

Research Article

An Energy-Balanced Path Planning Algorithm for Multiple Ferrying UAVs Based on GA

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When performing a search and rescue mission, unmanned aerial vehicles (UAVs) should continuously search targets above the mission area. In order to transfer the search and rescue information quickly and efficiently, two types of UAVs, the ferrying UAVs and the searching UAVs, are used to complete the mission. Obviously, this application scenario requires an efficient path planning method for ferrying UAVs. The existing path planning methods for ferrying UAVs usually focus on shortening the path length and ignore the different initial energy of ferrying UAVs. However, the following problem does exist: if the ferrying UAV with less initial energy is assigned a longer path, meaning that the ferrying UAV with less initial energy will ferry messages for more searching UAVs. When the lower-initial-energy ferrying UAV is running out of energy, more searching UAVs will no longer deliver messages successfully. Therefore, the mismatch between the planned path length and the initial energy will eventually result in a lower global message delivery ratio. To solve this problem, we propose a new concept energy-factor for a ferrying UAV and use the variance of all ferrying UAVs' energy-factor to measure the balance between the planned path length and the initial energy. Further, we model the energy-balanced path-planning problem for multiple ferrying UAVs, which actually is a multiobject optimization problem of minimizing the planned path length and minimizing the variance of all ferrying UAVs' energy-factor. Based on the genetic algorithm, we design and implement an energy-balanced path planning algorithm (EMTSPA) for multiple ferrying UAVs to solve this multiobject optimization problem. Experimental results show that EMTSPA effectively increases the global message delivery ratio and decreases the global message delay.

1. Introduction

In recent years, multi-UAVs have been used in many domains such as industry, agriculture, military, and disaster relief. Since there are many restrictions on network communication based on the infrastructure, such as terrestrial relay stations and satellites, flying ad hoc networks (FANETs) are generally used to realize communication between multiple UAVs [1–3]. Delay-tolerant networking (DTN), which is famous of its “storage-carry-forward” feature, can solve network interruption problems well [4, 5].

In the UAV search and rescue mission, we need to search the mission area continuously. Inspired by DTN mechanism,

two types of UAVs, searching UAVs and ferrying UAVs, are used in the mission. Searching UAVs take picture or shot video while ferrying UAVs transfer messages to the ground station [6]. Based on the message routing algorithm, messages are first stored in searching UAVs, and then, messages are transferred to ferrying UAVs at appropriate time; finally, messages are delivered to the ground station.

Intelligent path planning methods and great routing protocols can effectively reduce packet loss and message delay [7]. Regarding the path planning problem of the ferrying node, there have been many studies in recent years. In [8], Message Ferrying (MF) mechanism is first proposed. The paper pointed out that the path planning problem of a

ferrying node is a traveling salesman problem (TSP). In addition, the author designed a path for one ferrying node, while ordinary nodes are stationary. In [9], MF mechanism was extended. According to the mobility of ferrying nodes and ordinary nodes, MF mechanism is divided into MF initiated by ordinary nodes and MF initiated by ferrying nodes. Literature [10] designed the route for multiple ferrying nodes in DTN, and it points that there are three ways to interact between ferrying nodes: no interaction, interaction through ferrying nodes, and interaction through ordinary nodes. In [11], moving ordinary nodes are clustered into many clusters according to geographic location, and then, one ferrying node was designed to pass through centers of these clusters along a TSP route. In [12], for the case of moving ordinary nodes, the algorithm firstly selected appropriate points on the paths of the moving ordinary nodes, and then calculated the appropriate encounter time by strengthening the learning algorithm, so that ferrying node could accept ordinary nodes' messages in time. In [13], ferrying UAVs fly in a ping-pong mode along waypoints between the mission area and the ground station. In [14], for mission with no-flying zone, paths of ferrying UAVs are designed with determined and online path planning methods. The determined method generates picture points and then generates a route according to picture points, while the online method generates route first, and then generates picture points according to the route. However, since the online path planning method is inefficient in most cases, it is better to adopt the determined path planning method which is performed before flight [14].

Some literatures have further simulated the motion trajectory of a mobile robot. The simulation of the flight trajectory in [15] not only stays in simple kinematic equations but also considers the system's dynamic constraints and corresponding dynamic constraints. This study considers the optimization of minimizing motion time and minimizing height and distance, and uses an enhanced particle swarm algorithm to solve the trajectory planning problem. In addition, the path planning algorithm integrates a trajectory tracking algorithm which utilizes the Lyapunov-based constrained back-stepping approach and command filters. Reference [16] introduced a novel method to solve the optimal control problem with free initial conditions and verified it in the scenario of minimizing the flight time of the low-thrust orbital transfers. This method uses two evolutionary optimization methods: genetic algorithm-particle swarm optimization and imperial competition algorithm and three orthogonal equations in Hilbert space. The above two references both propose corresponding algorithms for the optimal control problem which is to find a control law for a given dynamical system over a period of time. However, this problem in this study only considers the initial energy-factor of the UAV without considering other constraints and control equations of the UAV, which can be regarded as an optimization problem.

In summary, the path planning problem of multiferrying UAVs can be solved by two steps. The first step is to get the set of ferrying UAVs' waypoints. The second step is to solve the multiple traveling salesman problem (MTSP) according to these waypoints. But the following problem does exist: if the ferrying UAV with less initial energy is assigned a longer

path, meaning that the ferrying UAV with less initial energy will ferry messages for more searching UAVs. When the lower-initial-energy ferrying UAV is running out of energy, more searching UAVs will no longer deliver messages successfully. This unbalanced allocation will result in more searching UAVs' message being unable to be transmitted to the ground station when the ferrying UAV is energy-exhausted, eventually resulting in a lower global message delivery ratio. Based on the above facts, we first put forward the concept of energy-factor, the variance of which reflects the balance between the length of the planning path and the initial energy. Then, we model the energy-balanced path planning problem which actually is a multiobjective optimization problem of minimizing the planned path length and minimizing the variance of energy-factor. Finally, an energy-balanced path planning algorithm based on the classic genetic algorithm (GA) is proposed to solve this multiobjective optimization problem.

The rest of the paper is organized as follows. In Section 2, we introduce a typical search and rescue scenario and model the network from aspects of mobility models, message routing algorithms, and energy consumption. In Section 3, we model the energy-balanced path planning problem for multiferrying UAVs. In Section 4, we introduce the energy-balanced path planning algorithm for multiferrying UAVs (EMTSPA) based on GA. In Section 5, we present a comparison of EMTSPA with other path planning algorithms. We conclude in Section 6.

