Task-Based Network Reconfiguration in Distributed UAV Swarms: A Bilateral Matching Approach

Dianxiong Liu, Zhiyong Du, *Member, IEEE*, Xiaodu Liu, Heyu Luan, Yitao Xu, and Yifan Xu

***Abstract*—In this paper, we study the problem of network reconfiguration when unmanned aerial vehicle (UAV) swarms suffer damage. Multiple UAVs are divided into several groups to perform various tasks. Each master UAV is connected to the ground control station and provides network services for small UAVs that perform various tasks, ensuring that the information of small UAVs can be transmitted back in a timely manner. When master UAVs are destroyed due to factors such as jamming or attacks, the associated small UAVs must select new master UAVs for network service and cooperate with other small UAVs to execute tasks. Based on the heterogeneity and relevance of tasks, we model and analyze the task relationship among different UAVs. Since both master UAVs and small UAVs have respective optimization objectives in the network reconfiguration process, we construct a many-to-one bilateral matching market to model the interaction between master UAVs and small UAVs. To realize an efficient solution for UAV network reconfiguration in complex environments, we propose a distributed matching algorithm and prove that the algorithm can converge to two-sided stable matching. Simulation results indicate that the proposed algorithm can significantly improve the task completion degree of the network compared with three other algorithms.**

***Index Terms*—UAV swarms, network reconfiguration, task-based, bilateral matching game, stable matching.**

I. Introduction

THE development of multi-unmanned aerial vehicle (UAV) swarms has been widely studied for complex task coordination [1]–[5]. Because the environment and tasks of UAVs undergo real-time changes, maintaining the stability of communication in such an environment is a critical issue for multi-UAV networks [5]. UAVs must be flexibly deployed and dynamically adjusted, especially for rapid network reorganization when UAV swarms are suddenly destroyed.

Manuscript received 13 August 2020; revised 14 May 2021; accepted 20 May 2022; approved by IEEE/ACM Transactions on Networking Editor D. Cansever. Date of publication 14 June 2022; date of current version 20 December 2022. This work was supported in part by the National Science Foundation of China under Grant 62101584 and Grant 61901520 and in part by the Key Laboratory Fund under Grant 6142101200205. *(Corresponding author: Zhiyong Du.)*

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Digital Object Identifier 10.1109/TNET.2022.3181036

Existing work focuses on scenarios in which UAVs provide services to ground wireless networks, such as serving as flight base stations to expand the coverage of ground cellular networks or as relay nodes between ground terminals and base stations [6]–[9]. In comparison, the internal communication of UAV swarms has not been thoroughly studied. Some articles consider time-frequency resource scheduling, power allocation, and routing optimization in UAV communication networks, where the environment is assumed to be stable [10]–[12]. However, the problem of robust communication and network reselection in the case of emergencies has not been considered. After a swarm crash, improper network selection and resource allocation can lead to a decrease in the overall efficiency of a system [13]. Therefore, network selection strategies in UAV swarms are necessary.

Existing articles on network selection have focused on ground cellular networks. The distribution of the network load affects the throughput of users, so throughput has become the main criterion to assess the quality of multiuser network selection [14]–[16]. Moreover, the authors in [17] studied a utility function related to bandwidth and delay. The above studies provide some reference for the mathematical modeling of UAV network selection but do not take the characteristics of UAVs into consideration. Unlike ground devices, UAVs have strong aerial mobility, allowing them to choose an appropriate network by adjusting their location.

In addition, UAVs communicate with each other to complete specific tasks rather than blindly pursuing the quality of communication. The authors in [18] modeled the task assignment problems of multi-UAVs as an integer programming problem in the case of heterogeneous UAV types. The authors in [19] established a task planning model, where the task execution sequence was considered. In [20], a multi-UAV system was used to convey collected data from isolated fields to a base station, where UAVs collaborate in forwarding the collected data to maximize the minimum battery level for all UAVs by the end of the service time. The existing research has focused on task allocation and ignored the resource optimization problem of the network under established task conditions [18], [19]. Although some related work has studied task allocation and UAV communication network optimization [12], [20], the network robustness and reconfiguration issues in complex dynamic environments have been ignored.

In this paper, we aim to solve the problem of task-based network reconfiguration in UAV swarms. UAVs are divided into multiple task groups, where each UAV group consists of one master UAV and several small UAVs [21]. Master UAVs coordinate with each other according to the task cooperation relationship. Small UAVs complete tasks assigned by the master UAV and occupy the network resources of the master UAV. When the master UAV suffers damage and cannot provide network service, small UAVs must quickly restore network connections. They can adjust the network position according to the task relevance and choose to access a new master UAV. In this scenario, not only the quality of the connection and bandwidth resources but also the consumption of propulsion energy [22] should be considered.

In our previous works, we studied the internal communication of UAV groups [23], [24] without considering the task-driven communication requirements of UAVs. In this paper, we analyze the influence of task relationships on network selection decisions. To investigate the task heterogeneity and relevance among UAV groups, we establish a task relevance model. The social relationship model [25] provides inspiration for the construction of the task relationship between master UAVs and small UAVs. Based on the resource scheduling strategy with service differentiation [26], the network requirements of small UAVs with different task types are distinguished. Moreover, a satisfaction function based on task completion is designed, and the network access decision of small UAVs is optimized to promote the task completion degree.

The large-scale and dynamic network topology of UAV groups makes it essential to select appropriate mathematical methods under the considered conditions. Considering the changing and uncertain network environment, a distributed optimization model is proposed. For the bilateral communication demands of master UAVs and small UAVs, we model the network selection problem as a bilateral many-to-one matching market [27]. A matching game model with fast convergence is constructed for rapid network reconfiguration facing UAV swarm contingencies. The designed matching game does not require global decision information, and the utility function is easy to design and can satisfy the communication needs of different UAVs [21].

Based on the matching model, we take the peer effects among small UAVs and the dynamic quotas of master UAVs into consideration [28], which cannot be done with traditional matching algorithms, such as deferred acceptance algorithms [29]. Therefore, we propose a task-based distributed matching algorithm for the reconfiguration of UAV networks. Small UAVs access the appropriate master UAVs according to their own task demands, and master UAVs allocate bandwidth resources to small UAVs. We prove that the proposed algorithm can converge to a stable solution rapidly and obtain a better task completion degree when handling large-scale UAV swarms. This approach can effectively solve the challenge brought by the dynamic UAV network. The main contributions of our work can be summarized as follows:

- We consider a task-based dynamic UAV network reconfiguration problem in the case of master UAV destruction. A tradeoff between the flight loss and available throughput of UAVs is considered from the perspective of task completion.
- A task relation model is established to account for task heterogeneity and relevance among UAV groups. We analyze the task relevance between master UAVs and small UAVs and distinguish the network requirements of small UAVs with different tasks.
- We model the network service relationship between a master UAV and small UAV as a many-to-one matching market with peer effects and the dynamic match quota. Moreover, a task-based satisfaction function is designed, and the task completion degree can be improved by optimizing the network access decision of small UAVs.
- A distributed algorithm for task completion degree perception based on the matching game is proposed. The proposed algorithm is proven to converge to a two-sided stable matching, and the simulation results show that the task completion degree of the proposed algorithm is higher than that of other algorithms.

The rest of this paper is organized as follows. In Section II, we present the system model. In Section III, we formulate the network access problem. Then, we construct a many-to-one matching market to solve the problem in Section IV. Furthermore, we propose a distributed task completion-aware network access algorithm in Section V and we present the simulation results and performance analysis in Section VI. Finally, we draw the conclusion in Section VII.

