Received 13 November 2023, accepted 11 December 2023, date of publication 18 December 2023, date of current version 22 January 2024.

Digital Object Identifier 10.1109/ACCESS.2023.3344462

RESEARCH ARTICLE

UAV Network Channel Allocation Method Based on Bipartite Graph Popular Matching Algorithm

WEIHAN LI[1] AND JIANWEI GUO[2]
[1]Haidian District, Beijing 100097, China
[2]School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China

Corresponding author: Jianwei Guo (19114023@bjtu.edu.cn)

ABSTRACT To address the challenges of selecting task schemes and ensuring secure channels duringdata collection and transmission by unmanned aerial vehicles, the study divides the secure transmission model into physical domain and social domain based on graph theory to ensure the security of unmanned aerial vehicles during task execution. Secondly, the multi to one matching problem was optimized through matching theory, achieving maximum benefits between drones and ground to ground (D2D) users. This study designed a stable matching scheme for drone task allocation based on bipartite graphs and a popular matching strategy for drone security spectrum resource allocation based on bipartite graphs. By adapting the design of a series of coherent actions of drones from information collection to information transmission, the efficiency and security of drone information transmission can be improved. The experimental results show that the average revenue of the designed algorithm for unmanned aerial vehicles is between 21 and 40, while the average revenue range for a single task is between 173 and 210. Compared with other algorithms in terms of security performance for drones and D2D users, the algorithm designed in the study shows strong advantages. Specifically, in terms of drone safety performance, the design algorithm's performance improves as the spectrum sharing limit increases. The advantage becomes more obvious when the sharing limit value reaches 1; From the perspective of D2D users, the average worst-case safety rate of the design algorithm increases with the increase of flight cycle and average power. Compared tofixed-trajectory drones, the overall performance gain of the research and design algorithm reaches about 18.2%, and compared with fixed power drones, the overall performance gain reaches about 15.5%. In summary, the research has made significant progress in task allocation and channel security spectrum resource allocation. The design algorithm achieves the optimal effect between computational complexity and performance, and overall maximizes the benefits between drones and D2D users.

INDEX TERMS Bipartite graph, stable matching, spectrum resources, task allocation, drones, popular matching.

I. INTRODUCTION

With the continuous popularization and development of drone technology in recent years, many industries have gradually shown certain application trends in the drone industry. Unmanned aerial vehicles (UAV) have the advantages of relatively low cost, diverse job perspectives, relatively flexible application deployment, and free operation from human control during the application process. These advantages can greatly improve work efficiency under special operating conditions. In addition, drones can utilize real-time interaction capabilities to transmit actual data to ground base stations, ensuring timely data transmission [1], [2], [3]. The process of collecting and transmitting data via drones entails two primary concerns. The first issue is the allocation of tasks during the data collection process; The second issue is channel allocation during data transmission. The two allocation issues run through the entire process of drone data collection and transmission. If the task allocation problem cannot be solved, it will result in no one being able to effectively allocate tasks based on their own energy and task needs during the task execution process. This will lead to a decrease in

The associate editor coordinating the review of this manuscript and approving it for publication was Oussama Habachi.

the application efficiency of drones. If the issue of channel allocation cannot be resolved, it may result in an absence of assurance regarding data transmission by drones post data collection. The security of the transmission channel will be insufficient, and information is prone to external leakage [2], [4], [5]. With the development of artificial intelligence technology and its application in the field of network security, the application of Internet of Things technology provides effective solutions for these two problems. By relying on Internet of Things technology, drones can not only establish airspace networks and air to ground networks, but also compensate for the shortcomings of ground networks in terms of longitudinal spatial scalability. The integration and optimization of data collection and transmission by UAV, and the guarantee of reliability and safety in information gathering, is addressed through task and channel allocation [6], [7], [8]. Therefore, from this point of view, this research takes bipartite graph technology as the optimization basis to optimize the continuous operation of UAV information collection and information transmission in an integrated way. This ensures stable and secure transmission of drone data, as well as laying the groundwork for future drone applications.

This study has the potential to enhance drone security during task execution by presenting a secure transmission model utilizing graph theory. The model is segregated into physical and social domains, ensuring drone security during task execution. This is of great significance for the safe application of drones in military reconnaissance, air transportation, emergency rescue, and other fields; It can promote collaborative operation between drones and ground to ground users: The matching theory in research optimizes the multi to one matching problem, achieving maximum benefits between drones and ground to ground users. This study aims to enhance the efficiency and effectiveness of coordination between drones and ground users during mission execution, optimizing the overall operational efficiency of the drone system. The focus is on improving the efficiency and security of drone information transmission by adaptively designing a series of coherent actions from information collection to transmission. This approach enhances the efficiency and security of drone information transmission. This will help ensure the secure transmission of information during drone missions and reduce potential risks caused by information leakage. By researching and designing algorithms, significant achievements have been achieved in task allocation and channel security spectrum resource allocation between drones and D2D users. This will help to further expand the application of drones in urban planning, environmental monitoring, disaster warning and other fields, bringing more convenience to social and economic development and people's lives. In summary, this study's accomplishments in task allocation and channel security spectrum resource allocation enhance drone system performance while promoting safe and efficient drone operation in various application scenarios, contributing to social and economic development and improving people's quality of life.

At the social level, the social motivation of this study lies in providing efficient, stable, and secure solutions for real-world drone application scenarios through the design of intelligent drone task allocation and channel security spectrum resource allocation schemes. First, there is a need to enhance the efficacy of drone resource utilization. This can be achieved by dynamically matching and optimizing the allocation of drone tasks and channel resources, resulting in effective use of limited resources, forestalling waste and redundancy, and overall fostering resource utilization efficiency. Secondly, data transmission security needs to be ensured: during the data transmission process, it ensures the information security and communication quality of drones, prevents network attacks and leaks, and is conducive to maintaining personal privacy and data security. Once again, the application technology of drone technology needs further development: this research achievement will help promote the wider application of drone technology in various fields, including logistics distribution, monitoring and inspection, emergency rescue and other scenarios, bringing convenience to social development. Furthermore, the optimization of drone scheduling and management necessitates the implementation of intelligent task allocation and channel security spectrum resource allocation. These measures will reduce the need for manual scheduling management, heighten scheduling accuracy, augment drone group collaboration abilities, and allow for greater adaptability in complex application scenarios.

At the technical level, the objective of binary matching is to achieve the optimal outcome in the optimization problem, which is to maximize the overall benefits for all participants. In the design of this intelligent drone task allocation and channel security spectrum resource allocation scheme, a stable matching model based on bipartite graphs and a popularity matching model are used to achieve long-term benefits in changing environments and optimal allocation of drone tasks and channel resources during flight cycles. In the task allocation scheme based on bipartite graph stable matching, the task information decomposition of UAV is achieved, and in a dynamically changing environment, UAV can balance various benefits and costs to make optimal decisions. Moreover, this model meets the three necessary conditions of policy anti-counterfeiting, jealousy elimination, and effectiveness, ensuring optimal matching in changing environments. In the drone safety spectrum resource allocation strategy based on bipartite graph popular matching, it ensures the efficient operation of drones while ensuring the security of drone data transmission. Through an analysis of physical and social domains, it is possible to enhance data security while maximizing transfer rates, and achieve effective solutions to multi-objective optimization matching issues. Overall, the motivation behind bipartite graph matching is to maximize overall benefits through rational decision-making and trade-offs in complex and changing environments as much as possible. The social motivation of this study is to provide effective practical guidance for the development and application of drone technology, resulting in innovation and advantages for socio-economic development.

The contribution of this study to society is reflected in the following aspects: it can improve the security of drones during task execution: by introducing a secure transmission model based on graph theory, it is divided into physical and social domains, ensuring the security of drones during task execution. This is of great significance for the safe application of drones in military reconnaissance, air transportation, emergency rescue, and other fields; It can promote collaborative operation between drones and ground to ground users: The matching theory in research optimizes the multi to one matching problem, achieving maximum benefits between drones and ground to ground users. This will help improve the efficiency and effectiveness of cooperation between drones and ground users during mission execution, and optimize the operational efficiency of the entire drone system; This study enhances the efficiency and security of drone information transmission by adaptively designing a series of coherent actions from information collection to information transmission, thereby improving the efficiency and security of drone information transmission. This will help ensure the secure transmission of information during drone missions and reduce potential risks caused by information leakage. By researching and designing algorithms, significant achievements have been achieved in task allocation and channel security spectrum resource allocation between drones and D2D users. This will help to further expand the application of drones in urban planning, environmental monitoring, disaster warning and other fields, bringing more convenience to social and economic development and people's lives. In summary, the achievements of this study in task allocation and channel security spectrum resource allocation not only improve the performance of drone systems, but also facilitate the safe and efficient operation of drones in various application scenarios, making contributions to social and economic development and improving people's quality of life.

In terms of originality, firstly, this study is based on graph theory, dividing the secure transmission model into physical and social domains to ensure the security of drones during task execution. It comprehensively guarantees the secure transmission of drones in different scenarios from multiple dimensions, which is more detailed and comprehensive than previous studies. This is an innovative point of this study. Secondly, the study optimized the many-to-one matching problem by using matching theory, achieving the maximum benefit between drones and ground to ground users. This optimization method is based on game theory and breaks through the limitations of traditional drone task allocation methods, further improving the efficiency of drones in executing tasks. It is another major innovation in this research. Overall, this study combines graph theory and game theory, with a new theoretical perspective and method, to completely change the task allocation and secure spectrum resource allocation methods of drones, providing strong theoretical support for the efficient and safe operation of drones, with high innovation.