2. Application Scene and Network Model

In this section, we will first introduce a typical search and rescue scene. Next, we will model the flying ad hoc network from aspects such as mobility model, message routing model, and energy consumption.

2.1. The Scenario of Application. This article takes four-rotor drones as an example for discussion. The search and rescue scene is shown in Figure 1. The searching UAVs hover in a fixed area and take pictures. The ferrying UAVs fly in a circular way according to the planned path. In addition, each ferrying UAV ferry messages for at least one searching UAV and messages of one searching UAV should be ferried by only one ferrying UAV. Based on DTN mechanism, messages are first stored in searching UAVs, then transferred to ferrying UAVs at appropriate time, and finally delivered to the ground station.

2.2. Mobility Model. References [17, 18] discuss the mobility model of UAV in three-dimensional space, while references [19–21] discuss it in a two-dimensional plane. In order to facilitate discussion, this paper discusses the mobility model of UAV in two-dimensional plane and ignores the collision between drones.

The motion of UAV can be represented by two kinds of mobility models. One is the famous Gauss-Markov mobility model, which reflects the correlation between the current state and future state of UAV. The other one reflects the character that UAV flies along the planned path in the search

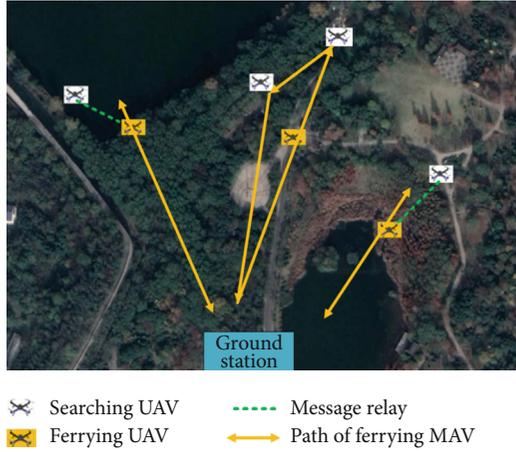


FIGURE 1: The scenario of application.

and rescue mission. We call it MapRoute mobility model in this article.

(i) Gauss-Markov mobility model

The mobility model of UAV is linear and deterministic [13], and the future position of UAV can be estimated by current position, direction, and speed. Therefore, the mobility model of UAV can be represented by the Gauss-Markov mobility model [22]. The Gauss-Markov equation is shown as follows:

$$\begin{cases} s_n = \alpha s_{n-1} + (1 - \alpha)\bar{s} + \sqrt{(1 - \alpha^2)}s_{x_{n-1}} \\ d_n = \alpha d_{n-1} + (1 - \alpha)\bar{d} + \sqrt{(1 - \alpha^2)}d_{x_{n-1}} \end{cases}, \quad (1)$$

where s_n and d_n are the new speed and direction of UAV at interval n ; α , where $\alpha \in [0, 1]$, is the tuning parameter used to vary the randomness; \bar{s}_n and \bar{d}_n are constants representing the mean value of speed and direction as $n \rightarrow \infty$ and $s_{x_{n-1}}$ and $d_{x_{n-1}}$ are random variables from a Gaussian distribution.

(ii) MapRoute mobility model

When carrying out search and rescue missions, UAVs usually fly in a straight line between the adjacent waypoints of the planned path. This mobility model is called MapRoute mobility model. In this model, the UAV has a target waypoint at any time during the flight. After reaching one target point, UAV stops time t ($t \geq 0$) and then continues to move to the next target point.

Suppose the interval time is ΔT , (x_n, y_n) and (x_{n-1}, y_{n-1}) are positions at $n * \Delta T$ and $(n - 1) * \Delta T$. s_{n-1} and d_{n-1} are speed and direction at $(n - 1) * \Delta T$. \vec{x} indicates the horizontal axis, and $\vec{N}_{pre}N_{next}$ is the vector from the previous waypoint N_{pre} to the next waypoint N_{next} . $\text{arc}(\vec{x}, \vec{N}_{pre}N_{next})$ represents the angle between the horizontal axis \vec{x} and the vector $\vec{N}_{pre}N_{next}$. So, in the MapRoute mobility model, the

position equation of UAV can be expressed as:

$$\begin{cases} x_n = x_{n-1} + s_{n-1} \cos d_{n-1} \\ y_n = y_{n-1} + s_{n-1} \sin d_{n-1} \\ d_{n-1} = \text{arc}(\vec{x}, \vec{N}_{pre}N_{next}) \end{cases}. \quad (2)$$

2.3. Message Routing Algorithm. In FANET, the communication connection is intermittent due to the fast flight speed of the drone. Therefore, traditional mobile ad hoc network routing algorithms such as AODV, DSR are not suitable for UAV communication [1]. The delay tolerant network (DTN) mechanism is a good solution to communication interruption problems.

Literature [23–25] proposed messages routing algorithms based on location information. The main idea of this type of algorithm is as follows: if there is a node in the communication range closer to the destination than the current stored node, messages will be transferred to the closer node. Otherwise, messages will be stored at the current node. However, this type of algorithm has obvious drawbacks. Since nodes may meet for multiple times, the node may receive messages that were just transferred from itself to other nodes. The phenomenon that messages are transferred back and forth is called ping-pong effect, which consumes unnecessary energy [13].

In [13], the GPS information is transmitted through a low-throughput network (IEEE 802.15.4); then, DTN_{geo} , DTN_{close} , and DTN_{load} based on geographic location prediction are proposed. Based on the Gauss-Markov mobility model, messages are transferred to the nodes closer to the ground station in the future time. By this way, it decreases the ping-pong effect to some extent. However, if the distance between the search area and the ground station exceeds the coverage range of the low-throughput network, there will be two problems. First, the message routing algorithms cannot completely eliminate the ping-pong effect. Second, since GPS data cannot be broadcast between all nodes through the low-throughput network, the routing algorithm is not feasible in the long-distance search and rescue mission.

Based on the literature [8], we design a service-based message routing algorithm. The main idea of the routing algorithm is as follows. Messages of searching UAV can only be transmitted to the nearest ferrying UAV or saved in the searching UAV. Messages can be transmitted to the ground station when the ferrying UAVs return back to the ground station. This routing algorithm ensures that messages can be reliably delivered to the ground station even without a low-throughput network. In addition, this routing algorithm completely eliminates the Ping-Pong effect.

The hop count is the number of hops a message passes until it reaches the destination. This metric allows to reflect the efficiency of the forwarding algorithm. The ping-pong effect increases the average number of message hops. Obviously, the service-based routing algorithm designed in this paper makes the hop count of messages to be 2.

