Two-stage stochastic programming research of UAVCN based on improved genetic algorithm under earthquake disaster

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ABSTRACT

Natural disasters often inflict significant damage on communication infrastructure, which plays a crucial role in emergency response operations. With technological advancements, UAV communication network (UAVCN) is now capable of providing sustained communication services. However, existing research typically focuses solely on the objective of maximizing communication coverage, while traditional genetic algorithms are susceptible to converging on local optima. Therefore, this study establishes a multi-objective planning model and employs an improved genetic algorithm for its solution. Initially, a two-stage stochastic planning method is proposed. The first stage determines the optimal layout of UAVCN to maximize communication coverage and throughput, while the second stage generates the optimal paths for UAVCN to minimize rescue time and energy consumption. In solving the two-stage model, an improved genetic algorithm (IGA) is adopted, which combines global search capabilities with rapid convergence. Finally, the 2017 Jiuzhaigou earthquake is selected as a case study to construct and simulate the two-stage model, thereby verifying the effectiveness and feasibility of the model and algorithm, and to obtain the optimal planning scheme.

Keywords: Earthquake, communication, UAV, stochastic programming, genetic algorithm

1. INTRODUCTION

Globally, frequent occurrences of natural disasters such as earthquakes, tsunamis, hurricanes, floods, and landslides often result in substantial human casualties and economic losses[1]. Consequently, communication systems have experienced significant impacts in numerous natural disasters, leading to extensive and prolonged communication outages in affected areas, which severely impede information transmission and emergency response reliant on communication systems[2,3].

Therefore, in the context of natural disasters, the rapid restoration of communication networks is a critical focus of this study. Traditional methods of rapidly restoring communication networks involve ground emergency communication platforms. They have limitations such as low flexibility and significant dependence on terrain and road conditions, making it difficult to reach target areas promptly[4]. In recent years, UAV communication network (UAVCN) has garnered considerable attention from researchers, equipment manufacturers, and communication service providers due to its convenient, flexible, and rapid deployment capabilities and remote data collection functions[5,6]. In emergency rescue, UAVCN can swiftly restore communication networks in affected areas[7].

From the discussion above, it is evident that while the application of UAVs in emergency rescue is widespread and extensively researched, there is limited research on UAVCN for restoring communication networks in disaster areas. Additionally, few studies simultaneously consider aspects such as area coverage, system throughput, flight time, and energy consumption. Although there is significant research on improving traditional genetic algorithms, they are not entirely applicable to the model in this paper. Therefore, this study proposes a two-stage stochastic planning method to identify the optimal layout and path of UAVCN. The contributions of the paper are summarized as follows:

(1) The layout and path planning model for UAVCN is improved by setting multiple objectives to more comprehensively meet the characteristics of communication services required by disaster-affected areas under real-world conditions.

(2) The improved genetic algorithm (IGA) is proposed, which overcome the limitations of local optima, resulting in improved algorithmic precision, reduced computation time, and lower costs.

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2. LITERATURE REVIEW

UAV technology plays an increasingly vital role in emergency rescue operations, capable of executing a range of complex tasks including the reconstruction of 3D maps[8], emergency surveying[9], and environmental assessment[10]. Following a disaster, rescue personnel are often unable to rapidly reach the affected sites due to complex terrain and damaged roads, making the layout and path planning of UAVs crucial[11]. Early research primarily focused on enhancing the performance of individual UAV. However, given the limited monitoring and coverage capabilities of a single UAV, the focus in emergency rescue has shifted towards how to coordinate multiple UAVs. Currently, research on UAV layout and path planning in rescue operations is gradually evolving towards multi-UAV collaboration to enhance the comprehensiveness and efficacy of rescue missions.

In addressing task allocation and path planning issues, decades of exploration have yielded various solutions[12]. Existing task allocation techniques can be broadly categorized into traditional mathematical programming and heuristic-based algorithms[13]. For path planning, strategies such as graph-based methods[14], random sampling search algorithms[15], node-based optimal search[16], artificial potential fields[17], and biomimetic evolutionary algorithms[18] have been developed. Each method has its focus, such as constructing robust path graphs, sampling between start and end points to generate paths, using heuristic functions for effective search, simulating interactions between objects for planning, and mimicking biological evolution to optimize paths.