II. RELATED WORKS

In recent years, research on unmanned aerial vehicle channels has been continuously deepening. The Zhong X team has designed a network system that serves UAV for device to device spontaneous docking. This system jointly optimizes the network from the perspectives of channel allocation and relay allocation, thereby maximizing the capacity of the relay network. The optimization problem can be divided into two sub-problems through alternating optimization. Then a reinforcement online learning method based on real-time capacity technology was proposed to solve the sub problem. The research results indicate that drone assisted D2D networks can achieve higher capacity effects through joint optimization [9]. The He Y team analyzed the transmission delay problem of drones in relay self-organizing networks. This study optimizes the channel allocation and relay performance of UAV from the perspective of information transmission security. The optimization process introduced a framework called alternating optimization, which was solved using the Newton method. The research results show that this method has achieved significant performance improvement in information transmission delay [10]. Yang C team analyzed the UAV assisted vehicle edge computing scheme. The study proposes a method that utilizes UAV for temporary learning schemes to assist in channel and task allocation. This method uses drones as temporary relay points for decision-making system calculation support. The research also includes the design and study of a more efficient data transmission method. This transmission method eliminates the cost minimization problem of human processing through composite selective tasks. The research results show that the designed method greatly improves the data transmission efficiency between drones and vehicles [11]. Shuaipeng Fei used five machine learning algorithms, including Cubist, Support Vector Machine (SVM), Deep Neural Network (DNN), Ridge Regression (RR), and Random Forest (RF). These algorithms fuse multiple sensor data from drones to predict wheat yield. Experiments have shown that the prediction accuracy of using UAV multi-sensor data fusion is significantly higher than that of a single sensor in each machine learning model. When further integrating these models for ensemble learning, the prediction accuracy improves [4]. Jiang Zhang et al. reviewed the generation of aerial orthophoto images in UAV remote sensing. This study focuses on the correction and stitching of aerial images, which is the key to generating UAV orthophoto images based on vision. They summarized three main visual orthophoto generation frameworks, namely 2D stitching framework, SfM framework, and SLAM framework, and detailed and compared relevant important algorithms to solve the problem of difficulties in cross platform evaluation of SLAM based orthophoto generation methods [3]. Adnan Fayyaz Ud Din et al. applied the theory of optimal dynamic programming. They proposed an innovative control architecture to maximize the glide range of UAVs. They proposed a unique reinforcement learning technique called "optimal dynamic programming" to address the control complexity arising from the unique design of UAVs. This method is computationally acceptable while effectively controlling the entire flight state of the UAV. The nonlinear simulations conducted under different environmental conditions indicate that their proposed method is more effective than traditional classical methods [2].The Hosen MS team has proposed a dynamic communication wireless self address network solution for public safety communication systems. This scheme can achieve wireless access of UAV in a short period of time in case of network congestion. Drones can reliably and efficiently transmit information from various devices. Additionally, the study suggests a fuzzy logic-based channel allocation method that can prioritize channel allocation [12]. The Zhao N team has designed a negative number unmanned aerial vehicle joint optimization strategy for joint trajectory and power allocation problems. Research is based on multi-agent deep learning technology to maximize network utility while meeting customer needs. Research provides a solution for joint optimization through deterministic strategy gradient methods. The research results show that the method network designed in the study is more robust and computationally simpler [13].

On the other hand, graph theory and related technologies have also been deeply applied in many fields. The Li X team has proposed a graph fusion framework for multi view clustering. Then the research applies the bipartite graph cardinality to it. The special structure of the Gnu data divides the data into different groups, and uses the self supervised weighting method to find the joint graph across views. This study manipulates the joint graph through direct constraints. The algorithm design allows for scalability with data size and exhibits robust stability [14]. Li Z proposed a nonlinear interaction graph neural network based on user project bipartite graph. This model can provide more personalized project recommendations under the theme driven and user driven conditions of the same community. Traditional computing methods tend to employ linear interaction and single-level community operations, which incur relatively high costs. Therefore, a hierarchical bipartite graph neural network is proposed for large-scale e-commerce project processing. It can predict user preferences on a large scale and match them with e-commerce projects. The research results show that this method has broad application prospects [15]. Wang K team applied the bipartite graph to community search. Aiming at the problem that the cohesive subgraph in the existing bipartite graph technology can not measure the marginal weight of the community, but can only measure the cohesion between different vertices, it proposed a group search technology based on weighted bipartite graph. The main goal of this technology is to find significant communities. Then, the study limited the search space to subgraphs smaller than the original graph, thus forming a new search structure. The research results show that the model designed in the study has higher indexing efficiency [16]. The employment of matching algorithms is progressively rising, and the Liang S team is utilizing prevalent matching algorithms for spatial matching and fixed image transformations. The learning transformation domain block matching method designed in the research can perform high-precision similar block clustering in the presence of noise interference, and perform multi-layer sparse transformation. The research and design methods not only have higher accuracy, but also can achieve high-performance local denoising [17]. The Zhang W team has proposed a matching algorithm for recognizing left and right hand position and angle features. This algorithm locates interfering factors during the process of recognizing gesture features. Then it can perform similarity judgment based on template matching and eliminate interfering factors. In addition, it also has certain effectiveness in real-time recognition and classification of Jingtai jewelry. The research results show that this method can effectively eliminate interference factors to achieve gesture recognition effect with a recognition rate of 96% [18]. Chen K proposed four different matching algorithms. The four algorithms are based on computer vision and can match features of outdoor scenes. Under different circumstances such as full rotation of the original image, continuous transformation of scene clarity, continuous transformation of scene, continuous scaling of specific areas, and resolution changes. The research and design methods allow for accurate matching of the transformed image with the original image while ensuring the number of feature points during the matching process. The study conducted experimental analysis on four matching algorithms, and the results showed that all four algorithms have robustness [19]. Therefore, the research content and contributions of drone channels are summarized and presented in an intuitive form, as shown in Table 1.

From the current research results in relevant fields, it can be concluded that there is a research on IoT based joint applications between D2D users and drones in terms of drone channels. However, most studies concentrate on transmission performance and analyzing the dynamic features of UAV, without comprehensively examining transmission security. The bilateral problem directionality and multi-objective optimization characteristics of both graph theory and matching theory can play an important role in unmanned aerial vehicle channel security issues. Therefore, from this perspective, the study combines the two and innovatively starts with the continuous action of drone information collection and transmission. Finally, it analyzes the transmission guarantee of drone data transmission.

III. DESIGN OF UAV TASK ALLOCATION AND CHANNEL SECURITY SPECTRUM RESOURCE ALLOCATION SCHEME BASED ON BIPARTITE GRAPH

A. TASK ALLOCATION SCHEME BASED ON STABLE MATCHING OF BIPARTITE GRAPH

The study analyzes the coherent behavior of unmanned aerial vehicle information collection and transmission. Consequently, the study incorporates an analysis of data collection. Under the intelligent perception of drones, users can receive certain rewards by performing perception tasks through private drones. The task publisher recruited a group of drones

TABLE 1. Literature summary table.

Reference number	Author	Document Name	Document Content	Document Contribution
[9]	X. Zhong, et al	Joint optimization of relay deployment, channel allocation, and relay assignment for UAVs-aided D2D networks	Joint optimization of channel allocation and relay allocation	Increase in the capacity of the relay network
[10]	Y. He, et al	Trajectory optimization and channel allocation for delay sensitive secure transmission in UAV-relayed VANETs	Channel allocation and relay performance optimization from an information security perspective	Reduction of information transmission delay
[11]	C. Yang, et al	Learning based channel allocation and task offloading in temporary UAV-assisted vehicular edge computing networks	Drone-assisted channel allocation and task allocation based on temporary learning schemes	Improvement in data transmission efficiency between drones and vehicles
[4]	S. Fei, et al.	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	Demonstrated better prediction accuracy for wheat yield with the use of multi-sensor data fusion from drones compared to a single sensor in every ML model. Prediction accuracy improved further when implementing ensemble learning	Improved the accuracy of wheat yield predictions by fusing multiple sensor data and using ensemble learning models
[3]	J. Zhang, et al.	Aerial orthoimage generation for UAV remote sensing	Offered a detailed summary and comparison of three primary visual orthophoto generation frameworks (2D stitching, SfM, SLAM) tackling the problem of difficulties in cross-platform evaluation of SLAM-based orthophoto generation methods	Provided insights into the key algorithms for generating UAV-based orthophoto images, and took steps towards solving the cross-platform evaluation difficulty for SLAM-based orthophoto methods
[2]	A.F.U., et al.	Robust flight control system design of a fixed wing UAV using optimal dynamic programming	The method was computationally feasible and effectively managed the entire flight state of the UAV. The robustness and effectiveness were further validated through nonlinear simulations under various environmental conditions, with results indicating higher efficacy compared to traditional classical methods	Proposed a novel control architecture for UAV flight, bringing forth greater efficacy and robustness in controlling UAV's flight state compared to conventional methods
[12]	M. S. Hosen, and Y. Peng	Dynamic channel allocation technique for cognitive radio based UAV networks	Wireless access of drones in the event of network congestion	Achievement of priority allocation of channels
[13]	N. Zhao, et al.	Multi-agent deep reinforcement learning for trajectory design and power allocation in multi-UAV networks	Solution for joint trajectory and power allocation problems based on multi-agent deep learning technology	Improve network robustness and computational complexity
[14]	X. Li, et al.	Multiview clustering: A scalable and parameter-free bipartite graph fusion method	Application of the cardinality of bipartite graph	Demonstrated scalability and stability
[15]	Z. Li, et al.	Hierarchical bipartite graph neural networks: Towards large-scale e-commerce applications	Large-scale e-commerce project processing, prediction of large-scale user preferences	Broad application prospects
[16]	K. Wang, et al.	Efficient and effective community search on large-scale bipartite graphs	Proposal of a group search technology based on weighted bipartite graph	Higher indexing efficiency of the model
[17]	S. Liang, et al.	Labmat: Learned feature-domain block matching for image restoration	High-precision similar block clustering in the presence of noise interference	High-performance local denoising
[18]	W. Zhang, et al.	Research on gesture recognition based on improved template matching algorithm	Similarity judgment based on template matching	Achieved a recognition rate of 96%
[19]	K. Chen, et al.	Efficient feature matching algorithms applied to robust image processing	Matching features of outdoor scenes based on computer vision	Robustness of all four algorithms

through the Internet of Things and conducted sensing tasks. The complete sensing system is shown in Figure 1.

In this environment, the task environment faced by drones is often variable. It is assumed in this study that drones will experience energy costs when selecting to wait for higher reward tasks. Therefore, drones will balance the benefits and costs for task planning [20], [21], [22]. Based on this, task informatization can be divided into two main stages: release and perception, as shown in Figure 2.

The study proposes a dynamic matching model that emphasizes long-term benefits in dynamic environments. The task of drones is stochastic, and the path of drones is also stochastic. Therefore, the research mainly focuses on dynamic stable matching under time-varying features.

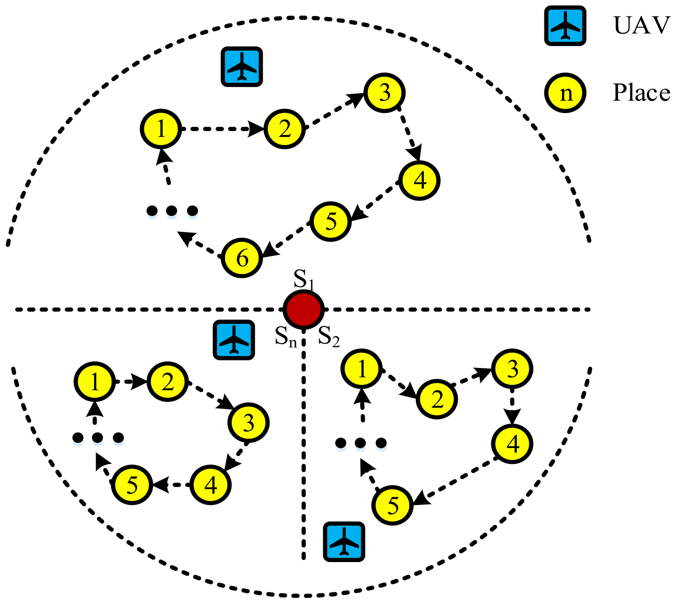

FIGURE 1. Complete sensing system.