2.4. Energy Consumption Model. Energy is mainly consumed in communication and movement during the flight. Literature [17, 26] pointed out that energy used for communication

is much smaller than energy used for movement, so we ignore the communication-related energy here.

According to the drone's MapRoute motion model, we know that energy consumption of UAVs can be divided into two parts: energy consumed in the linear motion and energy consumed in adjusting direction. Let E_v represent the energy consumed in the linear motion phase, while E_w represent the energy consumed in adjusting direction. Then, the total consumed energy E can be expressed as follows.

$$E = E_v + E_w. \quad (3)$$

Reference [27] proposed a quadrotor drone's energy consumption equation in a linear flight at a constant speed. Let v denotes the speed, d denotes the flight distance, and $P(v)$ denotes the speed-related energy consumption ratio. If v is constant, $P(v)$ will be unchanged, and energy consumption equation can be expressed as follows.

$$E_v = \int_0^{d/v} P(v) dt = P(v) * \frac{d}{v}. \quad (4)$$

Generally, in the long-distance mission of UAV, the energy consumed in the linear motion is much larger than the energy consumed in adjusting direction, so we ignore E_w here. According to formulas (4) and (5), if there is a fixed value θ ($\theta > 0$), the energy consumption of a drone at a constant speed can be expressed as:

$$E = \frac{P(v)}{v} * d = \theta * d. \quad (5)$$

Based on the above analysis, we simply consider that the energy consumption of UAVs in a constant-speed flight is directly proportional to the flight distance.

3. Modeling Energy-Balanced Path Planning Problem for Multiferrying UAVs

Message delivery efficiency and reliability are critical to an UAV search and rescue mission. Therefore, the goal of path planning is not only to shorten the length of path but also to increase the efficiency and reliability of message transmission.

In the following, we first give the evaluation metrics of message delivery, and then model the energy-balanced path planning problem for multiferrying UAVs. According to analysis, the problem is actually a multiobjective optimization problem of minimizing length and minimizing the variance of energy-factor. Finally, it is proved that solving this multiobjective optimization problem can increase the message delivery ratio and decrease the message delay under certain conditions.

3.1. Metrics. The message delivery effect is generally evaluated by message delivery ratio, message delay, etc. [13]. However, for a complete search and rescue mission, we insist that it is better to consider the global delivery effect of messages in the network. So, before giving the definition of energy-balanced path planning problem, we introduce some important global metrics and its definition firstly.

Definition 1 (global message delivery ratio (GMDR)). The delivery ratio is defined as the fraction of messages that have been successfully delivered to the destination out of the messages that have been generated. It is an indicator for a node. Global message delivery ratio (GMDR) is the average message delivery ratio of all nodes. Global message delivery ratio measures the reliability of message transmission in the global network.

Let k denotes the number of searching UAVs, n_i denotes the number of messages generated by searching UAV i and finally delivered to the destination successfully, and N_i denotes the number of messages generated by searching UAV i . So, GMDR can be expressed as:

$$\bar{D} = \frac{1}{k} * \sum_{i=1}^k \frac{n_i}{N_i}. \quad (6)$$

Definition 2 (global message delay (GMD)). Message delay is the sum of the communication delay occurred on each hop a message traverses to reach the destination. Global message delay is the average message delay for all messages arriving at the ground station successfully. Global message delay measures the efficiency of message transmission in a global network.

Let m denotes the number of messages arriving at ground station successfully, C_i denotes the delivery time of message i , $C_{(i)carry}$ denotes the time when message i is stored in the searching UAV, and $C_{(i)relay}$ denotes the time when message i is relayed by the ferrying UAV. So, GMD can be expressed as:

$$\bar{C} = \frac{1}{m} * \sum_{i=1}^m C_i = \frac{1}{m} * \sum_{i=1}^m (C_{(i)carry} + C_{(i)relay}). \quad (7)$$

3.2. Definition of Energy-Balanced Path Planning Problem for Multiferrying UAVs. Before giving the definition of energy-balanced path planning problem for multiferrying UAVs, we will give three base definitions firstly: PPL of multiferrying UAVs, EF of ferrying UAV, and variance of energy-factors. Finally, we abstract objective functions and restrictions from the problem.

Definition 3 (planned path length (PPL) of multiferrying UAVs). Planned path length of multiferrying UAVs is the sum of all ferrying UAV's PPL.

MTSP based on assignment is usually represented with a two-indexes integer linear programming formula [28, 29]. Unlike this, we define PPL of multiferrying UAV with three-indexes.

Suppose there is a graph $G = (N, A)$, where N is the set of n waypoints of multiferrying UAVs (vertices in the standard MTSP), A is the set of all arcs (edges). There is a set F of f ferrying UAVs (traveling salesmen in the standard MTSP). c_{st} represents the distance between point s and point t . $C = (c_{st})$ is a matrix of cost (distance) about set A .

Firstly, we define a binary variable as shown in formula (8). If ferrying UAV j is planned to fly from point s to point t , the value of x_{stj} is 1. Otherwise, the value of x_{stj} is 0.

$$x_{stj} = \begin{cases} 1 & \text{if arc } (s, t) \text{ is used in ferrying UAV } j \text{'s tour } (s \in N, t \in N, j \in F) \\ 0 & \text{otherwise.} \end{cases} \quad (8)$$

Then, the PPL of ferrying UAV j is

$$L_j = \sum_{s=1}^n \sum_{t=1}^n x_{stj} * c_{st}, j = 1, 2, \dots, f. \quad (9)$$

Therefore, PPL of multiferrying UAVs is

$$L = \sum_{j=1}^f \sum_{s=1}^n \sum_{t=1}^n (x_{stj} * c_{st}). \quad (10)$$

Definition 4 (energy-factor (EF) of ferrying UAV). Energy-factor of ferrying UAV is the ratio of a ferrying UAV's PPL to its initial energy.

Assuming that L_j represents the PPL of the ferrying UAV j , E_j represents the initial energy of the ferrying UAV j , and then, the EF e_j of the ferrying UAV j can be expressed as:

$$e_j = L_j/E_j. \quad (11)$$

Definition 5 (variance of energy-factors (VEF)). Variance of energy-factors is the variance of all ferrying UAVs' EF. It reflects the balance between the PPL and the initial energy of ferrying UAVs in the global network.