II. System Model

We consider a UAV swarm consisting of N master UAVs and M small UAVs, which are denoted by $\mathcal{N} = \{n_1, n_2, \ldots, n_N\}$, and $\mathcal{M} = \{m_1, m_2, \ldots, m_M\}$, respectively. Master UAVs are responsible for information gathering and cooperating with other master UAVs. Master UAVs collaborate with each other to execute tasks, which are determined in advance according to task planning. Each master UAV assigns tasks and provides network services to its associated small UAVs in its communication range. The small UAVs covered by a master UAV share communication resources. In other words, small UAVs represent the loads of the corresponding master UAV. An example of the system model is shown in Fig. 1. Some master UAVs may be temporarily unable to work due to the impact of bad weather, power shortages, or other factors during task execution. The small UAVs covered by these master UAVs thus cannot obtain network services to complete their tasks. In such situations, the network association must be rebuilt. These small UAVs should seek network services according to their mission requirements.

One master UAV provides a certain amount of bandwidth for the small UAVs accessing it according to the needs of the small drones, and small UAVs associated with the same master UAV share the network bandwidth. The data rate of small UAV m when it is associated with master UAV n is [13]:

$$\theta_{m,n} = w_{m,n} R_{m,n}, \tag{1}$$

where $w_{m,n}$ is the bandwidth allocation weight of small UAV m for master UAV n, which is the number of allocated subchannels. $R_{m,n}$ is the data rate between small UAV m

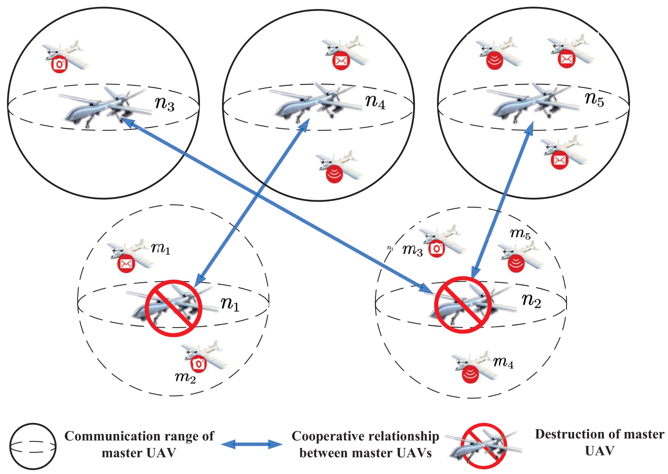

Fig. 1. An illustration of the considered scenario. 5 master UAVs are responsible for information gathering and have a cooperative relationship with some other master UAVs. Small UAVs are associated with different tasks and rely on the master UAVs for network service. 2 master UAVs are destroyed, and the associated small UAVs have to reselect master UAVs.

and master UAV n in a subchannel, which is determined by the channel capacity as

$$R_{m,n} = B_n \log_2\left(1 + \frac{P_t d_{m,n}^{-2}}{\sigma_n^2}\right), \tag{2}$$

where B_n represents the bandwidth of each subchannel in master UAV n's network in Hz, P_t is the signal transmit power of the master UAV network in each subchannel, and $d_{m,n}$ is the distance between m and n. Since the link exists between UAVs in the air, the channel power gain $d_{m,n}^{-2}$ accounts for only path loss, which is dependent on the relative positions of m and n. σ_n^2 is the environmental noise power in network n. In the rest of this paper, network n refers to the wireless access network provided by master UAV n. All the networks of master UAVs work on different channels; thus, there is no intermaster UAV interference. Moreover, the Doppler effect due to UAV mobility is assumed to be perfectly eliminated [22].

When some upper-level master UAVs cannot work due to emergencies, their subordinate small UAVs cannot complete existing tasks, so network reconfiguration is needed. When small UAVs need to select a new network, they can change their location to access a new master UAV, which will result in certain flight energy losses. We hypothesize that small UAVs fly to the relative area covered by a master UAV via the shortest straight distance. The flight energy consumption [22] can be defined as follows:

$$E_{m,n} = \frac{d_{m,n}}{V}\left(c_1 V^3 + \frac{c_2}{V}\right), \tag{3}$$

where V is the given UAV speed and c_1, c_2 are constants related to the weight of the aircraft and the external wind force. The first term is the resistance consumption caused by air friction during flight, which is proportional to the third power of speed. The second term is the energy consumption required to overcome lift. The energy consumption model is simplified in this paper, and the proposed solution is not limited to this specific flight energy consumption model. Other related models could also be considered, such as the case with variable UAV speed in [22] and rotary-wing UAV models in [8].

III. Task Completion-Aware Network Access Problem Formation

In large-scale UAV networks, master UAVs collaborate to complete investigation, monitoring, mapping, and other tasks in specified areas [30]. The master UAV subdivides its tasks into several subtasks and assigns them to its subordinate small UAVs. Small UAVs connect with the master UAV according to the task relationships. In this section, we formulate the small UAV network access problem as maximizing the global task completion degree of the network. The problem formulation details are given in the following. Some main variables and definitions are presented in Table I.

A. Task Relevance Formation

Small UAVs perform various tasks, such as terrain reconnaissance, message passing, and communication link maintenance. Some can obtain network services within the coverage range of master UAVs, while others cannot due to the destruction of their master UAV. If tasks performed by these small UAVs without network services are similar to those performed by the existing master UAV, it is said that the small UAV and master UAV have task relevance.

We model task relevance with regard to the small UAV and the master UAV by means of graph models as $\mathcal{G}_1 = \langle \mathcal{F}, \varepsilon_1\rangle$ and $\mathcal{G}_2 = \langle \mathcal{F}, \varepsilon_2\rangle$, where $\mathcal{F} = \mathcal{N} \cup \mathcal{M}$ is the vertex set. ε_1 and ε_2 are the directed edge sets of $\mathcal{G}_1$ and $\mathcal{G}_2$, respectively.

$\mathcal{G}_1$ models the task relevance from the perspective of small UAVs. Each directed edge from a master UAV to a small UAV represents a task-relevance association between them. We assume that each small UAV attempts to connect to the master UAV with the highest task relevance and the best network services. To this end, we assign a weight to each directed edge $n \rightarrow m$ as the task relevance index. Reference [31] introduces Jaccard's coefficient, which is defined as the size of the intersection divided by the size of the union of the sample sets. Here, we define the task relevance index $\Phi_{n,m}$ based on Jaccard's coefficient as

$$\Phi_{n,m} = \frac{|\mathcal{J}_m \cap \mathcal{J}_n|}{|\mathcal{J}_m \cup \mathcal{J}_n|}, \tag{4}$$

where $\mathcal{J}_m$ and $\mathcal{J}_n$ denote the task sets of m and n, respectively. Note that $\mathcal{J}_m \cap \mathcal{J}_n$ represents the common *task types* between m and n, while $\mathcal{J}_m \cup \mathcal{J}_n$ is the total *tasks* in m and n. A large value of $\Phi_{n,m}$ indicates that m shares strong task relevance with n. For example in Fig. 1, m_1 in n_4 is responsible for sending messages, and the master UAVs n_4 and n_5 have subordinate small UAVs with the same tasks; thus, m_1 has task relevance with n_4 and n_5. Moreover, if the master UAV has fewer subordinate small UAVs, it will have stronger task relevance with m_s. Thus, m_1 has more task relevance with n_4 than with n_5. Therefore, we define the throughput $\widehat{\theta}_{m,n}$ of small UAV m accessing master UAV n as:

$$\widehat{\theta}_{m,n} = \Phi_{n,m}\theta_{m,n}, \tag{5}$$

TABLE I
NOTATION LIST

Variable	Definition
$\mathcal{M}$	Set of small UAVs
$\mathcal{N}$	Set of master UAVs
$\mathcal{M}_n$	Set of small UAVs associated with master UAV n
$\theta_{m,n}$	Data rate of small UAV m associated with master UAV n
$\widehat{\theta}_{m,n}$	Throughput of small UAV m associated with master UAV n
$R_{m,n}$	Data rate on one subchannel of small UAV m associated with master UAV n
P_t	Transmit power of master UAVs in each subchannel
B_n	The bandwidth of each subchannel in master UAV n's network
W_n	The total number of subchannels in master UAV n's network
$d_{m,n}$	Distance between small UAV m and master UAV n
σ_n^2	The environmental noise power in master UAV n
$E_{m,n}$	Flight energy loss when small UAV m flies to the coverage area of network n
V	UAV flight speed
$\varPhi_{n,m}$	Task-relevance index from the perspective of small UAV m
$\varTheta_{m,n}$	Task-relevance index from the perspective of master UAV n
$\mathcal{J}_m$	Task set of small UAV m
$\mathcal{J}_n$	Task set of master UAV n
γ	normalization factor
μ	A feasible matching rule between $\mathcal{M}$ and $\mathcal{N}$
$\varPi$	Set of all feasible matching rules between $\mathcal{M}$ and $\mathcal{N}$
$\widehat{\theta}_{\text{real-time}}$	Throughput threshold of real-time task UAVs
$\widehat{\theta}_{\text{elastic}}$	Throughput threshold of elastic task UAVs
$S_{m,n}$	Network switching overhead when small UAV m switch to master UAV n
$w_{m,n}$	Allocated weight of small UAV m in master UAV n
$w^*_{m,n}$	Required weight to meet small UAV m's throughput requirement if it is in master UAV n

where $\varPhi_{n,m}$ represents the proportion of throughput that small UAV m can obtain from the newly selected master UAV.