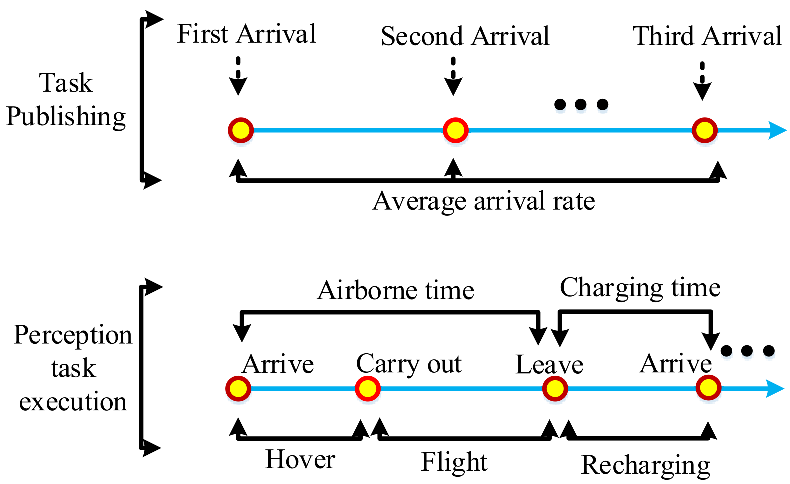

FIGURE 2. The two main stages of release and perception.

The dynamic matching mode of bipartite graph is shown in Figure 3.

The study and design of the bipartite graph dynamic matching model are presented as five-tuple expressions. The preference values of UAV under different sub regions are shown in Formula (1).

$$\bar{\omega}_i = \delta_i s r_{i,t} v_i \tag{1}$$

In formula (1), s and r are both represented by task elements; v represents the speed of the drone. There are three necessary conditions in the dynamic matching process. Firstly, a matching mechanism with strategic anti-counterfeiting needs to be such that no participant can deviate from their current true preferences to benefit themselves. Secondly,it is possible to reasonably eliminate the effect of jealousy. Finally, an effective task allocation plan cannot make one party solely profit without harming the interests of other drones. The condition for eliminating jealousy is shown in formula (2).

$$\left(s', t + \tau_{s',t}\left(r'\right)\right) >_u \left(s, t + \tau_{s,t}\left(r\right)\right) \tag{2}$$

In formula (2), t represents time; s and r are both task element representations. The task allocation plan also needs to meet the effectiveness requirements, and the primary conditions that an effective task allocation plan needs to meet are shown in formula (3).

$$\forall \Omega' \neq \Omega \tag{3}$$

In formula (3), Ω represents an effective allocation scheme for assigned tasks, as shown in formula (4).

$$\Omega \rightarrow \langle s_u, r_u \rangle \tag{4}$$

Allocation scheme Ω' represents the allocation task under time t', which can be expressed as formula (5).

$$\Omega' \rightarrow \left\langle s'_u, r'_u \right\rangle \tag{5}$$

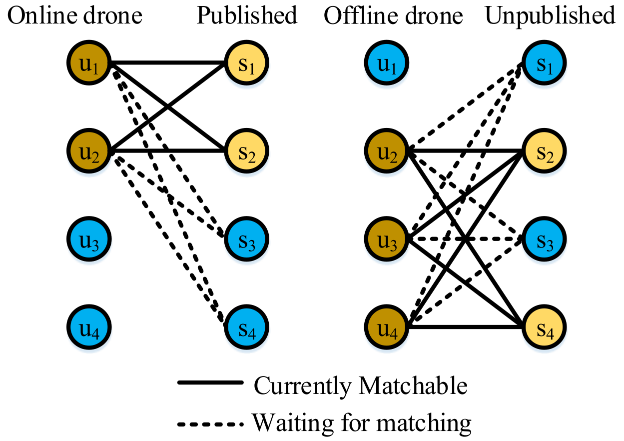

FIGURE 3. Dynamic matching mode of bipartite graph.

At this point, formula (6) needs to be met.

$$\left(s'_u, t_u + \tau_{s'_u,t_u}\left(r'_u\right)\right) > \left(s_u, t_u + \tau_{s_u,t_u}\left(r_u\right)\right) \tag{6}$$

There are also some drones that meet the conditions as shown in formula (7).

$$\left(s_{u'}, t_{u'} + \tau_{s_{u'},t_{u'}}\left(r_{u'}\right)\right) >_{u'} \left(s'_u, t_u + \tau_{s'_u,t_u}\left(r'_u\right)\right) \tag{7}$$

Based on three necessary conditions, an example of task allocation algorithm is formed as shown in Figure 4.

Figure 4 shows that at a certain moment, newly added drones enter the public queue to participate in task allocation; At this point, the sub region releases tasks, and the drones that were already in the queue can detach from the public queue for decision-making. Due to the principle of first in, first out being the basis for determining the task queue, priority will be given to the first arriving drones. If the drone receives a task, it is capable of executing said task. If the task is not accepted, alternative sub-areas are available for task waiting.

In the Bipartite graph dynamic matching model, we represent the matching relationship between UAV and tasks in the form of five tuples. Whenever the nodes in the Bipartite graph change due to UAV joining or completing a task, the preference value of each UAV for the task is recalculated, followed by matching them. This process will take place every time a new drone is added or a drone completes a task. The dynamic matching process entails three necessary conditions. Firstly, a matching mechanism with strategic anti-counterfeiting needs to be such that no participant can deviate from their current true preferences to benefit themselves. Secondly, the jealousy effect can be reasonably eliminated. Finally, an effective task allocation plan cannot make one party solely profit without harming the interests of other drones. To address the issue of time variation, we use a time window approach to adjust the algorithm of the graph. Within each time window, we recalculate the task preference values for each drone and perform matching. As the time window progresses, the graph structure adjusts accordingly. In order to solve the Assignment problem, we designed a task allocation algorithm. At a certain moment, newly added drones enter the public queue to participate in task allocation. At this time, sub regions publish tasks, and drones that were already in the queue can leave the public queue for decision-making. Due to the principle of first in, first out being the basis for determining the task queue, priority will be given to the first arriving drones. If the drone receives a task, it can execute it. If it does not accept it, it can enter other sub areas for task waiting. We understand that this is an NP hard problem, so we use heuristic algorithms to solve it. Although heuristic algorithms cannot guarantee finding the optimal solution, in practical applications, they can find a satisfactory solution within an acceptable time. Ant colony optimization (ACO) algorithm is a heuristic algorithm that simulates the foraging behavior of ant colonies. It can find local optimal solutions in the search space and has good robustness. Therefore, the study applies the ACO algorithm to the proposed allocation algorithm. The allocation algorithm steps are:

1) Enter the next moment t.

2) The swarm intelligence perception system prioritizes drones based on their social reputation, sensor accuracy, flight speed, and other indicators. Each drone will establish its own preference list based on the expected waiting time and the energy consumption information required to perform tasks in sub regions obtained through ACO algorithm.

3) If no tasks are published at the current time t, the algorithm will jump out of the loop. Otherwise, the swarm intelligence perception system will select a sub area for publishing tasks.

4) If the first in, first out queue associated with the selected sub region js is empty, the system will allocate the tasks published by the js sub region to the top ranked drone in the public waiting queue. Then, the system will return to the previous step and select the sub area for the next publishing task. In case, the first-in, first-out queue related to JS isn't empty, then the system will allocate the tasks published by JS to the top-ranked drone in the first-in, first-out queue.

5) If the drone accepts the task, the swarm intelligence perception system will officially deliver the task and record relevant information. If the drone refuses the task, it will select a first in, first out queue associated with a sub area with more expected benefits, and wait for the task to be released in that area. Then, the system will return to step 3 and select the sub area for the next publishing task.

6) Repeat steps 3 to 5 until no tasks are released within time t. Then, the system will return to step 1 and proceed to the next time t.

This study focuses on the design of drone task allocation and channel security spectrum resource allocation schemes based on bipartite graphs, mainly involving two specific schemes: task allocation scheme based on stable matching of bipartite graphs and drone security spectrum resource allocation strategy based on popular matching of bipartite graphs. Among them, bipartite graph is a special graph structure used here to describe the correlation between drones and tasks. Task allocation scheme based on stable matching of bipartite graphs: Firstly, research divides tasks into two

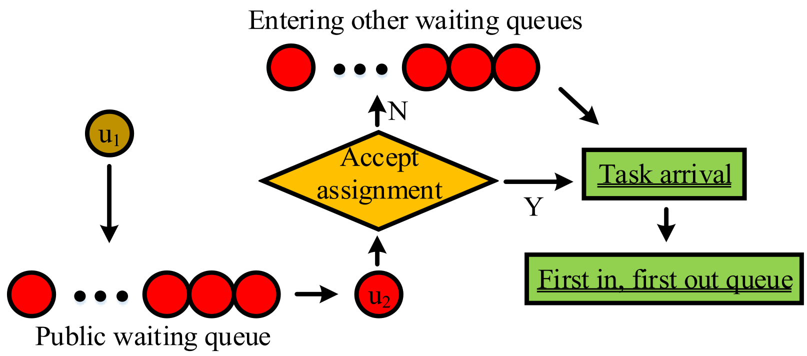

FIGURE 4. Task allocation algorithm.

main stages: publishing and perception. A dynamic matching model is then established to represent the preference values of drones in each sub-region in quintuples. This model can address long-term benefits concerns in changing environments. A task allocation scheme that strategically counters counterfeiting, eliminates jealousy effects and meets effectiveness requirements is deemed efficient. A UAV security spectrum resource allocation strategy based on bipartite graph popular matching: After the UAV successfully obtains the task, further planning of the data transmission path begins. In order to ensure the security of data during transmission, the research divides the transmission model into two main parts: physical domain and social domain. In the physical domain, drones may face the threat of eavesdropping during communication. To avoid this situation, drones can adjust their flight trajectory, reduce transmission power, and collaborate with D2D users on the ground. In social domains, only trusted D2D users can share channels. This strategy can improve the security of transmission.

In terms of task allocation strategy, first, initialize all drones and tasks, assign a weight to each drone based on their attributes, and then establish a priority queue for each task. Since the task needs to be matched in the bipartite graph, it is necessary to calculate the priority between each drone and the task. This can be achieved by calculating the time and energy consumption required for drones to perform tasks. Each drone will establish a preference list based on the priority of the task and the expected waiting time. For each task and drone, tasks can be assigned to each drone from their respective priority queues. In addition, we need to ensure that the allocation process meets the working time constraints of the drone. This task can be accomplished using a method akin to the Hungarian algorithm. However,since this problem is NP hard to solve, alternative heuristic algorithms, such as simulated annealing algorithms or genetic algorithms, may be necessary.