Let f donates the number of all ferries, \bar{e} donates the average value of all EFs, and $Var(e)$ donates the VEF. Then, \bar{e} and $Var(e)$ can be expressed as:

$$\bar{e} = \frac{1}{f} * \sum_{j=1}^f e_j, \quad (12)$$

$$Var(e) = \frac{1}{f} * \sum_{j=1}^f (e_j - \bar{e})^2. \quad (13)$$

Definition 6 (energy-balanced path planning problem for multiferrying UAVs). It is assumed that there is a set N of n waypoints (including the ground station). All ferrying UAVs depart from the ground station and return to the ground station. Each ferrying UAV transfers messages for at least one searching UAVs. Messages of each searching UAV are transferred by only one ferrying UAV. The initial energy of ferrying UAVs is different. L is the PPL of multiferrying UAVs, and $Var(e)$ is the VEF. The problem is to find an optimal path l for multiferrying UAVs, which can cover all points in N and minimize L and $Var(e)$.

Obviously, the problem is a multiobjective optimization problem, and the optimization model can be expressed as follows.

Objective function:

$$\text{Minimize } L \quad (14)$$

$$\text{Minimize } Var(e) \quad (15)$$

Restrictions:

$$\sum_{j=1}^f \sum_{s=2}^n x_{1sj} = f, \quad (16)$$

$$\sum_{j=1}^f \sum_{s=2}^n x_{s1j} = f, \quad (17)$$

$$\sum_{j=1}^f \sum_{s=1}^n x_{stj} = 1, t = 2, \dots, f, \quad (18)$$

$$\sum_{j=1}^f \sum_{t=1}^n x_{stj} = 1, s = 2, \dots, f, \quad (19)$$

$$2 \leq \sum_{s=1}^n \sum_{t=1}^n x_{stj} \leq n, j = 2, \dots, f, \quad (20)$$

$$x_{stj} \in \{0, 1\}, \forall (s, t) \in A, \forall j \in F. \quad (21)$$

Formulas (16) and (17) indicate that all ferrying UAVs depart from the ground station (point 1 indicates the ground station) and return to the ground station. Formulas (18) and (19) indicate that there is only one ferrying UAV passing through one waypoint. Formula (20) indicates that the ferrying UAV j should pass through at least two points and not more than n points.

3.3. Basic Properties of the Model. Based on the above definition and abstraction of energy-balanced path planning problem, we can find the flowing properties and theorems of the model which provide a basis for designing algorithms and experiments. It should be emphasized that the following properties and theorems are based on the premise that each drone is flying at a constant speed and all drones' speed is the same. For the convenience of follow discussion, we first give unified descriptions of the symbols and definitions in Table 1.

$$\begin{aligned} \bar{D} &= \frac{1}{T} * \int_0^T \frac{1}{k} \sum_{i=1}^k \frac{n_i(t)}{N_i(t)} dt = \frac{1}{kNT} \int_0^T \sum_{i=1}^k n_i(t) dt \\ &= \frac{1}{kNT} \sum_{i=1}^k \int_0^T n_i(t) dt. \end{aligned} \quad (22)$$

Property 7. If $N_i(t) = N$, then, $\bar{D}_{\max} = G/kNT\beta * \sum_{j=1}^f (h_j * E_j)$.

Proof. According to equation (6), we can further express GMDR with mission time T . Assuming that the number of messages generated by the ferrying UAV i during d_t is a

TABLE 1: Symbols and definitions.

Symbol	Definition
i	Searching UAV i
j	Ferrying UAV j
k	Number of searching UAVs
f	Number of ferrying UAVs
T	Mission time
d_t	Interval time
\bar{D}_{\max}	Maximum global message delivery ratio
$n_i(t)$	Number of messages delivered from searching UAV i to destination successfully during d_t
$N_i(t)$	Number of messages generated by searching UAV i during d_t
N	Constant value of $N_i(t)$
ter_i	Time when the ferrying UAV ferrying messages for searching UAV i is energy-exhausted
$n_i(\bar{t})$	The average number of messages generated by searching UAV i and delivered to destination successfully before ter_i
R	Number of loops that ferrying UAV j flies along the planned path before ter_i
G'	Number of messages generated by the searching UAV during a lap of the ferrying UAV
G	Message generation rate of the searching UAV
E_j	The initial energy of the ferrying UAV j
L_j	The PPL of ferrying UAV j
β	Energy consumption (watt/second)
v	Constant speed of the ferrying UAV
h_j	The number of searching UAVs assigned to the ferrying UAV j
h	Constant value of h_j
\bar{C}_i	Average message delay of ferrying UAV i
ΔC	Deviation time caused by the mobility of searching UAVs
\bar{L}	Average PPL of multiferrying UAVs
r	Radius of area where searching UAVs fly

constant value N (if $N_i(t) = N$), GMDR can be expressed as follows.

Otherwise, if a ferrying UAV's energy is exhausted, messages of related searching UAVs will no longer be transmitted to the ground station. Therefore, the summation term in equation (22) satisfies:

$$\int_0^T n_i(t) dt \leq \int_0^{ter_i} n_i(t) dt. \quad (23)$$

Then, the maximum GMDR \bar{D}_{\max} can be expressed as:

$$\bar{D}_{\max} = \frac{1}{kNT} \sum_{i=1}^k \int_0^{ter_i} n_i(t) dt. \quad (24)$$

Before time ter_i , the number of messages generated by the ferrying UAV i and delivered successfully to the ground station equals $n_i(\bar{t})$ multiply by ter_i , and it also equals the number of messages generated by the searching UAV during a lap of the ferrying UAV (G') multiply by the number of flight laps (R). Therefore, the integral term in equation (24) can be converted as follows:

$$\begin{aligned} \int_0^{ter_i} n_i(t) dt &= n_i(\bar{t}) * ter_i = R * G' \\ &= \frac{E_j}{\beta} * \frac{1}{L_j/v} * (L_j/v) * G = \frac{E_j}{\beta} * G. \end{aligned} \quad (25)$$

In addition, messages of several searching UAVs may be ferried by one ferrying UAV. Let the number of searching UAVs assigned to the ferrying UAV j be h_j . Then, the maximum GMDR \bar{D}_{\max} can be further derived from equations (24) and (25).

$$\bar{D}_{\max} = \frac{G}{kNT\beta} * \sum_{j=1}^f (h_j * E_j). \quad (26)$$

In summary, Property 7 is proved.

$$\bar{C}_i = \frac{L_j}{v}. \quad (27)$$

Property 8. If $L_j \gg r$, ($j = 1, 2, \dots, f$), then, $\bar{C} = 1/kv \sum_{j=1}^f (h_j * L_j)$.