In summary, joint research on UAVs layout and path planning is scarce. Moreover, as path planning is an NP-hard problem, heuristic algorithms can be used for effective solutions, but these algorithms have drawbacks such as slow convergence and susceptibility to local optima. To date, the layout and path planning problem for UAVs remains an open area of research. Therefore, this paper proposes a comprehensive and efficient solution by conducting stochastic planning for both the layout and path planning stages of UAVCN and employing an improved genetic algorithm (IGA) for solving.

3. PROBLEM DESCRIPTION

The path problem of drones in the second stage can be described as follows: For a directed complete graph $G = (L_e, E)$, where L_e is the set of demand points, node 0 represents the drone dispatch center, and each edge $E = \{j, m | j, m \in L_e \cap j \neq m\}$ corresponds to a non-negative distance d_{jm}, the communication demand time for each demand point $j \in L_e$ is fixed. The UAV dispatch center 0 has a group of UAVs $U \in \{1,2, \dots, u\}$ each with a maximum energy of E_{max}. After receiving dispatch orders, the UAVs depart from the dispatch center to the demand points, staying for a fixed time before moving on to service subsequent demand points.

3.1 Layout model

3.1.1 Notations. The notations and symbols of the model in this section are described in Table 1.

Table 1. Meaning of the notations.

Parameters	Meaning
U	Set of UAVs, $U \in \{1, 2, \dots, u\}$
u	Number of UAVs
L	Set of disaster points, $L \in \{1, 2, \dots, l\}$
l	Number of disaster points
(x_i, y_i, H_i)	Three-dimensional coordinates of the UAV
$(x_j, y_j, 0)$	Three-dimensional coordinates of the disaster point
d_{ij}	Distance between the UAV i and the disaster point j, km
d_{max}	Maximum communication range of the UAV, km
H_{max}	Hover height of the UAV, km

Parameters	Meaning
C_{ij}	Throughput function
γ	Communication bandwidth, Hz
SNR_{ij}	Transmission signal-to-noise ratio, dB
q_0	Small-scale frailty coefficient of communication, dB
β_{ij}	Path loss criterion
α^2	White noise power, dB
v_{max}	Velocity of light, km/s
g	Carrier frequency, GHz
ρ	Path loss index
ω_{im}	When $\omega_{im} = 1$, it means the UAV i is hovering over the disaster point m, otherwise $\omega_{im} = 0$
σ_{ij}	When $\sigma_{ij} = 1$, it means that the UAV i serves disaster point j, otherwise $\sigma_{ij} = 0$

3.1.2 Model foundation. The layout model employs two decision variables: ω_{im} and σ_{ij}, the specific meanings of which are provided in Table 1. The model takes into account the impacts of system throughput and communication coverage. The objective function aims to maximize system throughput and communication coverage, as expressed in equation (1).

$$max\, Y_1 = \begin{cases} Y_{11}/(1-Y_{12}), Y_{12} \neq 1 \\ Y_{11}, Y_{12} = 1 \end{cases} \tag{1}$$

$$Y_{11} = \sum_{i\in U}\sum_{j\in L}\sum_{m\in L}\omega_{im}\sigma_{ij}C_{ij} \tag{2}$$

$$Y_{12} = \sum_{i\in U}\sum_{j\in L}\sigma_{ij}/l \tag{3}$$

$$C_{ij} = \gamma log_2\left(1 + SNR_{ij}\right) \tag{4}$$

$$SNR_{ij} = q_0^2\beta_{ij}/\alpha^2 \tag{5}$$

$$\beta_{ij} = (v_{max}/4\pi g)^2/d_{ij}^{\rho/2} \tag{6}$$

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + H_i^2} \tag{7}$$

Equation (1) represents the composite optimization objective of maximizing the communication system's throughput as well as maximizing the coverage rate of UAVs; Equation (2) denotes the communication system throughput, defined by the transmission rate between UAVs and disaster points; Equation (3) defines the UAV coverage rate; Equation (4), based on Shannon's formula, denotes the transmission rate between UAVs and disaster points; Equations (5) and (6) represent the signal-to-noise ratio (SNR) of the transmission between UAVs and disaster points.