In channel security spectrum resource allocation, first, it is necessary to construct a graph to represent the security of each channel. This can be achieved by calculating the signal-to-noise ratio and interference of the drone on the channel, as well as considering other factors that may affect channel security. Based on the calculation results, construct a channel safety spectrum diagram, where each node represents a specific channel, and edges represent the possibility of drones switching between channels. Assign drones to channels: For each drone, a channel needs to be assigned based on its security. A method similar to task allocation algorithms can be used to establish a priority queue for each drone based on channel security. Then, assign a channel to each drone. Lastly, dynamic adjustments can be enacted based on the time windows of drones and tasks when allocating duties and channel resources. In this way, when a new drone is added to the task queue or a drone completes a task, the task and channel allocation can be recalculated. This algorithm ensures the long-term stability of the entire system in rapidly changing environments. In practical applications, this algorithm can find a satisfactory solution within an acceptable time.

Here, a heuristic task allocation method based on genetic algorithm is proposed. Genetic algorithm is an optimization algorithm that simulates the evolutionary process of organisms in nature, and is usually used to solve some NP hard problems. Genetic algorithms gradually improve solutions by simulating natural selection, crossover, and mutation processes. The following are the detailed steps:

1) Algorithm initialization: Firstly, randomly generate a set of solutions called a population. Each solution represents a feasible task allocation scheme referred to as an individual or chromosome. Chromosomes are composed of genes that represent the mapping relationship between tasks and drones.

Fitness evaluation: Traverse each individual and calculate their fitness. Fitness is an indicator that measures the quality of a task allocation plan. Here, fitness can be defined as the negative value of the total task completion time, drone energy consumption, or other indicators that measure task execution efficiency. In this way, the smaller the fitness, the better the solution.

2) Selection step: According to a certain selection strategy (such as roulette selection or tournament selection), select pairs of individuals from the current population based on fitness probability. This mimics the process of natural selection, where exceptional solutions have a higher chance of being selected, but less optimal solutions still have a probability of selection to maintain diversity in the search.

3) Cross step: Selected individuals are paired for cross operation. Crossing is the generation of new solutions by exchanging partial genes in chromosomes. For example,

crossing strategies such as single point crossing, multi-point crossing, or even crossing can be adopted. In the context of task allocation problems, it is necessary to perform cross-breeding operations under constraints, such as avoiding task assignment to multiple drones and ensuring that all tasks are assigned to drones.

4) Mutation step: Perform mutation on newly generated individuals. Variation involves introducing new features by altering one or more genes in a chromosome. The probability of mutation is usually small to ensure that the algorithm has a certain degree of randomness and flexibility. In this issue, we should ensure that mutation operations do not break task allocation constraints.

5) Replacement step: Replace individuals with lower fitness in the current population with newly generated individuals. This process is actually abandoning inferior solutions and leaving behind better ones, promoting the overall fitness of the population.

6) Termination condition: If a certain termination condition is met (such as reaching the maximum number of iterations, having sufficient fitness, etc.), the algorithm stops. If not, return to step 2 and continue with the next iteration.

B. UAV SAFETY SPECTRUM RESOURCE ALLOCATION STRATEGY BASED ON BIPARTITE GRAPH POPULAR MATCHING

After the drone successfully assigns tasks, it will start task route selection and data transmission. From the allocation and selection of data collection task points, the planning of task paths, to the process of task transmission, the security of drone transmission is to some extent lacking guarantee [23], [24], [25], [26]. Therefore, to ensure the efficient operation of drones, it is necessary to analyze the transmission security meanwhile. When designing a secure transmission model for the unmanned aerial vehicle Internet of Things, the secure transmission model is divided into two main parts: the logistics domain and the social domain. This division allows for the unmanned aerial vehicle flight cycle to be divided into small, fixed time slots. When the time slot is small enough, the topological network changes within continuous time slots can be ignored. The physical domain of the model is shown in Figure 5.

Figure 5 shows that after task allocation, the drone will choose to hover above a certain task point. During data transmission, drones usually start from the starting point and fly directly to the location directly above the base station. This is because the position directly above the ground base station is often the location with the best quality of information transmission in the air to ground link. No one has the opportunity to hover in this position for as long as possible to ensure the integrity of data transmission. However, air-to-ground communication is extremely susceptible to eavesdropping. Assuming that all eavesdroppers can eavesdrop on air to ground communication information in random subchannels, drones need to actively adjust their trajectory during flight to avoid eavesdropping on air to ground communication information. Meanwhile, the drone must decrease its signal transmission power in the vicinity of potential eavesdroppers and cooperate with D2D users on the ground who can manage eavesdropping interference. This is to ensure the security of cellular downlink transmission, and the specific secure transmission model is shown in Figure 6.

Figure 6 shows that each D2D user pair consists of two main components, namely a transmitter and a receiver. By sharing the spectrum, different D2D user pairs can ensure mutual information transmission security. In addition, under similar circumstances, social networks can encourage individuals to act as friendly jammers. Different D2D users and drones form a social domain together. Illegal and unauthorized D2D users in social domains can also cause information security issues. Therefore, it is possible to distinguish users within the social domain based on whether they have social trust information, and only share the social spectrum of the channel with trusted D2D users. This study adopts the orthogonal frequency division multiple access scheme as the basis, under which the system will allocate orthogonal subchannels with equal bandwidth to all drones. At this point, the drone can actively obtain channel status information between the base station and D2D users. At this point, although the drone can obtain the location of the eavesdropping user, the eavesdropping user can hide themselves by maintaining silence, so the error in location information is relatively large. Hence, this research employs Euclidean distance between a variety of devices to signify their three-dimensional coordinates, with formula (8) displaying their positional arrangement.

$$\begin{cases} x_k(t) = x_k^E(t) + \Delta x_k \\ y_k(t) = y_k^E(t) + \Delta y_k \end{cases} \tag{8}$$

In formula (8), Δx_k and Δy_k respectively represent the radius of the range defined with the uncertain position as the center; $x_k(t)$ and $y_k(t)$ respectively represent the accurate location coordinates of the eavesdropping user; t represents the time; $x_k^E(t)$ and $y_k^E(t)$ respectively represent the exact location coordinates of the eavesdropping user. The movement limit of the drone during the normal flight cycle can be expressed as:

$$\sqrt{\left(x_j(t+1) - x_j(t)\right)^2 + \left(y_j(t+1) - y_j(t)\right)^2} \leq v_{\max}\Delta \tag{9}$$

In formula (9), $v_{\max}$ represents the maximum flight speed; $x_j(t)$ and $y_j(t)$ represent the set of flight trajectory coordinates, respectively. The drone utilizes this constraint to ensure smooth planning from the starting point to the destination. When drones share subchannels with D2D users, eavesdroppers will eavesdrop on the channel. Due to the use of spectrum resource allocation in research, D2D users can act as eavesdropping jammers while sacrificing security in some areas for interference; Meanwhile, drones sacrifice some of their reachability rates to enhance information confidentiality. The worst-case average security rate of the drone

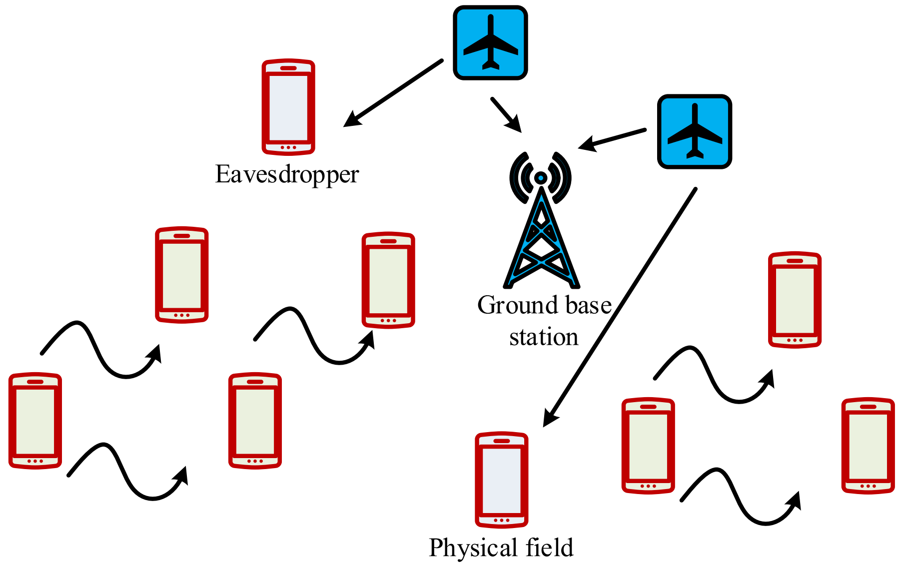

FIGURE 5. The physical domain of the model.

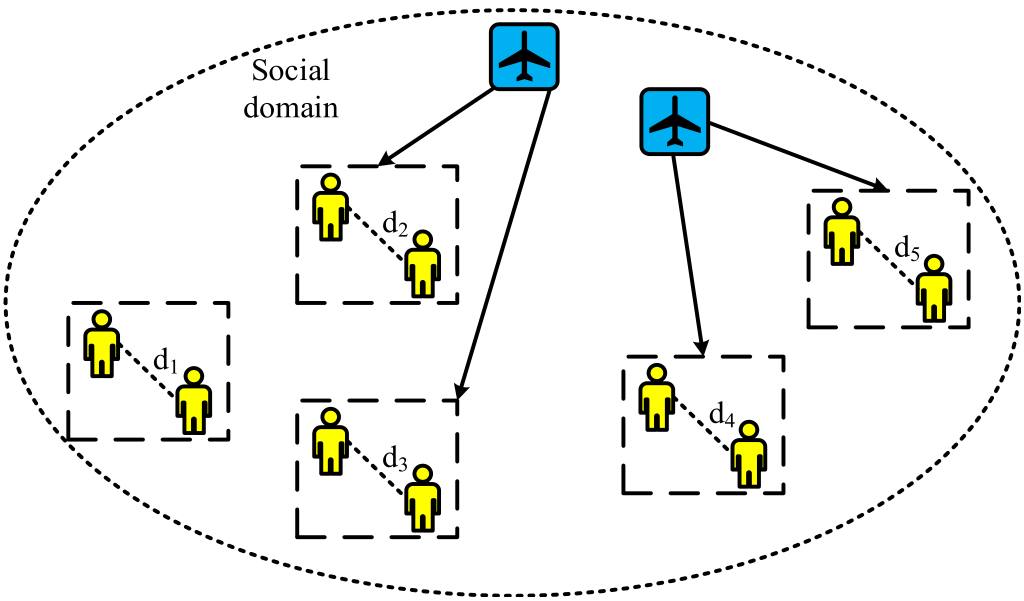

FIGURE 6. Secure transmission model.

channel is shown in formula (10).

$$C_s^{ave}\left(u_j\right)=\frac{1}{T}\sum_{t=1}^{T}\left[R_{j,b}\left(t\right)-\max_{e_k\in\varepsilon}\max_{\Delta x_k^2+\Delta y_k^2\le R_k^2}R_{j,k}\left(t\right)\right]^+ \tag{10}$$