Proof. If searching UAVs are stationary, the message delay of message equals the sum of the time that message waits for ferrying UAV and the time that messages are transferred by ferrying UAV [8]. Therefore, the average message delay of the searching UAV i (\bar{C}_i) is the time that the ferrying UAV flies for one lap.

If searching UAVs fly in the fixed area, we should consider the delay error caused by the movement of searching UAVs. Therefore, the average message delay of the searching UAV i can be expressed as equations (28).

$$\bar{C}_i = \frac{L_j}{v} + \Delta C \quad (28)$$

If the PPL of the ferrying UAV j (L_j) is much larger than the radius (r) of the active area of searching UAVs, ΔC will be ignored. Moreover, since one ferrying UAV can ferry messages for multiple searching UAVs, GMD can be expressed as equations (29).

$$\bar{C} = \frac{1}{k} \sum_{i=1}^k \bar{C}_i = \frac{1}{k} \sum_{j=1}^f h_j * \frac{L_j}{v} = \frac{1}{kv} \sum_{j=1}^f (h_j * L_j). \quad (29)$$

Therefore, Property 8 is proved.

Theorem 9. Suppose there are a PPL set L , an initial energy set E , and a positive number set X, Y . There is a one-to-one mapping relationship between L and X , and E and Y . Besides, $L = \{L_1, L_2, \dots, L_j\}$, $E = \{E_1, E_2, \dots, E_j\}$, $X = \{x_1, x_2, \dots, x_j\}$, $Y = \{y_1, y_2, \dots, y_j\}$, $0 < x_1 < x_2 < \dots < x_j$, $0 < y_1 < y_2 < \dots < y_j$. If ω ($\omega > 0$) satisfies $L_j = \omega h_j$, then, \bar{D}_{\max} takes the maximum when $Var(e)$ is the minimum.

Proof. In general, the more searching UAVs that the ferrying UAV travels, the longer PPL will be. In particular, we assume that the PPL of ferrying UAVs is proportional to the number of searching UAVs which ferrying UAV j travels. In other world, we assume there is ω ($\omega > 0$) that satisfies $L_j = \omega h_j$.

It is assumed that PPL of ferrying UAVs constitute vector $\vec{L} = (L_1, L_2, \dots, L_j)$ and initial energy constitute vector $\vec{E} = (E_1, E_2, \dots, E_j)$. Based on Property 7, we can deduce formula (30).

$$\bar{D}_{\max} = \frac{G}{kNT\beta\omega} * \sum_{j=1}^f (L_j * E_j) = \frac{G}{kNT\beta\omega} * (\vec{L} \bullet \vec{E}) \quad (30)$$

Since, the smaller $Var(e)$ is, the greater the balance between the PPL and the initial energy of ferrying UAV is. From formula (13), we know that longer L_j as well as higher E_j or shorter L_j as well as lower E_j can result in better balance. Obviously, when $\vec{L} = (x_1, x_2, \dots, x_j)$ and $\vec{E} = (y_1, y_2, \dots, y_j)$, $(\vec{L} \bullet \vec{E})$ is larger than other combinations' dot product. In other world, \bar{D}_{\max} takes the maximum when $Var(e)$ is the minimum. So, Theorem 9 is proved.

$$\bar{C} = \frac{h}{kv} \sum_{j=1}^f L_j = \frac{hf}{kv} * \bar{L} = \delta * \bar{L}. \quad (31)$$

Theorem 10. If $h_j = h$, then, there is δ ($\delta > 0$) that satisfies $\bar{C} = \delta * \bar{L}$.

Proof. When the number of searching UAVs (h_j) whose messages are transferred by the ferrying UAV j equals constant h (if $h_j = h$), we can reduce following equation (21) from Property (2). So Theorem 10 is proved.

4. Energy-Balanced Path Planning Algorithm for Multiferrying UAVs

Before path planning, we need to get all the waypoints of UAVs. The waypoints can be obtained mainly by clustering, division, and other algorithms [11, 14]. The path planning algorithm of this paper is based on the existing waypoints.

Because solving the shortest path is a part of energy-balanced path planning problem for multiferrying UAVs, and the standard MTSP problem is an NP-Complete problem. So, energy-balanced path planning problem for multiferrying

UAVs proposed in this paper is also an NP-complete problem. Therefore, we can solve it with the heuristic algorithms [30–32].

Energy-balanced path planning algorithm for multiferrying UAVs (EMTSPA) proposed in this paper is based on the genetic algorithm (GA). Standard genetic algorithms usually consist of these steps: chromosome coding, initialization, selection, evolution, and finally getting the best individual. EMTSPA has made a new design from the fitness function and so on. The flow chart of the algorithm shows in Figure 2.

4.1. Chromosome Coding and Initialization. In the search and rescue mission, each ferrying UAV departs from the ground station. Therefore, the first point of path should be the ground station in the chromosome coding. To better explain the algorithm, we assume that there are 4 ferrying UAVs (ferry 1-4), 9 waypoints (node 1-9), and 1 ground station (node 0).

The chromosome coding operation is divided into the following steps. (1) Build a base array of waypoints 1-9; (2) “shuffle” the base array; (3) generate array “lengths” which contains the number of waypoints that each ferrying UAV travels (except the ground station); (4) take points from the shuffled base array according to array “lengths.” The chromosome coding process is shown in Figure 3.

The above operation generates an individual in the first generation. Initial operation repeats the chromosome coding population-size times. After initial operation, the first-generation population is generated.

4.2. Fitness Function. There are two general methods to solve the multiobjective optimization problem: weight-based method and Pareto-based method [33–35]. From Theorems 9 and 10, we know that reducing the PPL and the VEF can improve the performance of GMDR and GMD under certain conditions. We solve the multiobjective optimization problem with weight-based methods which combine multiple indicators with weight value. The fitness value is used to measure the individual. So, the fitness function can be expressed as formula (32) where w_1 and w_2 are weights, L is the PPL of multiferrying UAVs, and $Var(e)$ is the VEF.

$$fitness = w_1 * \frac{1}{L} + w_2 * \frac{1}{Var(e)}. \quad (32)$$

We found from formula (32) that the smaller L and $Var(e)$ are, the larger fitness is. Conversely, when L or $Var(e)$ is larger, fitness is smaller. In the verification below, w_1 and w_2 are set to 10000.