From the perspective of master UAVs, each directed edge $m \to n$ in $\mathcal{G}_2$ represents a task-relevance tie from m to n. Task relevance here indicates that if the two UAVs have more common tasks, the master UAV can obtain more data from the small UAV. Hence, each master UAV wants to accept the small UAV with the highest task relevance. We define the task relevance index as the ratio between the current information resource of n and the total amount of information given by m:

$$\varTheta_{m,n} = \frac{K_{n,m}}{K_{m,n} + K_{n,m}}, \tag{6}$$

where $K_{m,n}$ is the information source or data that n can obtain from m and $K_{n,m}$ is the information resource in n that has the same task type as m. These two parameters reflect the information gain that master UAV n could achieve from small UAV m, which may be conceptual. For example, as shown in 1, master UAV n_5 with two small UAVs for sending messages and one small UAV providing wireless communication has stronger task relevance with the small UAV for sending messages than it does with the small UAV that provides wireless communication. That is, the task relevance indices are $\frac{2}{1+2}$ and $\frac{1}{1+1}$, respectively. Clearly, the task relationships between master UAVs and small UAVs can be viewed from the above two perspectives. Fig. 2 shows the task relevance illustration of Fig. 1 without directed edges.

B. Task-Driven Satisfaction Function

In addition to the different types of tasks, each small UAV has a different demand for network resources. Small

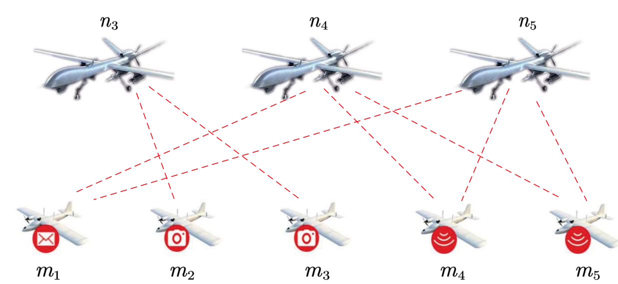

Fig. 2. The task relevance graph of Fig. 1. Note that only undirected edges are shown in the figure and directed edge weights can be determined by (4) and (6).

UAVs do not blindly pursue maximization of throughput but seek a master UAV that can satisfy its task communication requirements. The master UAV allocates its network resources to small UAVs to maximize the overall UAV satisfaction, namely, the task completion degree. In this paper, the tasks of small UAVs are divided into two types: real-time UAV tasks and elastic UAV tasks.

1) Real-Time UAV Tasks: Real-time UAV tasks have strict network transmission requirements and specific throughput threshold requirements; only when this threshold is reached can communication tasks be completed. For example, the master UAV performs monitoring tasks and assigns one subordinate small UAV to perform real-time video monitoring. The purpose of this task is to implement continuous video transmission, and to reach the throughput threshold, flight loss can be neglected. The satisfaction function is given as [32]:

$$g\left(\widehat{\theta}_{m,n}\right) = \begin{cases} 1, & \widehat{\theta}_{m,n} \geq \widehat{\theta}_{\text{real-time}} \\ 0, & \widehat{\theta}_{m,n} < \widehat{\theta}_{\text{real-time}} \end{cases}, \tag{7}$$

where $\widehat{\theta}_{real-time}$ is the throughput threshold of real-time UAV tasks. When the throughput threshold is reached, a small UAV can complete the task and the satisfaction degree is 1; otherwise, the satisfaction degree is 0.

2) Elastic UAV Tasks: Some small UAVs can send back images and terrain information for specified areas. Such missions are not performed in real time and do not have strict throughput requirements. We call these tasks elastic UAV tasks [33]. For elastic UAV tasks, the tradeoff between throughput and flight loss is considered, and the satisfaction function is shown below:

$$h\left(\widehat{\theta}_{m,n}\right) = \frac{\widehat{\theta}_{m,n} - \beta E_{m,n}}{\widehat{\theta}_{\text{elastic}}}, \tag{8}$$

where β is a normalization factor between throughput and flight loss and $\widehat{\theta}_{\text{elastic}}$ is the peak throughput requirement for small UAVs with elastic tasks. The satisfaction of UAVs increases as the available throughput improves. Notably, the proposed optimization problem and framework do not impose specific requirements on the satisfaction functions, and other forms, such as considering one of the two factors in the objective and the other in a constraint, could be used. An in-depth study of the satisfaction function design is beyond the scope of this work.

C. Optimization Problem

Due to the bandwidth-sharing nature of small UAVs associated with the same master UAV, the master UAV selection decisions of all small UAVs and the bandwidth allocation weights of the master UAVs affect the satisfaction functions of the small UAVs. Denote the master UAV selection vector by $\boldsymbol{a} = (a_1, a_2, \ldots, a_M)$, where $a_m \in \mathcal{N}$ denotes the master UAV selected by small UAV m. Denote the bandwidth allocation matrix by $\boldsymbol{w} = \{w_{m,n}\}$ subject to i). $W_{a_m} \geq w_{m,a_m} > 0$ and $w_{m,n} = 0$, $\forall n \neq a_m$; ii). $\sum_{m\in\mathcal{M}_n} w_{m,n} \leq W_n$, $\forall n \in \mathcal{N}$. Given $\boldsymbol{a}$ and $\boldsymbol{w}$, the utility of small UAV m can be defined as

$$f_m\left(\boldsymbol{a},\boldsymbol{w}\right) = \begin{cases} g\left[\widehat{\theta}_m\left(\boldsymbol{a},\boldsymbol{w}\right)\right], \text{if } m \text{ is a real-time task UAV} \\ h\left[\widehat{\theta}_m\left(\boldsymbol{a},\boldsymbol{w}\right)\right], \text{if } m \text{ is an elastic task UAV,} \end{cases} \tag{9}$$

where $\widehat{\theta}_m\left(\boldsymbol{a},\boldsymbol{w}\right)$ and $\widehat{\theta}_m\left(\boldsymbol{a},\boldsymbol{w}\right)$ are the satisfaction degrees calculated by (7) and (8), respectively.

Then, we can define the optimization problem as maximizing the global task completion degree, that is,

$$\max_{\boldsymbol{a}\in\boldsymbol{A},\boldsymbol{w}\in\boldsymbol{W}} \sum_{m\in\mathcal{M}} f_m\left(\boldsymbol{a},\boldsymbol{w}\right), \tag{10}$$

where $\boldsymbol{A}$ and $\boldsymbol{W}$ are the feasible sets of $\boldsymbol{a}$ and $\boldsymbol{w}$, respectively. The goal of the problem is to establish an association relationship between small UAVs and master UAVs and allocate resources reasonably to ensure the task completion of each small UAV. Considering the different task requirements, combined with the throughput and flight loss of small UAVs, the small UAV association problem is similar to a combinatorial optimization problem [34], apart from the bandwidth weight allocation. Finding the optimal solution in a centralized manner would be expensive, and the computational complexity is high, especially when the network scale is large. Therefore, we construct a self-organized network optimization architecture to solve the problem.

