7.1 Simulation Setup

In the simulation scenario, there is a 600×600 m^2 terrain with one ground dispatching center. The flight height of all UAVs is set to 500 m. The positions of the tasks and the UAVs are randomly distributed. The number of UAVs is $U = 5$, and the number of tasks are $M = 10, 15, 20, 25$. The constant initial speed of UAVs is set to 80 m/s. The weighting parameters in the utility function are $\omega_1 = \omega_2 = \omega_3 = 1/3$. The parameters in the score function are $\mu_u = 0.1$, $F_0 = 10$ and $F = 100$ [13].

Algorithm 2. CBBA phase 2 for UAV u at iteration t

Input: $\mathbf{b}_u, \mathbf{p}_u, \mathbf{z}_u, \mathbf{y}_u, \mathbf{t}_u$
Output: $\mathbf{B}_u, \mathbf{P}_u, \mathbf{Z}_u, \mathbf{Y}_u, \mathbf{t}_u$

$\mathbf{B}_u = \mathbf{b}_u, \mathbf{P}_u = \mathbf{p}_u$
$\mathbf{Y}_u = \mathbf{y}_u \bigoplus 0, \mathbf{Z}_u = \mathbf{z}_u \bigoplus \emptyset$
$\mathcal{M}_{u,reset} = \emptyset$
if $CM(u, m_*) = 1$ **then**
  for $m \in \mathbf{B}_u$ **do**
    if $t_u * m$ overlaps with $[t_0, t_{m^*}]$ **then**
      $\mathcal{M}_{u,reset} = \mathcal{M}_{u,reset} \bigcup \{u\}$
      $\mathbf{D}_{u,reset}(u) = S(\mathbf{p}_u) + S_u^{\mathbf{p}_u} \oplus_n m^*$
    end if
  end for
  if $\mathcal{M}_{u,reset} \neq \emptyset$ **then**
    $m_{u,reset} = argmin_u \mathbf{D}_{u,reset}$
    $\mathbf{B}_u = \mathbf{B}_u \ominus \{u_{u,reset}\}, \mathbf{P}_u = \mathbf{P}_u \ominus \{m_{u,reset}\}$
    $\mathbf{Y}_{u,reset} = 0, \mathbf{Z}_{u,reset} = \emptyset, \mathbf{t}_{u,reset} = 0$
  end if
end if
Phase 2: conflict resolution
Phase 1: bundle construction $(\mathbf{B}_u, \mathbf{P}_u, \mathbf{Z}_u, \mathbf{Y}_u, \mathbf{t}_u)$
Phase 2: conflict resolution

7.2 Numerical Results

Figure 2 shows the energy consumption of UAVs with different number of tasks. As can be seen from Fig. 2, the proposed scheme has lower energy consumption. In the proposed scheme, each UAV selects the optimal strategy based on the MFTG, which can effectively reduce the energy consumption. In the random option algorithm, UAVs choose the strategy randomly, leading to a higher energy consumption. As for the greedy algorithm, UAVs only focus on the shortest path while ignore the characteristics of different tasks.

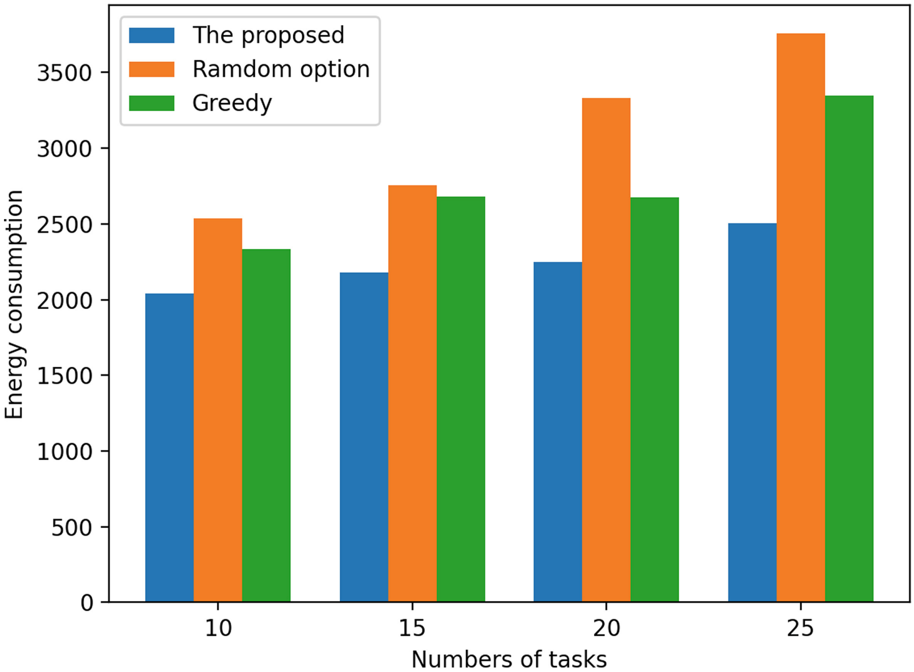

Fig. 2. The energy consumption with different numbers of tasks.

Figure 3 shows the scores of UAVs in a number of different tasks. As shown in Fig. 3, the proposed scheme can obtain a higher score. This is because the scheme takes into account not only the selfishness of UAVs, but also the interactions between them.