4.3. Genetic Operation

(i) Selection

The purpose of the selection operation is to select the appropriate individuals as parents of the individual in the next generation. EMTSPA uses a two-step selection elite strategy. (1) Copy the individual with the highest fitness from previous generation directly to next generation. (2) Randomly select two subsets from the previous generation with the same size,

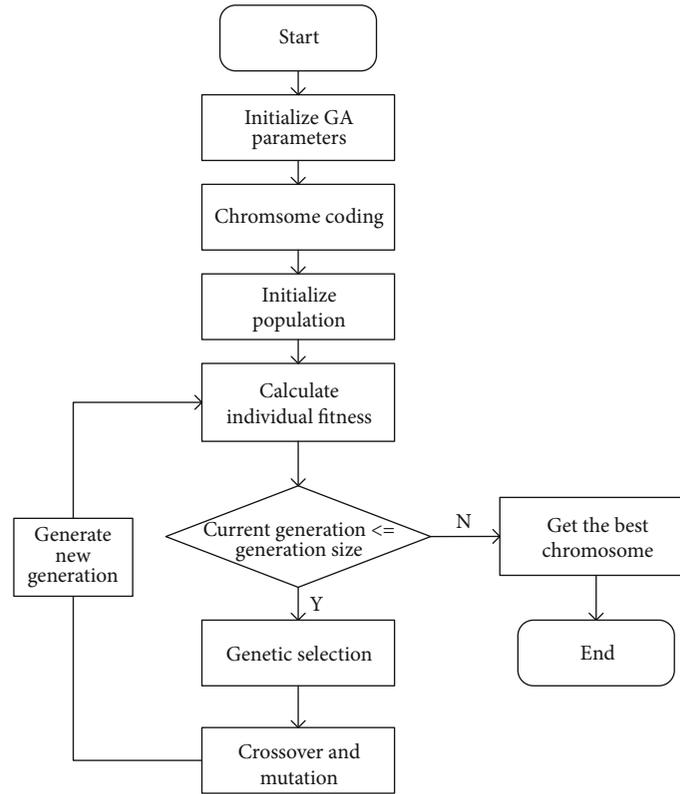


FIGURE 2: EMTSPA flow chart.

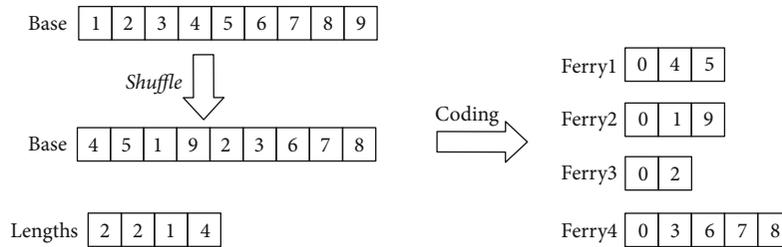


FIGURE 3: Chromosome coding process.

and then pick out two best individual from two subsets as parents of an individual in the next generation.

(ii) Crossover

After selecting the parents, crossover operation is performed to generate a new individual in next generation. We use Figure 4 to illustrate the main process of crossover operation. (1) Pick a continuous segment [1, 4, 5] from array “Father.base”. (2) Insert the continuous fragment into appropriate place (“start” to “end”) of array “Child.base”. (3) Insert other points except [1, 4, 5] of array “Mother.base” into array “Child.base” orderly; (4) finally, perform chromosome coding based on array “Child.base” with method described in Section 4.1.

(iii) Mutation

To avoid early convergence in the genetic algorithms, individuals need to be mutated. When the generated random

value is less than the setting parameter, the individual needs to be mutated. The mutation operation contains the following steps. (1) Select some ferrying UAVs (ferry 2 and ferry 4) from all ferrying UAVs. (2) Select a random-length segment from base arrays of selected ferrying UAVs and reverse the sequence of segment. As shown in Figure 5, segment [1, 9] is mutated to [9, 1], and segment [3, 6, 7] is mutated to [7, 6, 3]. The mutation operation is shown in Figure 5.

5. Experiments and Analysis

5.1. Setting of Parameters. We experiment in the ONE simulator. The ONE simulator is a popular opportunistic network environment simulator. It can simulate message transmission in different mobility models and different message routing protocol and can provide real-time visual simulation and result output [36, 37].

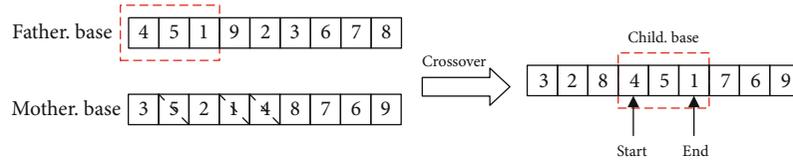


FIGURE 4: Crossover process.

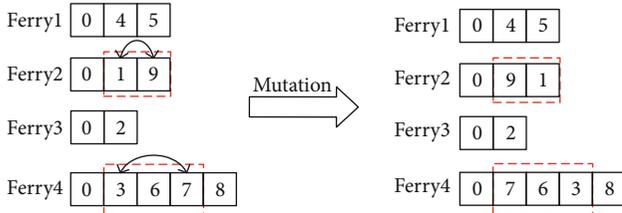


FIGURE 5: Mutation process.

In search and rescue missions, there are two types of flight modes for ferrying UAVs. (1) Along the path of TSP, multiple ferrying UAVs fly one after another. The following algorithm TSPA belongs to this type. (2) Along the path of MTSP, each ferrying UAV flies cyclically. The following algorithms MTSPA, B_MTSP, and EMTSPA belong to this type.

We mainly compare the performance of the following four algorithms in terms of the PPL of multiferrying UAVs and communication metrics. The four algorithms are as follows:

- (i) The general algorithm for standard MTSP (MTSPA). It does not consider other factors and selects a random number of waypoints for a ferrying UAV [6]
- (ii) The algorithm for MTSP considering pure balance (BMTSPA). It considers that all ferrying UAVs are the same and aims to make the length of all path completely the same [38]
- (iii) The algorithm for standard TSP (TSPA). It allows multiple ferrying UAVs to fly at equal intervals one after the other [39]
- (iv) The algorithm proposed in this paper for MTSP considering the balance between the initial energy and the PPL of multiferrying UAVs (EMTSPA)

From the perspective of algorithm design, EMTSPA has the following advantages over other algorithms. EMTSPA avoids too long PPL in TSPA; it supports the case where the initial energy of ferrying UAVs is different, while BMTSPA does not support; it avoids complete randomness in MTSPA. Below, we discuss further with the experimental results.

The experimental scene is shown in Figure 6. Suppose there are 4 ferrying UAVs (f10-f13), 9 searching UAVs (u1-u9), and 1 ground station (g0). Searching UAVs keep flying cyclically along the Z-shaped path shown in Figure 6, and centers of the active area are c1-c9. Ferrying UAVs depart from the ground station (g0), pass through waypoints

(c1-c9) along the planned path, and keep flying round by round. Suppose the communication range of the ferrying UAV is not smaller than the range of active area where the searching UAVs flies. In other words, when a ferrying UAV passes through the center of the active area, messages of the searching UAV can be sent to the ferrying UAV. Besides, the ground station remains stationary.