IV. Task Completion-Aware Network Access System as a Matching Market

In this section, a distributed solution framework is proposed by reformulating the optimization problem as a matching market.

A. Matching Market Formation

Note that only the small UAVs that are out of network service require network reconfiguration, that is, reselecting a master UAV to access. For notational simplicity, $\mathcal{M}$ is reused to denote the set of small UAVs out of network service. The throughput of small UAVs is related to the transmission speed of the master UAV network and the bandwidth allocation weight the master UAV can provide. Due to the limited bandwidth of the master UAV, the number of small UAVs it can accommodate is limited. To ensure the service quality of static small UAVs (those that have stable network service and do not require network reconfiguration), we employ a simple and efficient "first-come-first-served" bandwidth allocation policy: when sufficient bandwidth is available, the master UAV meets the demand of a newly accessed small UAV; otherwise, the remaining bandwidth resources of the master UAV are allocated. Accordingly, the weight $w_{m,n}$ for small UAV m prepared to access master UAV n is as follows:

$$w_{m,n} = \min\left\{w^*_{m,n}, W_n - \sum_{i\in\mathcal{M}_n} w_{i,n}\right\}, \tag{11}$$

where $\mathcal{M}_n$ is the set of small UAVs that have been associated with master UAV n and W_n is the total number of subchannels in master UAV n's network. Thus, the total bandwidth of master UAV n is $W_n B_n$, $W_n - \sum_{i\in\mathcal{M}_n} w_{i,n}$ is the remaining bandwidth resource of the master UAV, and $w^*_{m,n}$ represents the weight required to satisfy small UAV n's throughput requirement when associated with master UAV n. According to the throughput requirement, the desired weight for real-time task small UAVs is $w^*_{m,n} = w_{m,n}|_{\widehat{\theta}_{m,n}=\widehat{\theta}_{real-time}}$, and that for elastic task small UAVs is $w^*_{m,n} = w_{m,n}|_{\widehat{\theta}_{m,n}=\widehat{\theta}_{elastic}}$.

The above assumption implies that the bandwidth allocation policy is determined; thus the remaining focus for the problem of (10) is optimizing the master UAV selection for small UAVs $\mathcal{M}$. To this end, we propose a distributed method based on a two-sided matching game, in which a bilateral decision player makes the right decisions according to its preferences [27]. The main advantages of the matching game model are as follows: 1) it establishes the preference relationship according to the individual needs of small UAVs and master UAVs; 2) it belongs to a distributed resource allocation method, which can efficiently obtain a stable solution by employing the individual strategies of game players.

Definition 1: A two-sided matching game is defined by two sets of players $(\mathcal{M}, \mathcal{N})$ and two preference relations $\succ_m, \succ_n$.

Each player $m \in \mathcal{M}$; $n \in \mathcal{N}$ builds a list of preferred players to be selected from the other side. The matching items in $\mathcal{M}$ and $\mathcal{N}$ are sorted by preference. The matching game can be represented as [27],

$$\mathcal{G}\left(\mathcal{M}, \mathcal{N}, \succ_m, \succ_n, q_m, q_n\right), \tag{12}$$

where $\succ$ is the matching preference relation. This relationship is a complete, transitive, and reflective duality in $\mathcal{M}$ and $\mathcal{N}$. Each player ranks the matching items in the opposite user set by preference. The maximum number of users that each player can match is called the matching quota q. Once the matching relation of the decision maker is established, the matching game model is constructed.

The network selection interaction between the master UAVs $\mathcal{N}$ and the small UAVs $\mathcal{M}$ outside of network service can be treated as a matching game. In the rest of this section, detailed models of the matching preference are proposed.

B. Small UAVs' Preference

Due to the various tasks performed by small UAVs, their preferences for master UAVs differ. For the two different tasks, the matching rule is formulated as follows.

For real-time UAV tasks, each small UAV m finds a master UAV network to satisfy the threshold requirement. Real-time task UAVs select a master UAV network according to

$$g\left(\widehat{\theta}_{m,n}\right) \to 1 \Rightarrow find\left\{\widehat{\theta}_{m,n} \geqslant \widehat{\theta}_{real-time}\right\}. \tag{13}$$

According to the throughput demand of small UAVs with real-time tasks, the preference relation can be expressed as:

$$n \succ_m n' \Leftrightarrow \begin{cases} \widehat{\theta}_{m,n} \geq \widehat{\theta}_{real-time} \\ \widehat{\theta}_{m,n'} < \widehat{\theta}_{real-time}. \end{cases} \tag{14}$$

That is, master UAV n that can reach the throughput threshold will receive a higher priority than master UAV n' that cannot meet the throughput threshold. In addition, if two master UAVs can satisfy the throughput threshold, they will have equal priority. The master UAV that provides the greatest throughput will be selected first because the higher the throughput is, the greater the chances that small UAVs will be accepted by the master UAV. If the throughput provided by master UAV n does not reach the throughput threshold, n will not appear in the preference list of small UAV m.

For elastic UAV tasks, small UAVs are concerned about the flight loss caused by flying to the coverage area of the master UAV network. Therefore, when a small UAV wants to access a master UAV network, it seeks the maximum utility after a compromise between the two aspects. The elastic task small UAV selects a master UAV according to

$$\max_{n \in \mathcal{N}} h\left(\widehat{\theta}_{m,n}\right). \tag{15}$$

Accordingly, the preference relationship of elastic task UAV m can be expressed as:

$$n \succ_m n' \;\Leftrightarrow\; h\left(\widehat{\theta}_{m,n}\right) > h\left(\widehat{\theta}_{m,n'}\right). \tag{16}$$

A master UAV providing greater utility will receive a higher priority. In this regard, the preference list of a small UAV is sorted from high to low in terms of utility.

Following the above modeling and analysis, each small UAV forms its preference list according to its task requirements, where elements in the list are the master UAV networks.

C. Master UAVs' Preference

Master UAVs' admission decision for small UAVs is assumed to be determined by two factors: task relevance and network switching overhead. As mentioned previously, the task relevance between master UAVs and small UAVs depends on their tasks. For the master UAV, the more relevant the task is, the more information it can obtain from small UAVs. On the other hand, a small UAV will incur network switching overhead when it switches to a master UAV that has no cooperative relationship with its former master UAV. To improve the efficiency of its network service, each master UAV requires that the overhead caused by small UAVs during network switching be as small as possible. Therefore, we define the optimization function of master UAV n as maximizing $F_n(m)$,

$$\max_{m \in \mathcal{M}} F_n(m) = \varTheta_{m,n} - \gamma S_{m,n}, \tag{17}$$

where $\varTheta_{m,n}$ is the task relevance index defined in (6), $S_{m,n}$ is the network switching overhead, and γ is a normalization factor. The proposed solution is not limited to specific optimization objective models. Other modeling approaches, such as optimizing one of the two factors in the objective and treating the other as a constraint, could also be feasible.

We consider the time loss during network switching as the overhead. Note that master UAVs with cooperative relationships have the same network signal transmission mode [35]. Master UAVs with different cooperative relations vary in terms of network launch mode, working frequency, physical layer, and network coverage [13]. For example, a UAV with a collaborative detection task has a relatively wide coverage area but relatively scattered signals, while a UAV with a real-time information delivery task has relatively strong signals but a relatively small coverage area. If a small UAV without network service connects to a master UAV with no cooperative relationship with the small UAV's original master, the small UAV must switch its network protocol or signal reception mode. Thus, the network switching overhead is not uniform [36] but depends on the specific case.