In formula (10), T represents the flight cycle; $R_{j,k}\left(t\right)$ represents the real-time achievable rate of D2D communication channel eavesdropping for eavesdropping users; $R_{j,b}\left(t\right)$ represents the real-time reachable rate of the base station; e_k represents the eavesdropper. At this point, assuming that all drone and D2D users aim to improve their own profits, the optimization objective of drone u_j can be expressed as:

$$P1:\max_{\omega,x,y,P}\frac{1}{M}\sum_{j=1}^{M}C_s^{ave}\left(u_j\right) \tag{11}$$

In formula (11), x and y are both positional variables; P is the power variable; ω represents the channel allocation decision variable. The goal of D2D users is to maximize the rate while fully utilizing security constraints. All D2D users make decisions through local channel decision-making, and the optimization goal of the users is shown in formula (12).

$$P2:\max_{\omega}\frac{1}{TN}\sum\nolimits_{i=1}^{N}\sum\nolimits_{i=1}^{T}R_i\left(t\right) \tag{12}$$

In formula (12), $R_i\left(t\right)$ represents the real-time reachable rate of D2D user receiving end; N represents the elements of the signal decision matrix; T represents the time element. Under the premise of fixed drone trajectory and power, the study utilizes binary variables to jointly optimize the goals of drones and D2D users, forming a multi-objective optimization problem. The main optimization objective of drones is the confidentiality rate, while the main optimization objective of D2D users is the achievable rate. Matching theory is a mathematical tool that optimizes the personal interests of all matching participants to achieve multi-objective and optimization among different groups. This theory assumes that all matching participants are rational, so conflicts may arise between different individuals due to different interests. There may be conflicts between drone benefits and D2D user interests in this study. Optimizing the safety performance of drones separately may reduce the accessibility rate of D2D users; Unilaterally increasing the user's accessibility rate may reduce the safety performance of drones. In this case, the Pareto optimal solution of bilateral interests obtained through matching theory is often the most practical.

Therefore, this study proposes a hierarchical maximum size popular matching algorithm to achieve popular matching under the same group effect. The multi-objective optimization matching problem proposed in the study essentially belongs to the bidirectional matching problem of disjoint sets. The overall goal is to simultaneously satisfy the interests of both users. Without considering the same group effect, the utility function of drones only considers the same channel interference introduced by D2D users, while users only consider the same channel interference formed by drones in the opposite direction. At this point, the preference list of different users is fixed, and the optimization objective can be consistent with a single optimization objective. At this juncture, bilateral many-to-one matching can be described as a unidirectional projection of a many-to-one matching function. The mapping direction is shown in formula (13).

$$\begin{cases} D \cup U \cup \emptyset \Rightarrow D \cup U \cup \emptyset \\ d_i \in D \\ u_j \in U \end{cases} \tag{13}$$

Due to the fact that the spectrum reuse limit of drones under stable matching cannot be met in practical many-to-one matching, stable matching is not the best match for both drones and D2D users. Therefore,recent research has shownthat matching stability to popularity has become more flexible, transitioning from local stability to global stability. The deviation in popularity can be defined in the form of formula (14).

$$\varphi\left(\Omega, \Omega'\right) = \sum_{d_i \in D} v_i\left(\Omega\left(d_i\right), \Omega'\left(d_i\right)\right) + \sum_{u_i \in U} v_j\left(\Omega\left(u_j\right), \Omega'\left(u_j\right)\right) \tag{14}$$

In formula (14), Ω represents matching; Ω' represents that matching Ω is a popular match if and only if it is for any match obtained from $D \cup U \cup \emptyset$; d represents D2D user. The hierarchical matching algorithm designed in this study mainly searches for the largest popular matching, as shown in Figure 7.

In the initial stage, all D2D users in the underlying system detach from the offline state and transition to the online state. On this basis, all top-level D2D users have moved from online status to offline status. Hierarchy differentiation is beneficial for some D2D users who are rejected by drones to have a second chance of matching. Bottom-tier users that have been rejected by the drone will be designated to the top tier, where users of higher priority matching permissions compared to those at the lower level are present. The overall complexity of the algorithm at this point is shown in formula (15).

$$Z = O\left(\max\left\{\left|\varepsilon'\right|\right\} + \left|D' \cup U'\right|, \left|D'\right| \cdot \left|U'\right|\right) \tag{15}$$

In formula (15), $\max\left\{\left|\varepsilon'\right|\right\} + \left|D' \cup U'\right|$ represents the complexity of establishing the graph; $\left|D'\right| \cdot \left|U'\right|$ represents the matching complexity. At this point, if no drones receive requests from top-level D2D users, it can be determined that matching limited to the current region is popular. Because the receiving conditions for requests from drones in the region are that D2D users are within the channel receiving range and are suitable for receiving. Based on their preference list, underlying D2D users will send requests to drones, with drones being more likely to fulfill requests from top-level users than from underlying ones. This also indicates that matching is popular and there are no blocking edges.

The algorithm process includes the following steps:

In the initial stage, the D2D user in the first layer is online and requests spectrum reuse from the top ranked drone in the preference list, which has not previously rejected the D2D user.

If all drones in the first layer reject the online D2D user, then the user moves to the queue Q, and the second layer D2D user becomes available for online.

Whenever the drone replica receives a spectrum multiplexing request, it will reject or receive it based on the preference list.

The complexity of the algorithm depends on building and matching the graph.

This algorithm proves that the obtained matching is the maximum size popular matching relative to the original image. Firstly, divide D into a set containing the first layer D2D users and a set containing the second layer D2D users. Similarly, the set of drones matched to the first and second layer D2D users is represented by U1 and U2, respectively.

The algorithm demonstrates that any D2D users not matched in the matching process are situated in the second layer of D2D users while all unmatched drones are located in the first layer of drones.

In addition, the algorithm also proves that if a matching Ω 'obtained from Ω is given, and Ω'> Ω, then the popularity deviation is greater than 0. Therefore, this algorithm can find the maximum size popular matching in many to one matching problems without considering the same group effect. Taking into account the same group effect, this algorithm can also

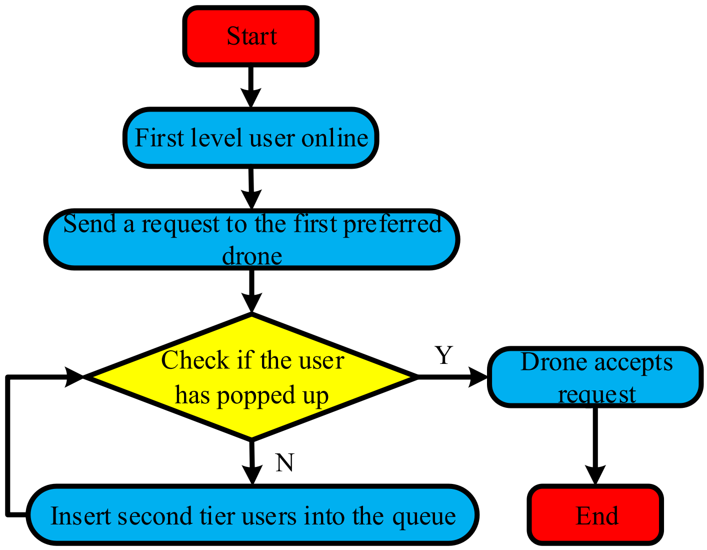

FIGURE 7. Hierarchical matching algorithm.

maintain popularity in the initial construction of popular matching structures.

IV. ANALYSIS OF THE EFFECTIVENESS OF UNMANNED AERIAL VEHICLE TASK ALLOCATION AND CHANNEL SECURITY SPECTRUM RESOURCE ALLOCATION SCHEMES

A. ANALYSIS OF THE EFFECTIVENESS OF DRONE TASK ALLOCATION SCHEMES

The experimental environment is set as follows: Firstly, the simulation is conducted in a $1 \times 1 \times 1$ km three-dimensional space with 8 drones and 50 pairs of D2D users. There is a base station located in the center of the space, while D2D users are evenly distributed throughout the entire area, ensuring that the distance between the sending and receiving ends does not exceed 50 meters. The Unit of time we set is timeslot. There are 160 timeslots in total, and each timeslot is 1 second long.During each time slot, every drone will fly towards the base station's vicinity from its starting position, achieving a maximum speed of 10 meters per second. The base station has four specific locations with coordinates of (−400, −400), (400, −400), (400, 400), and (−400, 400). Every two drones will fly from location n to location (n mod 4+1), with values ranging from 1 to 4. If the drone is unable to reach the base station within the designated time slot, it will directly fly to the destination. In addition, 8 eavesdroppers were randomly distributed in the network, and their estimated position error radius ranged from 20 meters to 80 meters. The flying altitude of drones ranges from 80 meters to 120 meters. In terms of transmission power, the ground equipment has a transmission power of 10 dBm, and the average transmission power of the drone is 20 dBm, with a maximum of 4 times the average value. The path loss coefficient of ground communication is 3, the unit channel gain is −60 dB, and the noise power is −120 dBm. Drones have a spectrum sharing limit of 5, a mutual interference threshold of −90 dB, and D2D users have a security rate threshold of 0.5 bps/Hz. In the social domain, the Erdos Renyi model was used to construct a social relationship graph, with a probability of establishing a social link of 0.6. When analyzing the effectiveness of unmanned aerial vehicle task allocation schemes, the parameters were set based on the energy model and stochastic environment of the rotor type unmanned aerial vehicle, as shown in Table 2.

Meanwhile, comparative analysis was conducted using exhaustive search algorithm, static stable matching algorithm, random algorithm, and the algorithm designed in this study. The average perceived energy consumption and average perceived system revenue of different sub regions are shown in Figure 8.

Figure 8 (a) shows that with the increasing number of data nodes in the sub region, the average energy consumption of the three algorithms shows a gradual upward trend. This can be attributed to the increment in collection points, which leads to a longer shortest path. From the comparison, it can be seen that the energy consumption of the algorithm designed in the study is between the other two algorithms. This reflects the balance between computational complexity and energy consumption performance. Figure 8 (b) shows that the average revenue of the system increases with the increase of the number of sub regions, and the curve position of the research and design algorithm ranks second, between the revenue values of 800 and 2100. Although this algorithm's efficiency is slightly inferior to an exhaustive search, the latter can lead to significant computational waste. The research and design algorithm achieved the optimal effect between performance and efficiency. The changes in average revenue of drones and average revenue of individual tasks are shown in Figure 9.