We take searching UAVs flying within a certain range as an example to explain the path planning algorithm. In this article, it is assumed that when ferry UAVs fly through the center of the searching UAVs flight area, ferrying UAVs could receive messages stored in the searching UAVs. Therefore, the set of all points that the multiferrying UAVs need to pass is the all center points of each searching UAV's flight area. However, the searching UAVs maybe not move in a small range in practical applications. When the searching UAV has a large flight area, we can first divide the area into a number of small subareas using a square with a communication radius of the drone. In this case, the points where the multiferrying UAVs pass are the centers of these subareas. Because this is another category of problems, and in order to concisely grasp the key of the energy equalization algorithm proposed in this paper, we assume the searching UAVs fly in a "Z" flight in a square area to explain the algorithm.

Other test parameters are shown in Table 2.

5.2. Results and Analysis

5.2.1. Convergence Behaviour of EMTSPA. Because the above four algorithms with different fitness functions are all based on genetic algorithms, EMTSPA proposed in this study is used as an example to verify the convergence of the genetic algorithm. When the population size is set to 20, one convergence behaviour of fitness function is shown in Figure 7.

5.2.2. Average Planned Path Length. Due to the randomness of the genetic algorithm, in order to compare the performance of the above four algorithms, this paper conducts 50 rounds of tests on the four algorithms to test the average path planning length and energy-factor variance of each algorithm and compares the corresponding average and minimum value.

According to Theorem 10, generally speaking, the smaller the average length, the smaller the global average message delay. Therefore, the average PPL is an important comparison index in path planning. The average PPL of each algorithm in 50 experiments is shown in Figure 8. Moreover, Figure 9 shows the average and minimum values of the average PPL obtained by each algorithm.

It can be seen from Figure 8 that the genetic algorithm has randomness, but the average PPL obtained by the algorithm is stable in a certain range. This is because these four

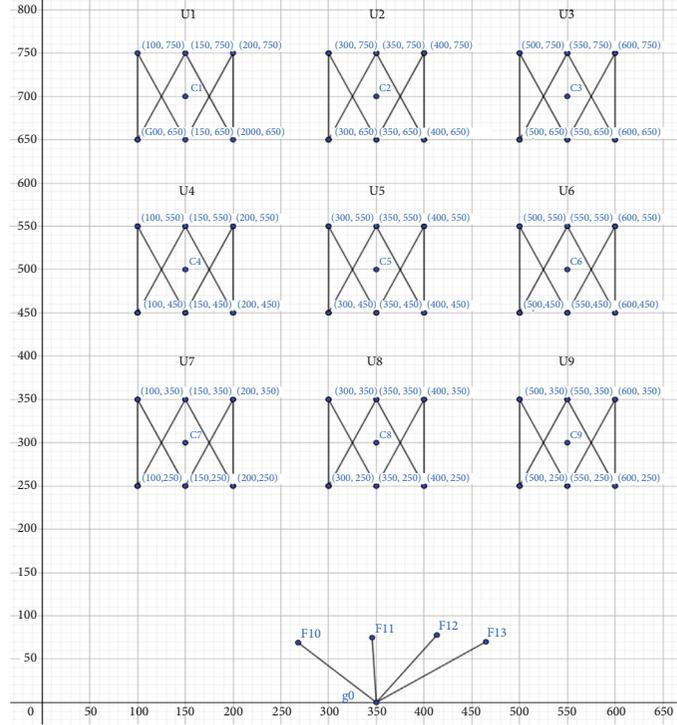


FIGURE 6: Search and rescue scene.

TABLE 2: Experimental parameters.

Scene	
Scene range	800 m \times 800 m
Number of UAVs	13 (ground)
Number of ferrying UAVs	4
Number of ground station	1
Motion	
Speed of UAVs	4.5 meters/second
Communication	
Range of UAVs' communication	200 meters
Message generation rate	5/second
Message size	1400 byte
Message routing algorithm	Service-based routing algorithm
Number of message copies	1
Energy	
Initial energy of f10,f11,f12,f13	50, 10, 20, 80 watts
Energy consumption ratio	0.006 watts/meter
Genetic algorithm	
Number of generation	1000
Mutation ratio	2%
Population size	200
Testing frequency	100

algorithms all aim at least to shorten the distance. Therefore, it is reasonable to compare the performance of each algorithm with the average and minimum values. As shown in Figure 9, the average PPL of EMTSPA, MTSPA, and BMTSPA

are similar while the average PPL of TSPA is the largest. Specifically, in terms of the average value of average PPL, EMTSPA is 33.3% better than TSPA. In terms of the minimum value, EMTSPA is 36.7% better than TSPA.

5.2.3. Variance of Energy-Factors. The variance of energy-factors reflects the balance between the PPL and the initial energy of ferrying UAVs. It can be seen from Theorem 9 that the smaller the VEF is, the larger the GMDR is under certain conditions. The experimental results of the energy-factor variance in 50 experiments are shown in Figure 10. The average and minimum values are shown in Figure 11.

It can be seen from Figure 10 that VEFs of TSPA and MTSPA fluctuate greatly, while the VEFs of BMTSPA and EMTSPA are stable. This is because TSPA and MTSPA only consider shortening PPL, EMTSPA considers optimizing VEF, and BMTSPA considers optimizing the variance of the planned length of each aircraft. When PPLs of each aircraft are the same in each round of experiments, VEF must be equal.

A comparison of the VEF is shown in Figure 8. EMTSPA is far superior to other algorithms in the performance of VEF. Since the planned path of each ferrying UAV by TSPA are the same, the VEF of TSPA is much larger than other algorithms when the initial energy is different. Although the VEF of MTSPA is smaller than BMTSPA, MTSPA has a stronger randomness. Specifically, in terms of the average value of VEF, EMTSPA is 99.1% better than TSPA, 97.6% better than MTSPA, and 97.3% better than BMTSPA.

5.2.4. Global Message Delivery Ratio. This study aims to improve the message delivery rate and reduce the message delay by designing a better multiferrying drone path.