The constraints of the layout model are as shown in equations (8)-(16).

$$\sum_{j\in L}\sum_{m\in L}\omega_{im}\sigma_{ij} \geq 1, \forall i \in U \tag{8}$$

$$\sum_{i\in U}\sigma_{ij} \leq 1, \forall j \in L \tag{9}$$

$$\sum_{i\in U}\omega_{ij} \leq 1, \forall m \in L \tag{10}$$

$$\sigma_{ij}d_{ij} \leq d_{max}, \forall i \in U, \forall j \in L \tag{11}$$

$$\omega_{ij}d_{ij} \leq d_{max}, \forall i \in U, \forall j \in L \tag{12}$$

$$\sigma_{ij}C_{ij} \leq c, \forall i \in U, \forall j \in L \tag{13}$$

$$\sum_{i\in U}\sum_{j\in L}\sigma_{ij}C_{ij}\le C_{max},\forall i\in U,\forall j\in L \tag{14}$$

$$\omega_{im}\in\{0,1\},\forall i\in U,\forall j\in L \tag{15}$$

$$\sigma_{ij}\in\{0,1\},\forall i\in U,\forall j\in L \tag{16}$$

Equation (8) indicates that any given UAV must serve at least one demand point; Equations (9) and (10) state that any disaster point may be served by no more than one UAV; Equations (11) and (12) outline the coverage constraints of the UAVCN; Equation (13) ensures that the throughput at any disaster point must exceed the minimum throughput required to maintain communication; Equation (14) asserts that the total throughput served by a UAV at demand points does not exceed the UAV's maximum communication capacity; Equations (15) and (16) specify the value ranges for the decision variables.

3.2 Path planning model

3.2.1 Notations. The notations and symbols of the model in this section are described in Table 2.

Table 2. Meaning of the notations.

Parameters	Meaning
U	Set of UAVs, $U\in\{1,2,\ldots,u\}$
u	Number of UAVs
L_e	Set of demand points, $L_e\in\{1,2,\ldots,l_e\}$
l_e	Number of demand points
(x_j,y_i)	Coordinates of demand points
d_{jm}	Distance between the demand points j and demand points m, km
T_{ij}	Time for UAV i to service a demand point j, min
Tl_{jm}	Time of the UAV from demand point j to demand point m, min
T_{tj}	Time for UAV to rescue a demand point j, min
v	Flying speed of UAV, $\mathrm{m/s}$
v_0	Hover speed of UAV, $\mathrm{m/s}$
P_0	Hover power of UAV, W
P_1	Flying power of UAV, W
P_p	UAV blade power, W
P_q	UAV induced power, W
V_{tip}	UAV tip speed, $\mathrm{m/s}$
E_{max}	Maximum power of UAV, mAh
ε_{ij}	When $\varepsilon_{ij}=1$, it means the UAV i provides communication to the demand point j, otherwise $\varepsilon_{ij}=0$
φ_{ijm}	When $\varphi_{ijm}=1$, it means the UAV i provides communication to demand point j and then to demand point m, otherwise $\varphi_{ijm}=0$

3.2.2 Model foundation. The path planning model employs two decision variables: ε_{ij} and φ_{ijm}, with specific meanings as provided in the table. The model accounts for the impact of rescue time and UAV energy consumption. The objective function is to minimize rescue time and UAV energy consumption, as shown in equation (17).

$$max\, Y_2 = Y_{21} \times Y_{22} \tag{17}$$

$$Y_{21} = max_{i\in U}\left(\sum_{j\in L_e}\sum_{m\in L_e}\left(\varepsilon_{ij}T_{tj} + \varphi_{ijm}Tl_{jm}\right)\right) \tag{18}$$

$$Y_{22} = \sum_{i\in U}\left(\sum_{j\in L_e}\sum_{m\in L_e}\varphi_{ijm}P_1Tl_{jm} + \sum_{j\in L_e}\varepsilon_{ij}P_0T_{tj}\right) \tag{19}$$

$$Tl_{jm} = d_{jm}/v \tag{20}$$

$$d_{jm} = \sqrt{\left(x_j - x_m\right)^2 + \left(y_j - y_m\right)^2} \tag{21}$$

$$P_1 = P_p\left(1 + 3v^2/V_{tip}^2\right) + P_q\sqrt{\sqrt{1 + v^4/4v_0^4} - v^2/2v_0^2} \tag{22}$$

Equation (17) represents a composite objective function that minimizes rescue time and total energy consumption; Equation (18) denotes the longest rescue time among all UAVs; Equation (19) signifies the total energy consumption of all UAVs; Equation (20) defines the flight time of a UAV between two demand points; Equation (21) specifies the flight distance between two demand points; Equation (22) represents the power of a UAV during flight.