Figure 9 shows that the average revenue of the designed algorithm for UAV shows an increasing trend with the number of sub regions, with revenue values ranging from 21 to 40. The position of the curve is second only to the exhaustive algorithm, and it also achieves a balance between

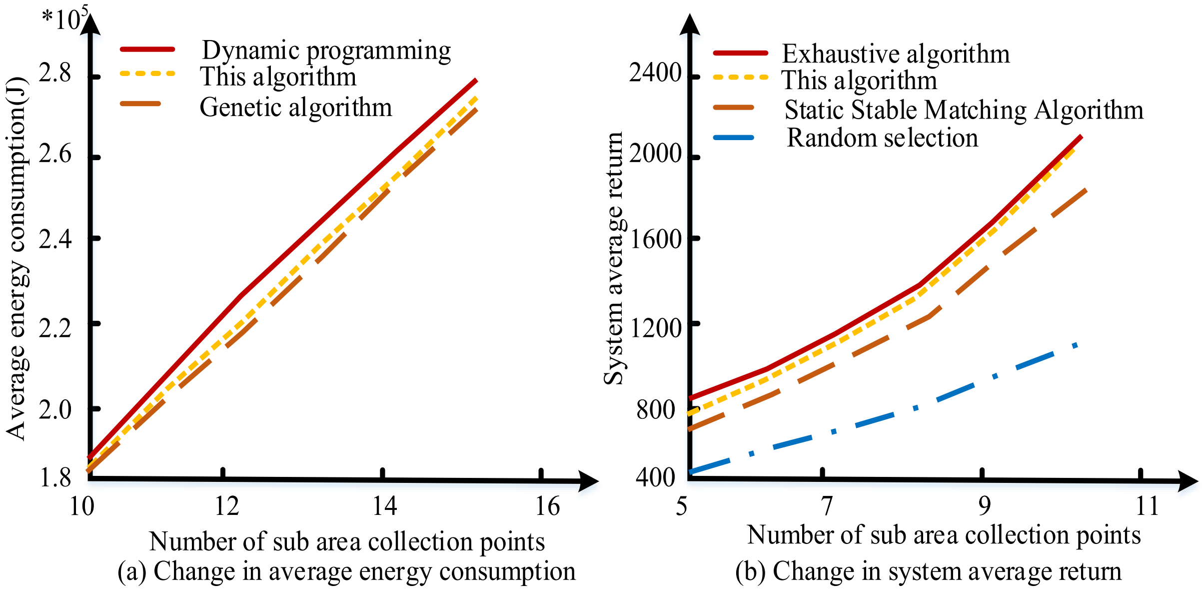

FIGURE 8. Perceived average energy consumption and perceived system average revenue in different sub regions.

TABLE 2. Test parameters for human-machine task allocation scheme.

Test parameter setting	Numerical value
Number of sub regions	5
Number of drones	10
Sensor accuracy	1
Initial Social Reputation Value	0
Data collection point data volume interval	0.8-12Mbits
Drone propulsion power	340W
Drone hover power	220W
Drone hover power	11.1V
Battery capacity	2*104mAh
Charging time ratio	0.25
Slot	1s
The length interval between data collection points	100-1000m
Advance speed	2-16m/s
Number of collection points in a single area	15

computational complexity and profitability. In terms of the average return effect of a single task, the algorithm designed by the research also achieved a benefit advantage; The curve's growth occurs within the return values of 173 and 210.

B. ANALYSIS OF THE EFFECTIVENESS OF CHANNEL SECURITY SPECTRUM RESOURCE ALLOCATION SCHEME

The study on drone task allocation schemes utilized a three-dimensional spatial network range to evaluate its efficiency. Meanwhile, research will be conducted to set the base station in the central area, and users will be evenly distributed within the area. The specific parameter settings are shown in Table 3.

To avoid route confusion caused by excessive overlap of test drone trajectories, this study selected five representative drone trajectory routes as the analysis route, as shown in Figure 10.

Figure 10 displays the simultaneous formation of flight trajectories between location 1 and location 2 by two UAV. Although the takeoff point and time of the unmanned aerial vehicle are the same, the spectrum flying strategy is also different due to the different flight heights of the unmanned aerial vehicle. Therefore, the flight trajectory exhibits subtle differences. The changes in algorithm iteration times and the average worst-case confidentiality rate of UAV are shown in Figure 11.

From Figure 11, it can be seen that the study compared popular matching channel allocation algorithms, popular matching algorithms, stable matching channel allocation algorithms, and stable matching algorithms. The data shows that iteration times for all four algorithms increase as the number of drones increases, indicating a convergence effect. In addition, from the comparison, it can be seen that the algorithm designed in the study is superior to other algorithms in terms of both the number of iterations of the algorithm itself and the number of iterations of channel allocation applications. At the same time, in the comparison of the average worst-case confidentiality rate, the average worst-case confidentiality rate of the algorithm designed in the study increases with the increase of social link probability. Compared with other algorithms, the algorithm studied ensures performance while greatly reducing complexity. We also achieved a midpoint in performance and complexity.The comparison between the security performance of the algorithm and the average reachable rate is shown in Figure 12.

From Figure 12, it can be seen that the study compares exhaustive algorithms, popular matching algorithms,

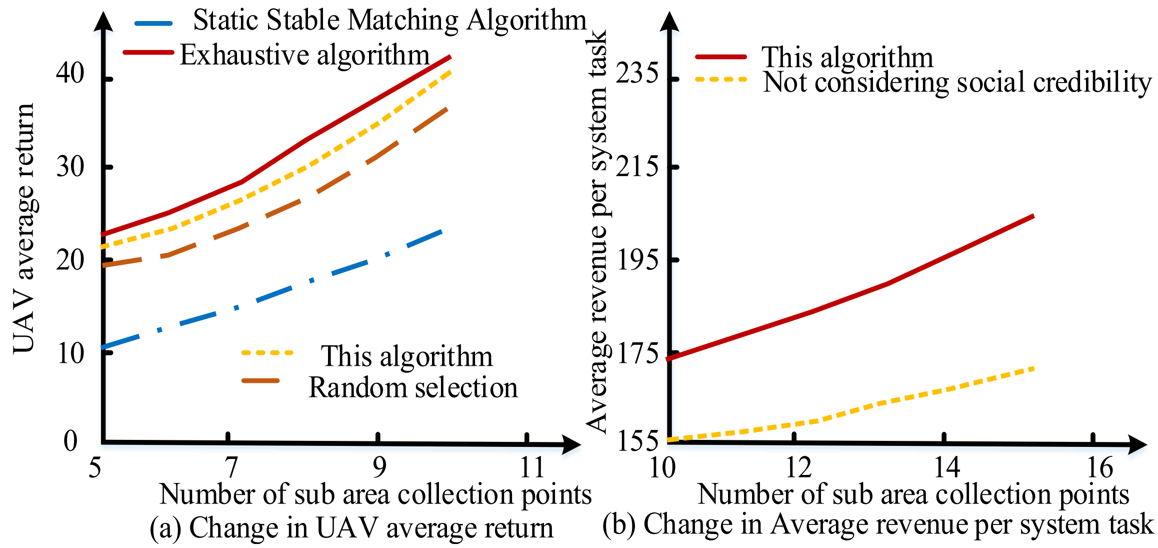

FIGURE 9. Changes in average revenue of drones and average revenue of individual tasks.

TABLE 3. Experimental parameters of channel security spectrum resource allocation scheme.

Test parameter setting	Numerical value
Network range	1*1*1km3
Number of drones	8
Number of D2D user pairs	50
Distance between sender and receiver	50m
Number of time slots	160
Time slot duration	1s
Maximum rate	10m/s
Location 1 coordinates	（-400，-400）
Location 2 coordinates	（400，-400）
Location 3 coordinates	（400，-400）
Location 4 coordinates	（-400，400）

stable matching algorithms, and game algorithms formed by alliances. The research results demonstrate a comparison between exhaustive algorithms, popular matching algorithms, stable matching algorithms, and the alliance formation game algorithm designed by our institute in terms of drone safety performance and reachability rate. From the perspective of drone safety and D2D user safety, the algorithm developed in this study presents notable benefits. With the increase of drone spectrum sharing limit, its security performance gradually enhances, especially after the sharing limit value reaches 1, its advantages become more obvious. In contrast, other algorithms, especially exhaustive algorithms, although slightly higher in security performance, can lead to a large amount of computational waste, so they are not applicable in practical applications. In terms of the achievable rate of drones, although the algorithm designed in this study gradually decreases with the increase of drone spectrum sharing limit, its value is second only to the exhaustive algorithm at each sharing limit point. Overall, the alliance formation game algorithm designed in this study not only ensures the safety performance of drones and D2D users, but also effectively controls the decrease in reachable rate. Compared with other algorithms, it has higher practical value and superiority. Specifically, it shows a trend of rapid improvement in the early stage and a decrease in the later stage, with advantages gradually becoming apparent after the shared limit value is 1. Meanwhile, by comparing with other algorithms, it can be seen that the security performance numbers of the algorithm designed in the study are only lower than those of the exhaustive algorithm at each shared limit point; Exhaustive algorithms can cause a significant amount of computational waste and are not applicable in practical applications. In addition, in terms of reachability rate, the designed algorithm's drone reachability rate gradually decreases with the increase of drone spectrum sharing limit. The reachable rate values of the algorithm studied and designed are only lower than those of the exhaustive algorithm at each shared limit point. From the perspective of D2D users, the security performance curve of D2D users studying and designing algorithms gradually increases with the increase of drone spectrum sharing quotas. There is a noticeable pattern of rapid improvement in the initial stage,followed by a decline in later stages, with the advantage eventually becoming apparent once the shared limit value reaches 0. Meanwhile, by comparing with other algorithms, it can be seen that the security performance numbers of the algorithm designed in the study are only lower than those of the exhaustive algorithm at each shared limit point; Exhaustive algorithms can result in a considerable amount of computational waste and are impractical in real-world scenarios. In addition, in terms of reachability rate, the designed algorithm's drone reachability rate gradually decreases with the increase of drone spectrum sharing limit. The reachable rate values of the algorithm

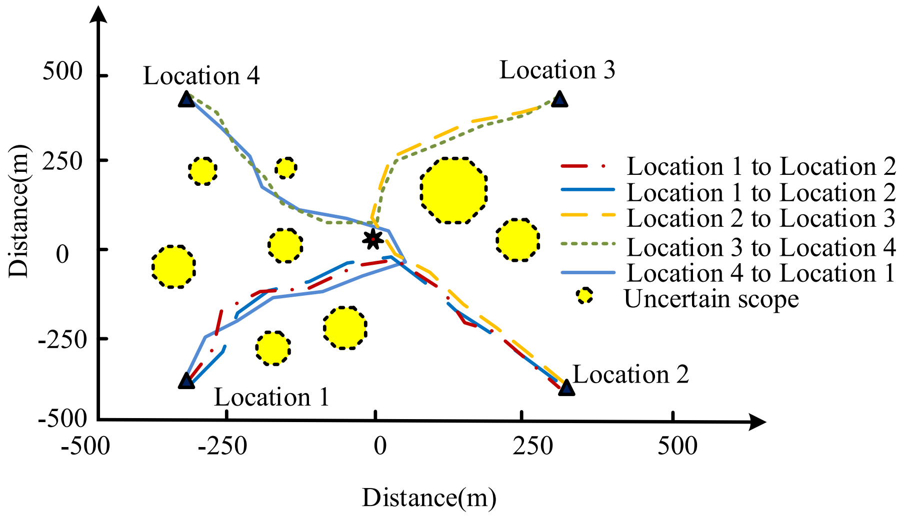

FIGURE 10. Drone trajectory route.