Denote the previously associated master UAV of small UAV m by $\bar{a}_m$. According to the cooperative relationship and electromagnetic environment diversity between $\bar{a}_m$ and n, there are three switching cases. *Case 1*: $\bar{a}_m$ and n have a cooperative relationship under the same electromagnetic environment; *Case 2*: $\bar{a}_m$ and n have no cooperative relationship under the same electromagnetic environment; and *Case 3*: $\bar{a}_m$ and n have no cooperative relationship under different electromagnetic environments. We define the network switching overhead in the following three switching cases by

$$S_{m,n} = \begin{cases} s_1, \text{network switching case } 1 \\ s_2, \text{network switching case } 2 \\ s_3, \text{network switching case } 3 \end{cases}. \tag{18}$$

The following relationship holds

$$s_3 > s_2 > s_1 = 0. \tag{19}$$

We can see from (17) that master UAVs are more inclined to accept small UAVs with high task relevance and low network switching costs. Thus, for two small UAVs m and m', the preference of master UAV n is as follows:

$$m \succ_n m' \Leftrightarrow F_{m,n} > F_{m',n}. \tag{20}$$

If the small UAVs lead to equal utility, that is, $F_{m,n} = F_{m',n}$, the master UAV will further consider the distance $d_{m,n}$. A smaller $d_{m,n}$ corresponds to less flight time for the small UAV, which results in higher network efficiency. Therefore, the master UAV is inclined to select nearby small UAVs, that is,

$$\begin{aligned} &\text{if} \quad\quad F_{m,n} = F_{m',n}, \\ &\text{then} \;\; m \succ_n m' \Leftrightarrow d_{m,n} < d_{m',n}. \end{aligned} \tag{21}$$

The preference list of the master UAV reflects the consideration of overall network efficiency. The selection of small UAVs is also conducted.

D. Peer Effects and Dynamic Quotas

A simple example is given to introduce peer effects among UAVs. Consider three small UAVs m_1, m_2, m_3 and master UAV n with $(m_1, n) \succ_n (m_2, n) \succ_n (m_3, n)$. If the initial optimal network choice for m_2 is n and m_1 chooses master UAV n, n will prefer m_1. If small UAV m_2 is connected to master UAV n and the remaining bandwidth of master UAV n is insufficient, the bandwidth weight of small UAV m_2 is

$$w^*_{m_2,n} > W_n - w_{m_1,n}. \tag{22}$$

The throughput obtained by m_2 will be less than expected; that is, only m_2 accesses n. This problem is a typical peer effect that arises in matching games [28]. Since the network choices of small UAVs influence each other, each small UAV is concerned not only about what kind of master UAV to choose but also what kinds of small UAVs should become its "peers". In this situation, if the remaining bandwidth resources of n cannot meet the requirements of m_2, m_2 can choose another master UAV network.

In addition, the number of resources and matching quotas of players are generally fixed in previous matching game research. However, in UAV systems, each small UAV has individual throughput and flight loss requirements, and different tasks lead to dynamic communication requirements. The matching process is much more complicated in such network scenarios. For example, even though m_2 has other network choices at this time, m_3 would be rejected by n due to the access of m_2. The remaining bandwidth resources of n would be wasted in a traditional matching game because the rejected player would no longer consider a network that rejected it previously [29]. However, if m_3, which has lower priority, is allowed to access n and meet its throughput requirement while m_2 accesses another feasible master UAV, the waste of resources can be prevented. Therefore, previous matching methods are not suitable for network environments with dynamic quotas and peer effects. Thus, a new matching algorithm should be designed in which small UAVs can dynamically change preference lists in real time to find the best matching result.

V. Proposed Distributed Task Completion-Aware Network Access Algorithm

Due to the peer effects and various requirements of small UAVs, the network-access strategy of a small UAV may be affected by the selection results of other UAVs. In the case of limited network resources, small UAVs whose task requirements are not met will rebuild their preferences list and restart the matching cycle. Unlike in the traditional deferred acceptance algorithm [29], a master UAV can accept a small UAV that it has previously rejected, and a small UAV that has been accepted can later be rejected from the network because of a lower priority. The existence of peer effects and dynamic quotas makes it difficult for traditional deferred acceptance algorithms to converge to a stable solution. Therefore, a new method based on the UAV swarm is designed to solve this problem.

A. Proposed Task Completion-Aware Matching Algorithm

As shown in Algorithm 1, the distributed task completion-aware network-access algorithm consists of two main stages: the establishment of a bilateral preference list and matching evaluation.

In the first stage, the master UAV builds its matching preference list according to its location information and task requirements. Due to the influence of peer effects, each small UAV does not know the actual throughput it can obtain before it is connected to a master UAV. Small UAVs build their matching preference lists according to the task relevance and the distance from the master UAV. In the second stage, each small UAV applies to the highest-priority master UAV, and master UAVs select small UAVs according to their preference list and available bandwidth resources. Small UAVs experience one of three possible outcomes: "accepted", "accepted with insufficient resources" or "rejected". If the allocated resources are insufficient, a small UAV will update its preference list and apply it to the next priority master UAV. If no alternative choice exists, the original strategy will be maintained. If the small UAV finds a better option and changes its network choice, then the rest of the network resources can be allocated to other small UAVs that have been rejected by the network.

The proposed algorithm takes into account the task requirements of small UAVs. To reduce the time delay, the master UAV allocates bandwidth reasonably to meet the needs of small UAVs. Importantly, the proposed algorithm allows small UAVs to update their preference lists in real time considering peer effects and dynamic quotas. Moreover, the network resource allocation converges to a stable matching.

B. Convergence and Stability of the Algorithm

Stable matching is a key factor in the optimization of matching games [27]. Denote the set of all feasible matching rules between $\mathcal{M}$ and $\mathcal{N}$ by Π. Let $\mu \in \Pi$ be a feasible matching rule, and let $\mu(m)$ and $\mu(n)$ be the corresponding matching players of m and n on the other side under matching rule μ, respectively. In the following, stable matching is defined, and we prove that the proposed algorithm can converge to stable matching in a finite number of iterations.

Algorithm 1 Task Completion-Aware Matching Algorithm

Input: The position information, flight speed, communication environment, tasks, and other related information of master UAVs and small UAVs.
Stage I: Build preference lists for small UAVs and master UAVs
The preference lists of small UAVs are constructed according to (14) and (16).
The preference lists of master UAVs are constructed according to (20) and (21).
Stage II: Matching evaluation
Each small UAV m applies for master UAVs according to its initial preference list.
loop
  Each master UAV n accepts applicants according to the preference list.
  if the remaining bandwidth resource of selected master UAV n is insufficient to meet the requirements of m **then**
    $w_{m,n} = W_n - \sum_{i\in\mathcal{M}_n} w_{i,n}$
  end if
  if small UAV m can't get sufficient resource **then**
    m updates its preference list
  end if
  if m applies for n, and all bandwidth resources of n have been occupied, **then**
    Denote the small UAV with the lowest priority in $\mathcal{M}_n$ as m'.
    if $m \succ_n m'$ **then**
      if $w_{m',n} > w^*_{m,n}$ **then**
        m is accepted by master UAV n and allocated the bandwidth weight $w_{m,n} = w^*_{m,n}$.
        m' updates the allocated bandwidth by $w_{m',n} = w_{m',n} - w^*_{m,n}$, as well as its preference list.
      else
        m is accepted by master UAV n and allocated the bandwidth weight $w_{m,n} = w_{m',n}$.
        m updates its preference list because of the insufficient resources.
        m' is removed from the network and update its preference list.
      end if
    else
      m updates the preference list and deletes master UAV n in the list.
    end if
  end if
  if The matching list of m has been looped **then**
    m restarts the matching list loop.
  end if
  Each small UAV allocated with insufficient resource in its master UAV will apply for the next master UAV in the list. If there is no better choice, it will stay in current master UAV; otherwise, it accesses the new master UAV.
  Repeat the loop until no small UAV can improve its master UAV selection during the matching.
end loop

Definition 2: A stable matching μ means that no pair of $\{(m,n)|m\in\mathcal{M}, n\in\mathcal{N}\}$ can block the matching result [27]:

$$\nexists (m,n) \;\; s.t. \;\; m \succ_n \mu(n) \;\; \text{and} \;\; n \succ_m \mu(m). \tag{23}$$

Theorem 1: The proposed algorithm will converge to a stable matching of the game after a finite number of iterations.