Figure 4 shows the equality capability index of UAVs in terms of different amounts of tasks. According to the equalization ability index in the engineering system, the balanced and reasonable task allocation of the three algorithms is measured. Define CP_i as the equality capability index, which is

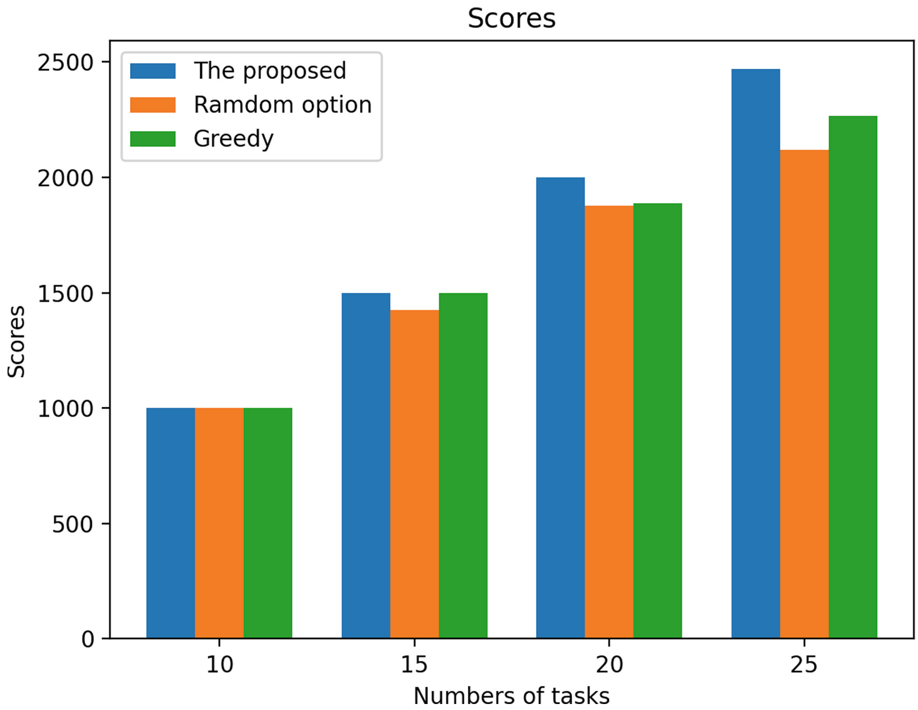

Fig. 3. The scores with different numbers of tasks.

$$CP_i = \frac{k - \bar{m}}{3\sigma_m}, \tag{27}$$

where k is the number of tasks allocated to UAV u. $\bar{m}$ is the average number of tasks allocated to each UAV. σ_m is The standard deviation. When $0.67 < CP_i < 1$, the allocation is relatively balanced. From Fig. 3, we can observe that the proposed scheme can obtain a more balanced allocation. This is because the proposed scheme achieve a consensus on the tasks through the conflict resolution.

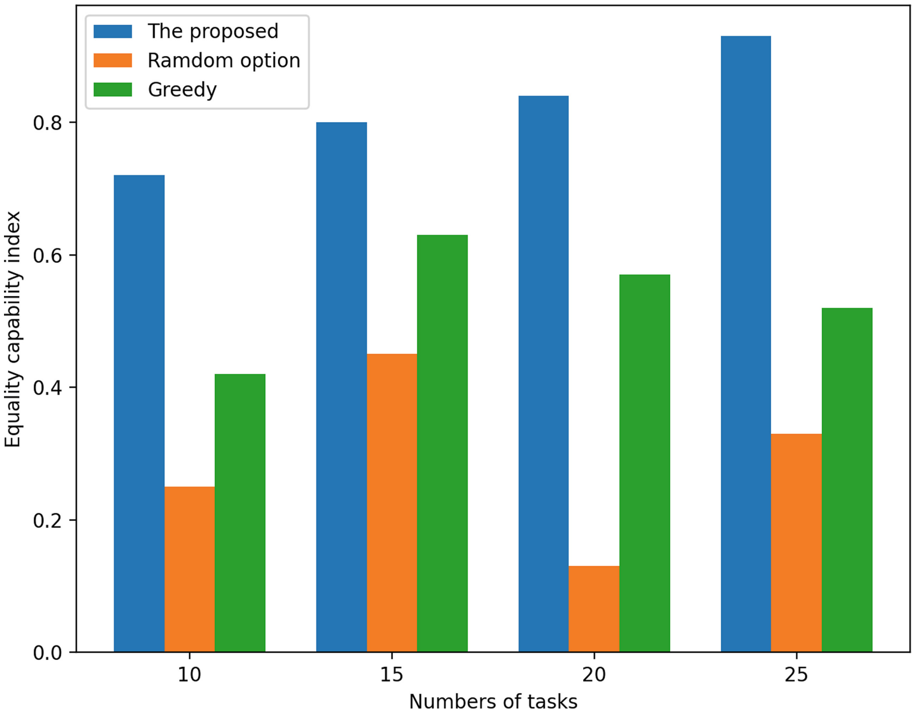

Fig. 4. The equality capability index with different numbers of tasks.

8 Conclusion

In this paper, we have presented a novel logistics task allocation scheme in the multi-UAV network. First, to model interactions between UAVs, a static MTFG framework is proposed to consider the selfishness and external aerodynamic factors, where all the UAVs can obtain the minimum energy consumption. Then, we have employed the CBBA to obtain the optimal strategy for each UAV in the dynamic environment. At last, the simulation results show that the proposed scheme can efficiently reduce the energy consumption of UAVs and allocation the tasks. For the future work, the variety of task model and deep reinforcement learning method for path planning will be investigated.

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