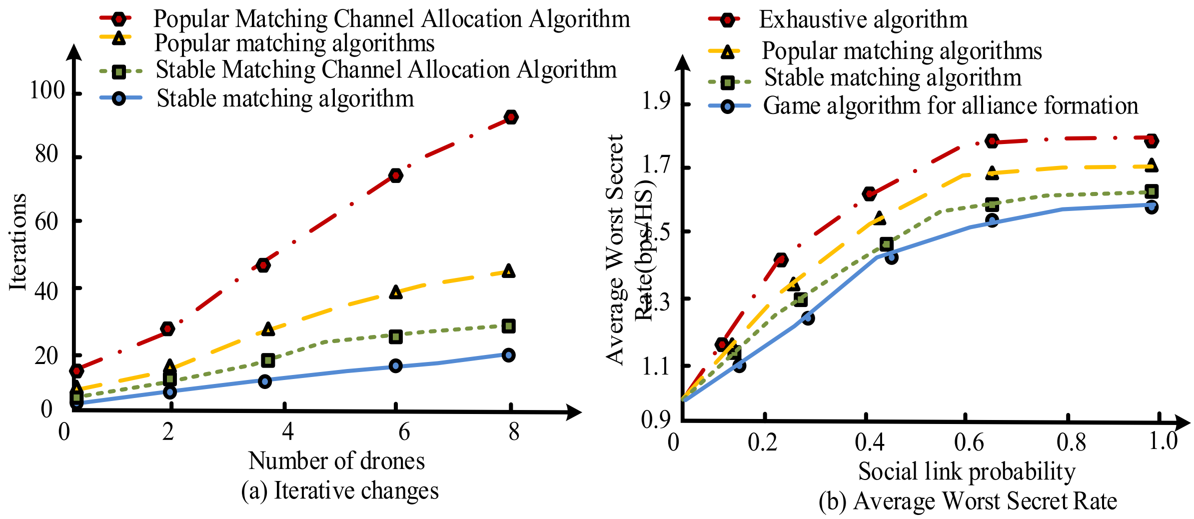

FIGURE 11. Changes in algorithm iteration times and average worst secret rate of unmanned aerial vehicles.

studied and designed are only lower than those of the exhaustive algorithm at each shared limit point. The comparison and variation of the average worst-case safety rate of UAV are shown in Figure 13.

Figure 13 shows that the average worst-case safety rate of UAV studied and designed with algorithms increases with the increase of flight cycle and also with the increase of average power. In addition, it can be seen that the algorithm designed in the study has a significant overall performance gain in the average worst-case safety rate during the information transmission process of UAV. Compared to fixed trajectory drones, the overall performance of the average worst-case safety rate has been improved by about 18.2%, while compared to fixed power drones, the overall performance has been improved by about 15.5%. This indicates that the algorithm can effectively improve the security performance of UAV during information transmission, enabling them to ensure the safe transmission of information and achieve high economic benefits during the execution of tasks.Compared to the average worst safety rate curve of UAV on fixed trajectories, the research and design algorithm yields an overall performance increase of approximately 18.2% for the average worst safety rate curve. Compared with the average worst safety rate curve of fixed power UAV, the overall performance gain of the average worst safety rate curve of the research and design algorithm is about 15.5%. This demonstrates the superior performance of the algorithm developed in the research.

Compared with existing spectrum resource allocation schemes, the algorithm studied not only ensures channel security but also improves spectrum utilization, enabling drones to more effectively utilize spectrum resources during data transmission. In addition, compared to other existing algorithms, the algorithm studied has a slower growth rate in iteration times, indicating that when dealing with complex problems, the algorithm studied can converge faster, thereby improving computational efficiency. Moreover, compared to existing unmanned aerial vehicle communication security solutions, the algorithm studied not only ensures the safety

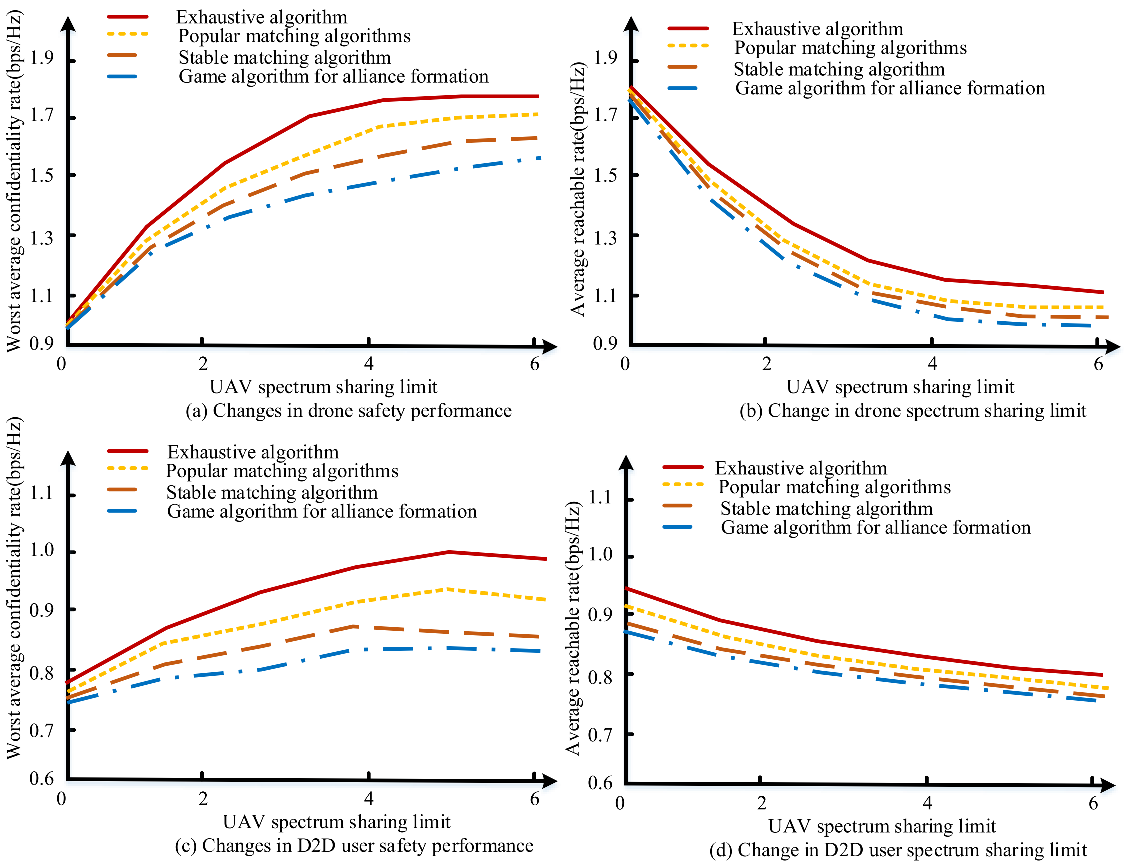

FIGURE 12. The security performance and average reachable rate of algorithms.

rate, but also improves the flight efficiency and spectrum utilization efficiency of UAV, with obvious advantages.

In terms of practicality, the algorithms studied can be widely applied to various scenarios that require UAV for data collection and transmission, such as agriculture, environmental monitoring, emergency rescue, military reconnaissance, etc. In these applications, drones need to perform tasks in various complex environments, such as mountains, forests, water bodies, etc. Optimizing task and spectrum resource allocation strategies is critical for drones. In addition, with the development of 5G and IoT technology, the application of drones will become more widespread. This algorithm can help achieve efficient, secure, and reliable operation of unmanned aerial vehicle networks, providing important technical support for intelligent applications such as intelligent cities and agriculture. However, the practicality of this algorithm also depends on various factors in the actual environment, such as the number of drones, the complexity of tasks, and the complexity of the environment. Thus, conducting application-based research in particular environments is imperative. Overall, this study provides a new, efficient, and secure solution for task allocation and spectrum resource allocation of drones, which has important theoretical and practical significance for promoting the development of drone technology. Therefore, robustness testing was conducted on the drone task allocation scheme and spectrum resource allocation scheme, with specific parameters shown in Table 4.

In robustness testing, the study repeated 100 experiments and recorded the results of each experiment. In approximately 95% of the experiments, the results of each indicator were within a very close range, demonstrating good consistency. In addition, even in certain specific situations, such as an increase in the number of drones or a decrease in the number of D2D users, the experimental results only show slight changes. This indicates the robustness of the research, that is, our task allocation and spectrum resource allocation schemes can maintain efficient and stable performance in various situations.

Compared to other methods, research innovatively adopts matching theory to optimize many-to-one matching problems, which can maximize the benefits between drones and ground users. At the same time, a stable matching scheme for drone task allocation based on bipartite graphs and a popular matching strategy for drone security spectrum resource allocation based on bipartite graphs have been innovatively researched and designed. These two strategies optimize a series of coherent actions of drones from information collection to information transmission, improving the efficiency and security of drone information transmission. In terms of the security performance of unmanned aerial vehicles and D2D users, the algorithms designed and studied have shown strong advantages: specifically, the security performance of unmanned aerial vehicles improves with the increase of spectrum sharing limit, and the advantage is more obvious

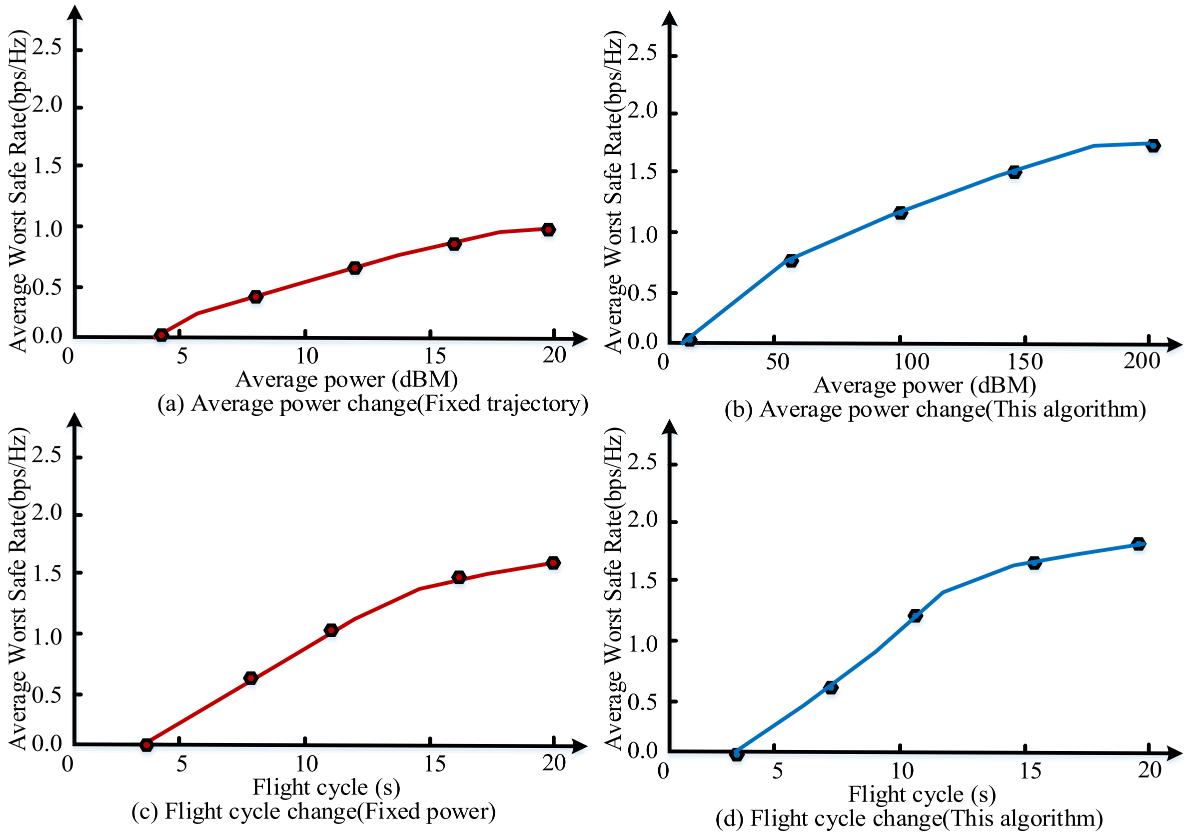

FIGURE 13. Comparison and variation of average worst-case safety rate for unmanned aerial vehicles.