Proof: In the UAV network-access scenario, the number of small UAVs and master UAVs are finite, so the preference lists are limited. Ideally, a small UAV can complete its matching connection before the end of the preference lists loop. For small UAV m that prefers to access master UAV n:

$$n \succ_m n', \forall n' \in \mathcal{N}, n' \neq n \tag{24}$$

Due to the limited bandwidth of master UAVs, the bandwidth requirement of small UAVs may not be satisfied. Suppose that a small UAV m is not satisfied with its current matching result after the first round of matching, which means that it is rejected by all the master UAVs or the master UAV n cannot allocate sufficient bandwidth. n will restart its matching list cycle to find a better option. The matching results and subsequent decisions of m are influenced by its peers who choose the same master UAV and the bandwidth resources of the selected master UAV. Suppose that n now selects master UAV n_0:

1) If all the bandwidth resources of n_0 have been allocated and all the small UAVs currently associated with n_0 are preferred over m, then

$$m' \succ_{n_0} m, \forall m' \in \mathcal{M}_{n_0}. \tag{25}$$

If no small UAV in $\mathcal{M}_{n_0}$ changes its current selection, m will not be accepted by n_0.

2) If there is some m_0 in $\mathcal{M}_{n_0}$ in the existing matching result,that has a lower priority than that of m and the occupied resources of m_0 can satisfy the requirement of m, that is,

$$\begin{cases} \exists m_0 \in \mathcal{M}_{n_0}, m \succ_{n_0} m_0 \\ w_{m_0,n} > w^*_{m,n_0} \end{cases}, \tag{26}$$

then m occupies partial bandwidth resources of m_0 to satisfy its requirement, and the matching list of m_0 will be updated due to insufficient resources.

3) If there is some m_0 in $\mathcal{M}_{n_0}$ of the existing matching result that has a lower priority than m, and the occupied resources of m_0 cannot meet the requirement of m, that is,

$$\begin{cases} \exists m_0 \in \mathcal{M}_{n_0}, m \succ_{n_0} m_0 \\ w_{m_0,n_0} \leqslant w^*_{m,n_0} \end{cases}. \tag{27}$$

m_0 will be removed from master UAV n_0, update its preference list and delete master UAV n_0. The matching list of m is then updated due to insufficient resources.

Based on the current matching results and the remaining resources of the master UAV, small UAVs decide whether to maintain the current matching or replace the matched network. This scheme enables all the bandwidth resources of the master UAV to be effectively utilized. Since the matching process follows the preference relationship, the proposed algorithm ensures convergence. Therefore, following the matching preference relationship, these players will not form matching terms that hinder existing matches. The proposed algorithm ensures that the network resource allocation achieves a two-sided stable matching. ■

VI. Simulation Results

A. Simulation Settings

UAV groups are assumed to be distributed in a three-dimensional plane, where several heterogeneous master UAVs

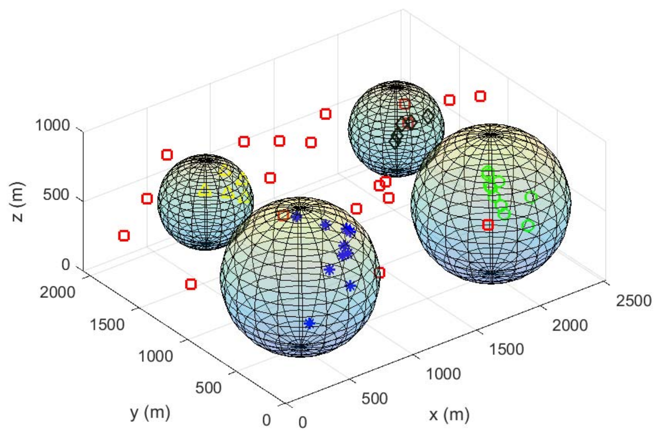

Fig. 3. The initial UAV swarm with 30 assigned UAVs and 20 small UAVs.

are deployed in the network with coverage radii of $5km$ or $3km$. These master UAVs have different network coverages and bandwidths. In addition, some small UAVs are randomly assigned in each network coverage area for the original load of master UAVs, which are called assigned UAVs. The properties, such as the position of the small UAVs, are randomly generated in each sample. An example of an initial network topology is shown in Fig. 3, where black squares are master UAVs, green circles, black diamonds, yellow triangles, and blue asterisks represent associated assigned UAVs of the four master UAVs, respectively, and red squares represent small UAVs that are outside of network service due to master UAV failure. The transmission bandwidth of the master UAVs is $5MHz$ or $10MHz$, the transmit power of the master UAVs is $25dBm$, and the environmental noise power is set to $\sigma_n^2 = 10^{-7}W$. The relative speed of the small UAVs is $V = 100km/h$, $c_1 = 9.26 \times 10^{-4}$, and $c_2 = 2250$ based on the classic model of aircraft energy consumption in aerodynamics theory [22].

B. Convergence Behavior

We first test the convergence performance of the proposed algorithm. As shown in Fig. 3, we consider 30 assigned UAVs and 20 unassigned UAVs that need to select a master UAV. The 3-dimensional locations of the 4 master UAVs are $[500\ m, 500\ m, 500\ m]$, $[2000\ m, 500\ m, 500\ m]$, $[600\ m, 1600\ m, 500\ m]$, and $[2100\ m, 1600\ m, 500\ m]$, respectively. The matching results after a single run are shown in Fig. 4. The 20 unassigned small UAVs are relatively evenly distributed, and master UAVs with more bandwidth resources can accept more small UAVs. Fig. 5 records the network selection decision behavior of the 20 unassigned small UAVs, where each curve represents the evolution of one small UAV's network selection result and the y-axis is the master UAV index (0 indicates that the small UAV is rejected by all master UAVs). All the small UAVs reach stable network access in 14 iterations. The average task completion degree of the network in Fig. 6 also indicates that the algorithm converges in approximately 14 iterations. Moreover, the average task completion degree is approximately an increasing function of the iteration index. This is because the bandwidth allocation policy and the matching rule of the algorithm ensure that the global optimization objective continues improving in each iteration.

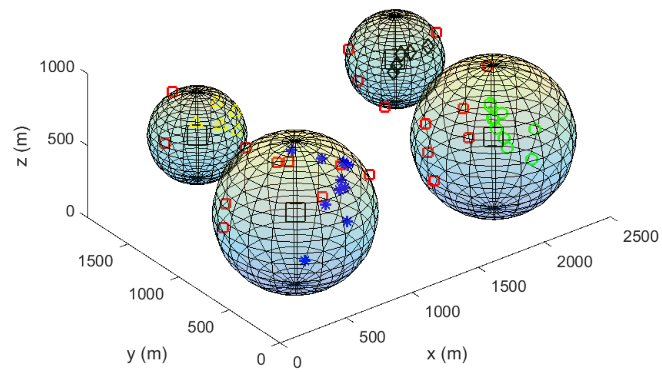

Fig. 4. The final network topology of Fig. 3 after the proposed algorithm converged.

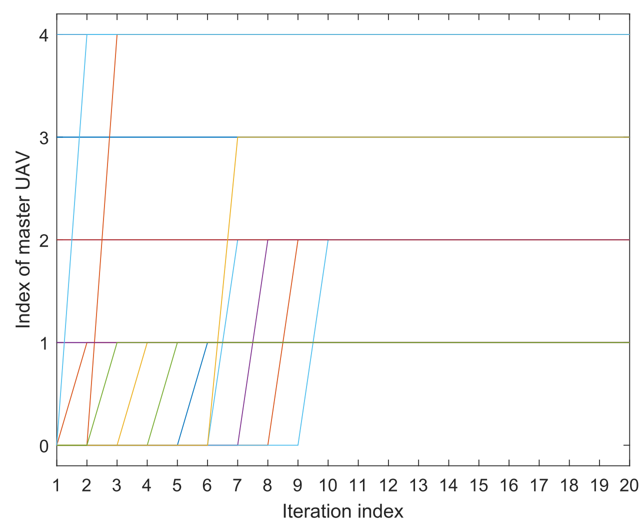

Fig. 5. Small UAVs' network selection behaviors during a sample run of the proposed algorithm. Note that some curves overlapped.