The constraints of the layout model are as shown in equations (23) and (24).

$$\sum_{i\in U}\sum_{j\in L_e}\varepsilon_{ij} = l_e \tag{23}$$

$$\sum_{i\in U}\varepsilon_{ij} = 1, \forall j \in L_e \tag{24}$$

$$\sum_{j\in L_e}\varepsilon_{ij} \geq 1, \forall i \in U \tag{25}$$

$$\sum_{j\in L_e}\sum_{m\in L_e}\varepsilon_{ij}\varepsilon_{im}\varphi_{ijm} \geq 1 \tag{26}$$

$$\sum_{j\in L_e}\varphi_{ijm} = \sum_{j\in L_e}\varphi_{imj}, \forall i \in U, \forall j \in L_e \tag{27}$$

$$\sum_{j\in K}\sum_{m\in K}\varphi_{ijm} \leq |K| - 1, \forall K \in L_e, 2 \leq |K| \leq l_e - 1, \forall i \in U \tag{28}$$

$$\sum_{j\in L_e}\sum_{m\in L_e}\varphi_{ijm}P_1Tl_{jm} + \sum_{j\in L_e}\varepsilon_{ij}P_0T_{tj} \leq E_{max}, \forall i \in U \tag{29}$$

$$\varphi_{ijm} = \{0,1\}, \forall i \in U, \forall j \in L_e, \forall m \in L_e \tag{30}$$

Equation (23) ensures that UAVs provide emergency communication rescue for all points requiring service; Equation (24) states that a demand point can only be assisted by one UAV; Equation (25) mandates that a UAV must assist at least one demand point; Equation (26) details the scenario where a UAV provides assistance to point j before assisting point m; Equation (27) guarantees the continuity of the path; Equation (28) is designed to prevent sub-loop formation in the path; Equation (29) ensures that the energy consumption of a UAV does not exceed its maximum capacity; Equation (30) pertains to the value range of the decision variables.

4. ALGORITHM DESCRIPTION

The improved genetic algorithm possesses parallel search characteristics, enabling the maintenance of parallel optimization of the population. The specific operational steps of the improved genetic algorithm are as follows:

Step 1. Set control parameters: population size M, initial temperature T, cooling coefficient v, final temperature T'.

Step 2. Population initialization: initialize the population P through the Tent chaos algorithm.

Step 3. Calculate fitness: determine the fitness values of each individual in the population.

Step 4. Set iteration variable: iteration variable $q = 0$.

Step 5. Selection operation: select individuals to enter the new population according to the designed selection method.

Step 6. Crossover operation: perform crossover operations on two selected individuals with crossover probability P_c according to the adaptive crossover probability formula.

Step 7. Mutation operation: perform mutation operations on two selected individuals with mutation probability P_m according to the adaptive mutation probability formula.

Step 8. Simulated annealing operation: perform simulated annealing on the newly mutated individuals, calculate the new individual's fitness value.

Step 9. Iteration judgment: If $q < q_{max}$, go back to Step 5; otherwise, proceed to Step 10.

Step 10. Check if the algorithm satisfies the termination condition; if satisfied, the algorithm stops execution; otherwise, perform the cooling operation and go back to Step 4.

5. CASE STUDY

5.1 Data preparation

On August 8, 2017, Jiuzhaigou County in Sichuan Province was struck by a magnitude 7.0 earthquake, causing severe damage to infrastructure, with 17 townships experiencing power outages, multiple communication facilities destroyed, and hundreds of base stations incapacitated. This study takes the "8·8" Jiuzhaigou earthquake as the backdrop and selects 103 administrative villages in Jiuzhaigou County as the research subjects. The latitude and longitude of each disaster point are obtained through Baidu Maps and converted into planar XY coordinates (blue points in Figure 1, with a new reference point as the coordinate origin.

5.2 Results analysis

5.2.1 Layout analysis. Solving with the objective function of maximizing system throughput and coverage, the optimal objective value obtained using the combined method of the K-means algorithm and genetic algorithm is 3410, $Y_1 = 3410$, and the optimal objective value obtained using the combined method of the K-means algorithm and the improved genetic algorithm is $Y_1 = 4294$, as shown in Figures 1 and 2. At the same time, an iterative comparison was made between the Genetic Algorithm (GA) and the Improved Genetic Algorithm (IGA) to solve the layout model, as shown in Figure 3.

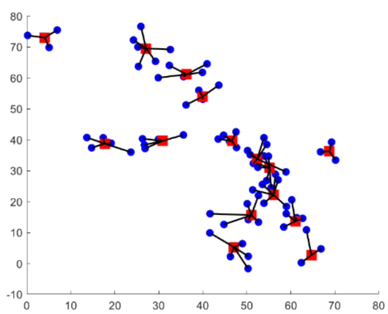


Figure 1. Layout result.