TABLE 4. Robustness testing.

Test parameter settings	Numerical value
Runs	100
network range	1/1km3
Number of drones	8
Number of D2D user pairs	50
Distance between sender and receiver	50m
Number of time periods	160
Duration of time period	1s
maximum speed	10m/s
Position one coordinate	(400, -400)
Position two coordinates	(-400, -400)
Position three coordinates	(400, 400)
Position Four Coordinates	(-400, 400)

when the sharing limit reaches 1. From the perspective of D2D users, the average worst-case safety rate of the design algorithm increases with the increase of flight cycle and average power. Compared to fixed trajectory drones, the overall performance improvement of the algorithm studied and designed is about 18.2%, and compared to fixed power drones, the overall performance improvement is about 15.5%. In terms of maximizing the benefits between drones and D2D users, the algorithm studied and designed achieves the optimal effect between computational complexity and performance, and overall achieves the maximization of benefits between drones and D2D users. The design method of this study effectively solves the problem of selecting task plans and ensuring a secure channel for drone data collection and transmission, and has high application value.

V. CONCLUSION

The results indicate that under the research design method, the average income of drones ranges from 21 to 40; The average return on a single task is between 173 and 210; The optimal effect was achieved between performance and efficiency. In terms of the convergence effect of iteration times, the safety performance curve of drone and D2D user research and design algorithms gradually increases with the increase of drone spectrum sharing restrictions. After the shared limit values are 1 and 0, the advantage gradually becomes apparent. In terms of accessibility, the designed algorithm's drone accessibility gradually decreases with the increase of drone spectrum sharing restrictions. In addition, the overall performance gains of the average worst-case safety curve for research and design algorithms are approximately 18.2% and 15.5%. This indicates that algorithms designed for research have more advantages. The energy consumption of the algorithm designed by the research institute is between the other two algorithms, reflecting the balance between computational complexity and energy performance. However, this also exposes the potential limitations of our method in balancing energy consumption and computational complexity, and future research can delve deeper into this issue.

REFERENCES

[1] A. Srivastava and J. Prakash, "Techniques, answers, and real-world UAV implementations for precision farming," *Wireless Pers. Commun.*, vol. 131, no. 4, pp. 2715–2746, Jul. 2023.

[2] A. F. U. Din, I. Mir, F. Gul, S. Mir, S. S. N. Alhady, M. R. A. Nasar, H. A. Alkhazaleh, and L. Abualigah, "Robust flight control system design of a fixed wing UAV using optimal dynamic programming," *Soft Comput.*, vol. 27, no. 6, pp. 3053–3064, Mar. 2023.

[3] J. Zhang, S. Xu, Y. Zhao, J. Sun, S. Xu, and X. Zhang, "Aerial orthoimage generation for UAV remote sensing: Review," *Inf. Fusion*, vol. 89, pp. 91–120, Jan. 2023.

[4] S. Fei, M. A. Hassan, Y. Xiao, X. Su, Z. Chen, Q. Cheng, F. Duan, R. Chen, and Y. Ma, "UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat," *Precis. Agricult.*, vol. 24, no. 1, pp. 187–212, Feb. 2023.

[5] M. K. Singh, A. Choudhary, S. Gulia, and A. Verma, "Multi-objective NSGA-II optimization framework for UAV path planning in an UAV-assisted WSN," *J. Supercomput.*, vol. 79, no. 1, pp. 832–866, Jan. 2023.

[6] I. Mademlis, A. Torres-González, J. Capitán, M. Montagnuolo, A. Messina, F. Negro, C. Le Barz, T. Gonçalves, R. Cunha, B. Guerreiro, F. Zhang, S. Boyle, G. Guerout, A. Tefas, N. Nikolaidis, D. Bull, and I. Pitas, "A multiple-UAV architecture for autonomous media production," *Multimedia Tools Appl.*, vol. 82, no. 2, pp. 1905–1934, Jan. 2023.

[7] Z. Chen, "Research on internet security situation awareness prediction technology based on improved RBF neural network algorithm," *J. Comput. Cognit. Eng.*, vol. 1, no. 3, pp. 103–108, Mar. 2022.

[8] X. Zou and S. Zou, "Cognitive computing smart system: How to remove ambiguities," *J. Comput. Cognit. Eng.*, vol. 2, no. 3, pp. 1–9, Dec. 2022.

[9] X. Zhong, Y. Guo, N. Li, and Y. Chen, "Joint optimization of relay deployment, channel allocation, and relay assignment for UAVs-aided D2D networks," *IEEE/ACM Trans. Netw.*, vol. 28, no. 2, pp. 804–817, Apr. 2020.

[10] Y. He, D. Wang, F. Huang, R. Zhang, and J. Pan, "Trajectory optimization and channel allocation for delay sensitive secure transmission in UAV-relayed VANETs," *IEEE Trans. Veh. Technol.*, vol. 71, no. 4, pp. 4512–4517, Apr. 2022.

[11] C. Yang, B. Liu, H. Li, B. Li, K. Xie, and S. Xie, "Learning based channel allocation and task offloading in temporary UAV-assisted vehicular edge computing networks," *IEEE Trans. Veh. Technol.*, vol. 71, no. 9, pp. 9884–9895, Sep. 2022.

[12] M. S. Hosen and Y. Peng, "Dynamic channel allocation technique for cognitive radio based UAV networks," in *Proc. Int. Conf. Artif. Intell. Big Data Anal.*, Oct. 2021, pp. 152–155.

[13] N. Zhao, Z. Liu, and Y. Cheng, "Multi-agent deep reinforcement learning for trajectory design and power allocation in multi-UAV networks," *IEEE Access*, vol. 8, pp. 139670–139679, 2020.

[14] X. Li, H. Zhang, R. Wang, and F. Nie, "Multiview clustering: A scalable and parameter-free bipartite graph fusion method," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 44, no. 1, pp. 330–344, Jan. 2022.

[15] Z. Li, X. Shen, Y. Jiao, X. Pan, P. Zou, X. Meng, C. Yao, and J. Bu, "Hierarchical bipartite graph neural networks: Towards large-scale e-commerce applications," in *Proc. IEEE 36th Int. Conf. Data Eng. (ICDE)*, Apr. 2020, pp. 1677–1688.

[16] K. Wang, W. Zhang, X. Lin, Y. Zhang, L. Qin, and Y. Zhang, "Efficient and effective community search on large-scale bipartite graphs," in *Proc. IEEE 37th Int. Conf. Data Eng. (ICDE)*, Apr. 2021, pp. 85–96.

[17] S. Liang, B. Iskender, B. Wen, and S. Ravishankar, "Labmat: Learned feature-domain block matching for image restoration," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2021, pp. 1689–1693.

[18] W. Zhang, H. Liu, H. Ma, and W. Zhao, "Research on gesture recognition based on improved template matching algorithm," in *Proc. IEEE 2nd Int. Conf. Inf. Technol., Big Data Artif. Intell. (ICIBA)*, vol. 2, Dec. 2021, pp. 462–467.

[19] K. Chen, N. Ye, and J. Xie, "Efficient feature matching algorithms applied to robust image processing," in *Proc. 7th Int. Conf. Intell. Comput. Signal Process. (ICSP)*, Apr. 2022, pp. 111–116.

[20] Y. Changhua, A. Lei, L. Xin, G. Han, and G. Z. Gao, "Multi-UAV cooperative task allocation for multi-point reconnaissance and communication service," *Nanjing Xinxi Gongcheng Daxue Xuebao*, vol. 15, no. 1, pp. 94–103, Jan. 2023.

[21] J. A. Ricardo, L. Giacomossi, J. F. S. Trentin, J. F. B. Brancalion, M. R. O. A. Maximo, and D. A. Santos, "Cooperative threat engagement using drone swarms," *IEEE Access*, vol. 11, pp. 9529–9546, 2023.

[22] F. Machida, Q. Zhang, and E. Andrade, "Performability analysis of adaptive drone computation offloading with fog computing," *Future Gener. Comput. Syst.*, vol. 145, pp. 121–135, Aug. 2023.

[23] A. El-Mesady, O. Bazighifan, and Q. Al-Mdallal, "On infinite circulant-balanced complete multipartite graphs decompositions based on generalized algorithmic approaches," *Alexandria Eng. J.*, vol. 61, no. 12, pp. 11267–11275, Dec. 2022.

[24] A. El-Mesady and O. Bazighifan, "Decompositions of circulant-balanced complete multipartite graphs based on a novel labelling approach," *J. Function Spaces*, vol. 2022, pp. 1–17, Jul. 2022.

[25] A. El-Mesady, Y. S. Hamed, and H. Shabana, "On the decomposition of circulant graphs using algorithmic approaches," *Alexandria Eng. J.*, vol. 61, no. 10, pp. 8263–8275, Oct. 2022.

[26] A. El-Mesady, O. Bazighifan, and S. S. Askar, "A novel approach for cyclic decompositions of balanced complete bipartite graphs into infinite graph classes," *J. Function Spaces*, vol. 2022, pp. 1–12, May 2022.

WEIHAN LI was born in December 1978. He received the master's degree. He is currently an Associate Professor. He has published more than 30 academic articles and more than 20 research projects. His research interests include information systems and simulation systems.

JIANWEI GUO was born in September 1975. He received the M.M. degree from the Central University of Finance and Economics. He is currently pursuing the Ph.D. degree in control science and engineering with Beijing Jiaotong University. He has published 11 academic articles and eight research projects.