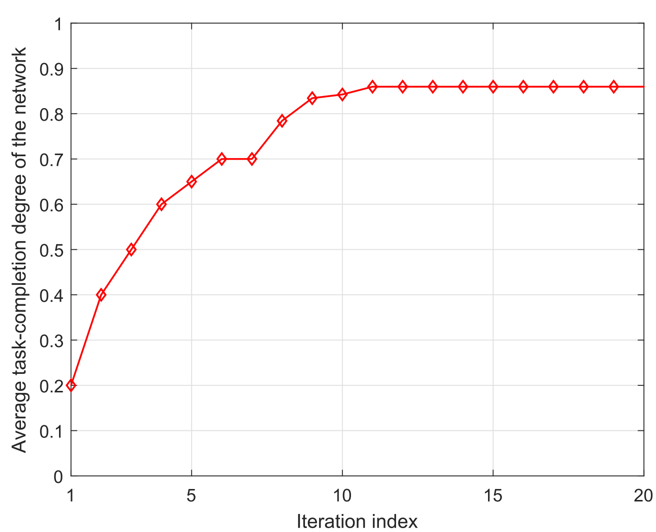

Fig. 6. The average task completion degree of the network during a sample run of the proposed algorithm.

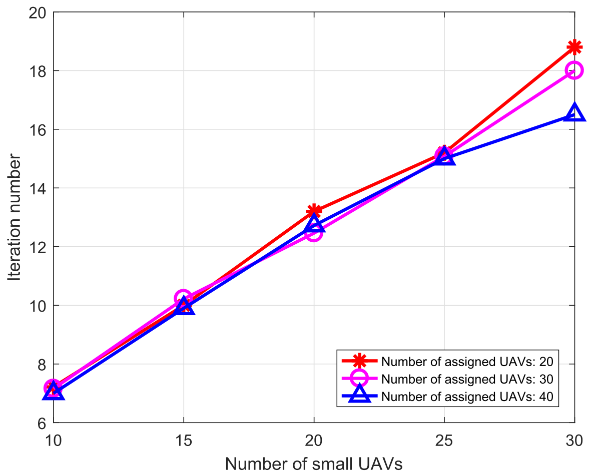

Fig. 7. The average number of iterations to converge for the proposed algorithm with different assigned UAV numbers and unassigned UAV numbers.

To further study the convergence performance of the proposed algorithm, Fig. 7 compares the convergence speed in different cases. As shown in the figure, the average number of iterations for convergence generally linearly increases as the number of unassigned small UAVs increases. Nevertheless, the algorithm converges in fewer than 20 iterations in all cases. Interestingly, the convergence speed does not slow when the number of assigned UAVs increases. Specifically, when the number of assigned UAVs is 20, the algorithm convergence speed is worse than that in the cases of 25 and 30 unassigned small UAVs. The underlying reason is that fewer assigned UAVs corresponds to more available bandwidth, which leads to a larger optimization space and a longer convergence time. This phenomenon indicates that the proposed algorithm can effectively handle decision optimizations in the case of insufficient resources, and the whole system can converge quickly.

Finally, we study the reconfiguration process when one of the master UAVs is destroyed during the matching iteration. We consider a scenario in which master UAV 4 ($[2100\ m, 1600\ m, 500\ m]$) is destroyed before the algorithm converges, as shown in Fig. 8. As a result, five assigned UAVs (black diamonds) and two unassigned small UAVs (red squares) that initially move to the network for service become out of network service. The proposed algorithm still converges to a stable topology, as shown in Fig. 9: two unassigned small UAVs and three assigned UAVs move to and access master UAV 3; one assigned UAV accesses master UAV 1; and one assigned UAV accesses master UAV 2. Fig. 10 shows that although the failure of master UAV 4 leads to a significant decline in the average task completion degree, the network can reconfigure quickly (approximately 5 iterations) and achieve satisfactory global performance.

C. Performance Comparison of Task Completion Degree

To analyze the algorithm performance, we compare the proposed matching algorithm with the following three approaches.

1) *Distance priority algorithm,* which considers the distance between the small UAV and the master UAV, where the small UAV selects the nearest master UAV for access.
2) *Task-relevance priority algorithm,* which considers the task relevance between the master UAV and the small UAV, where small UAVs choose to access the master UAV with the strongest task relevance.
3) *Random access algorithm,* where small UAVs are randomly connected to any master UAV with idle resources.

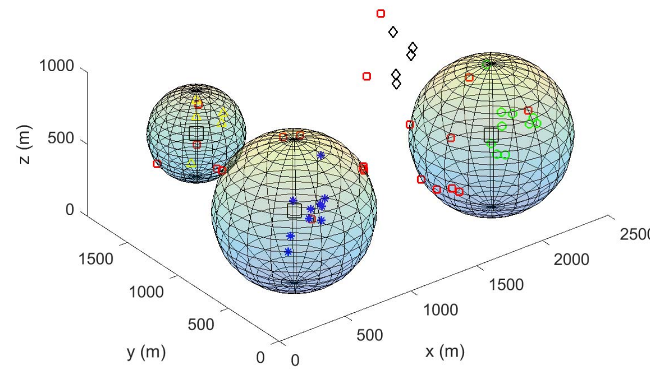

Fig. 8. A sample scenario: master UAV 4 is destroyed.

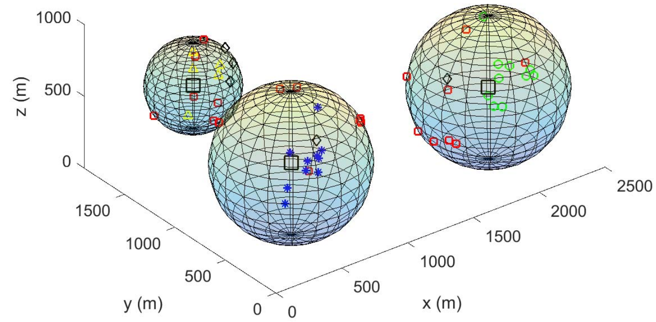

Fig. 9. The reconfigured network topology of Fig. 8.

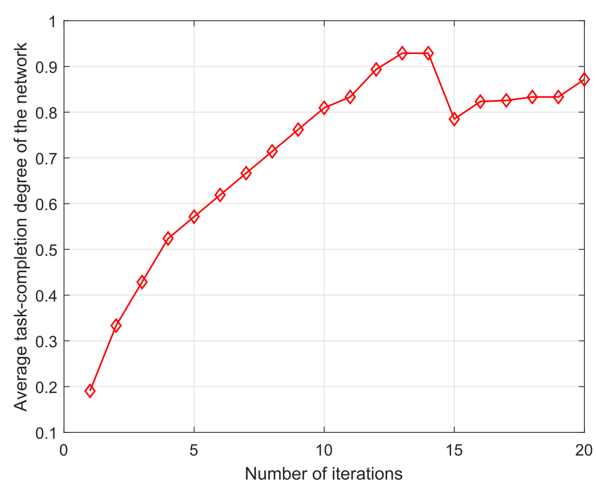

Fig. 10. The average task completion degree of the network during the reconfiguration process.

The above network of 4 master UAVs is considered. In each algorithm, a fixed number of UAVs are randomly distributed outside the network coverage area of all master UAVs, and they need to select a master UAV to access. The task completion degree is taken as the average of 1000 independent algorithm runs (randomly generated distributions of unassigned small UAVs) for each algorithm.