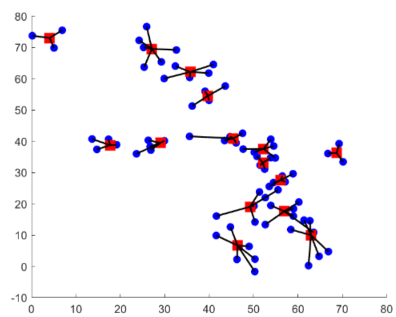


Figure 2. Layout results (improved algorithms).

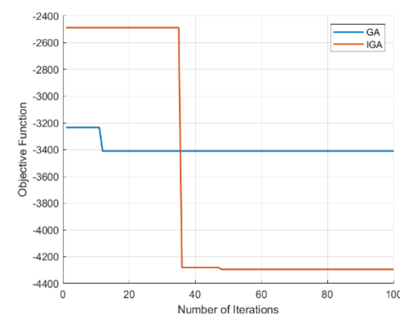


Figure 3. Iterative comparison.

5.2.2 Path planning analysis. In this subsection, we use four UAVs as an example to explore the optimal path and the effectiveness of the algorithm. The layout results obtained by combining the K-means algorithm and the improved genetic algorithm are used as demand points. The objective function is to minimize rescue time and energy consumption. The optimal objective value obtained using the genetic algorithm is 91697, $Y_2 = 91697$. The optimal objective value obtained using the improved genetic algorithm is 82797, $Y_2 = 82797$, as shown in Figures 4 and 5. Similarly, the iterative process of Genetic Algorithm (GA) and Improved Genetic Algorithm (IGA) in the solution path planning model is compared, as shown in Figure 6.

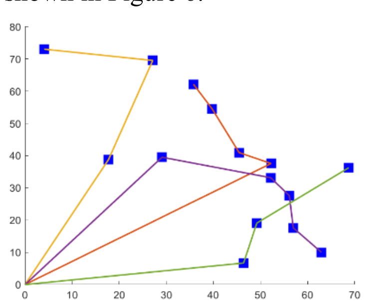
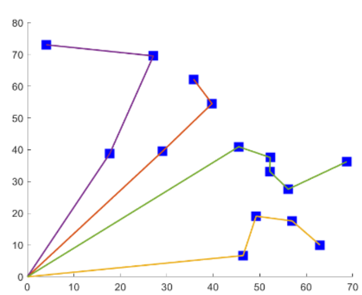


Figure 4. Path planning results.



Figures 5. Path planning results (improved algorithms).

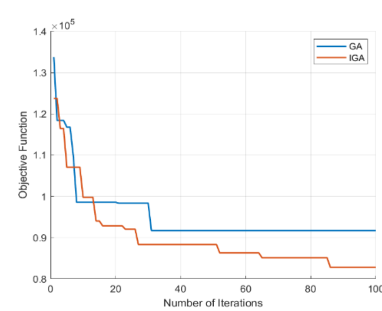


Figure 6. Iterative comparison.

5.2.3 Algorithm analysis. From the algorithm comparison in Figures 3 and 6, it is observed that in the initial stage, the Improved Genetic Algorithm (IGA) exhibits a faster rate of decline compared to the Genetic Algorithm (GA). In the steady state phase, with an increase in the number of iterations, IGA's objective function value is lower and tends to stabilize, indicating that IGA outperforms GA in local search and fine-tuning.

6. CONCLUSIONS

Especially in the critical period following a disaster, the damage to traditional communication infrastructure often severely hinders rescue efforts. In response to these challenges, this study proposes a two-stage stochastic planning method to optimize the layout and path planning of UAVCN for the rapid restoration of post-disaster communication networks. The first stage focuses on the layout of UAVCN, aiming to maximize system throughput and the coverage area of the disaster-affected region, ensuring that key areas can quickly obtain necessary communication services. In the second stage, after obtaining the optimal layout, the study investigates the flight path planning of UAVCN to reduce the total time and energy consumption of task execution, optimizing the operational efficiency of the UAV fleet.

To address the issues of traditional genetic algorithms being prone to local optima and inefficient in solving complex optimization problems, this study proposes an improved genetic algorithm. The new algorithm significantly enhances performance by introducing more refined population initialization strategies, adaptive crossover and mutation mechanisms, and multi-objective optimization capabilities. A series of simulation experiments demonstrate the superiority of the improved algorithm.

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