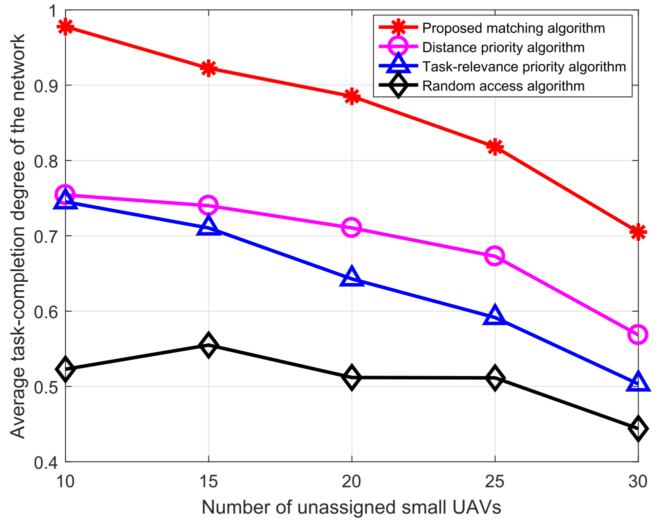

Fig. 11. The impact of unassigned small UAV number on the average task completion degrees of different algorithms when 30 assigned UAVs are randomly distributed in 4 master UAVs.

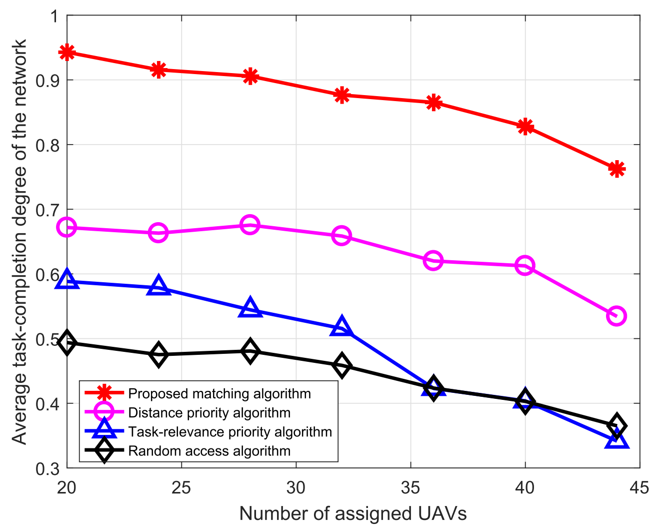

Fig. 12. The impact of assigned UAV number on the average task completion degrees of different algorithms when 20 unassigned small UAVs are randomly distributed in 4 master UAVs.

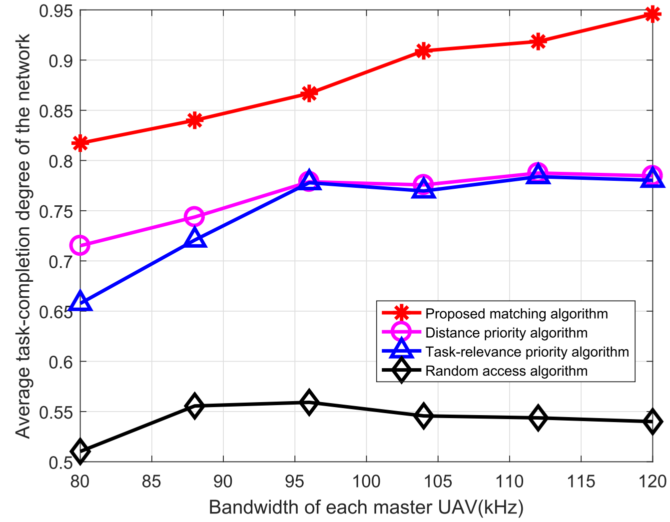

Fig. 13. The impact of each master UAV's total bandwidth on the average task completion degrees of different algorithms with 20 unassigned small UAVs and 30 assigned UAVs.

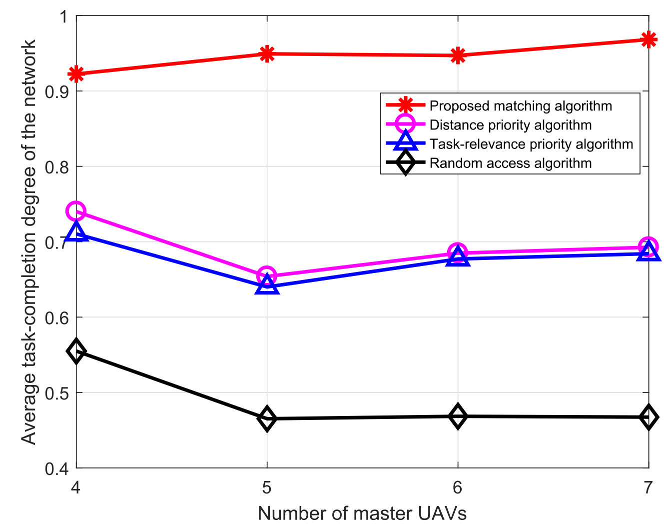

Fig. 14. The impact of master UAV number on the average task completion degrees of different algorithms with 20 unassigned small UAVs and 30 assigned UAVs.

Fig. 11 presents the impact of the number of unassigned small UAVs on the task completion degree with 30 assigned UAVs. Clearly, except for that of the random algorithm, the performance generally declines as the number of unassigned small UAV numbers increases. This is because the limited network resources cannot meet the communication needs of a large number of small UAVs, and some small UAVs have no network to access. However, the proposed algorithm outperforms the other three algorithms, and the random algorithm is the worst in all cases. The reason is that the proposed algorithm takes the task relevance of UAVs into account and performs specific modeling for UAVs' task completion degree.

As shown in Fig. 12, we study the impact of the number of assigned UAVs on the task completion degree. The results show a similar trend with that in Fig. 11: as the number of assigned UAVs increases, the performance of the 4 approaches declines. The proposed algorithm again outperforms the other three algorithms. Since a small UAV can dynamically change its preference list according to changes in network bandwidth resources, unassigned small UAVs following the proposed algorithm can reasonably occupy the remaining resources in the network. Therefore, the worst performance of the proposed algorithm is approximately 0.75, which is much better than that of the other three algorithms.

As shown in Fig. 13, we study the impact of the total bandwidth of each master UAV on the average task completion degree. The subchannel bandwidth of each master UAV is $B_n = 10kHz$, and we vary W_n to change the total bandwidth of each master UAV. The performance of the proposed algorithm is significantly better than that of the other three algorithms. In addition, the average task completion degree of the proposed algorithm increases rapidly as the total bandwidth of the network increases, while the other three algorithms do not show such a relationship. For the proposed algorithm, as the bandwidth increases, more small

UAVs can obtain satisfactory bandwidth, thereby increasing the global task completion degree. For the other algorithms, small UAVs blindly access the master UAV network but cannot satisfactorily satisfy the task requirements. Therefore, the proposed algorithm can fairly effectively utilize the bandwidth of master UAVs.

In Fig. 14, the impact of the number of master UAVs on the average task completion degree is simulated. The locations of the master UAVs are randomly generated, and the bandwidth and communication ranges vary across master UAVs. Generally, the total bandwidth of the network increases as the number of master UAVs increases. The proposed algorithm is superior to the other three algorithms, and it drives small UAVs to find the master UAV with the highest task relevance rather than simply maximizing throughput. On the other hand, the other 3 approaches fail to accurately assess master UAVs from the perspective of task relevance. Therefore, their task completion degrees are not significantly improved.

VII. Conclusion

This paper studied the problem of reconfiguration of UAV networks driven by tasks. For the scenario of master UAVs providing network service for small UAVs, we proposed a task relevance model among UAVs. Considering the different UAV task requirements, we designed a satisfaction function based on task completion. The task completion degree was improved by optimizing the network selection decisions of small UAVs. The master UAV network section interaction between master UAVs and small UAVs was modeled by a many-to-one matching game, and a distributed matching algorithm based on task completion was proposed to solve the peer effects and dynamic quota problems in the proposed model. We proved that the algorithm converges to a two-sided stable matching. Furthermore, the simulation verified that the algorithm improves the task completion degree of the global UAV network.

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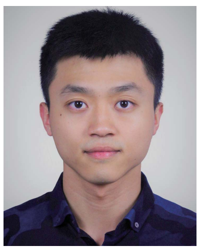

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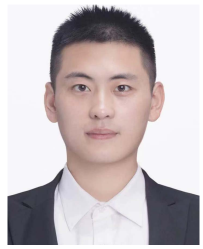

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