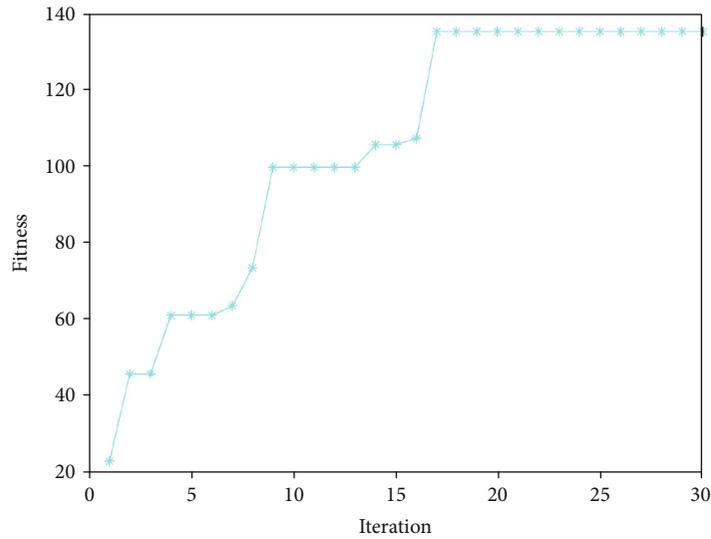


FIGURE 7: Convergence behaviour of EMTSPA.

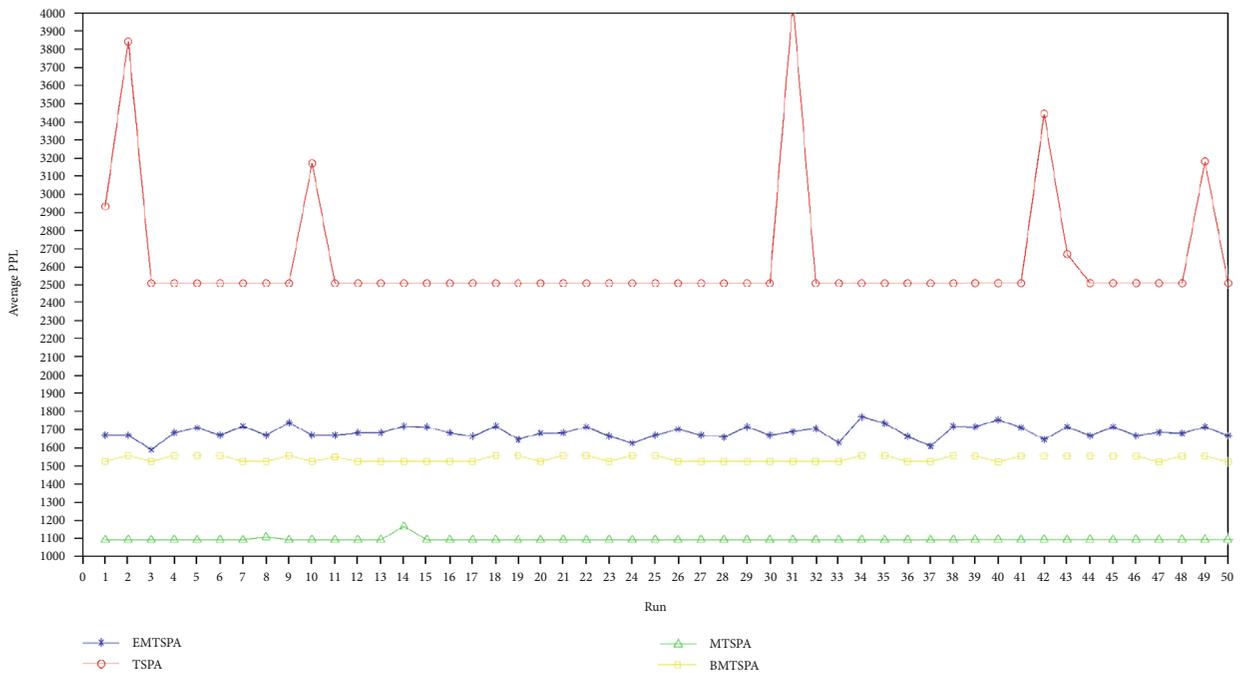


FIGURE 8: Average PPL in 50 rounds of test.

Therefore, it is necessary to test the planned path in a simulation environment. Considering the randomness of the genetic algorithm, we have run several times to get the path and find the average and minimum values of average PPL and VEF. In this series of experiments, suitable paths whose average PPL and VEF are close to the above results (Figures 9 and 11) are chosen.

This series of experiments attempts to discover the effects of the paths designed by four algorithms on GMDR and GMD before the drone’s energy is exhausted. We have taken six different mission time (200 s, 400 s, 600 s, 800 s, 1000s, 1200 s) to test GMDR. The experimental results of GMDR

are shown in Figure 12. (The unit of y-axis is %, and the unit of x-axis is second).

It can be seen from Figure 12:

- (i) GMDR of EMTSPA is slightly lower than GMDR of BMTSPA when test time is short. We are convinced as follows. In EMTSPA, the ferrying UAV with longer PPL is responsible for more message-ferrying task. Due to the short test time, the ferrying UAV with longer PPL fails to deliver messages to the ground station in time. It results that GMDR of EMTSPA is slightly lower than GMDR of BMTSPA.

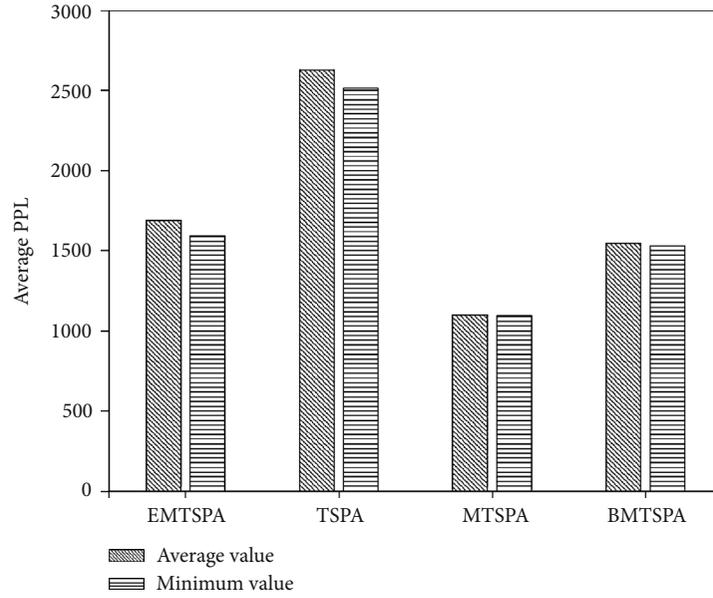


FIGURE 9: Comparison of average PPL.

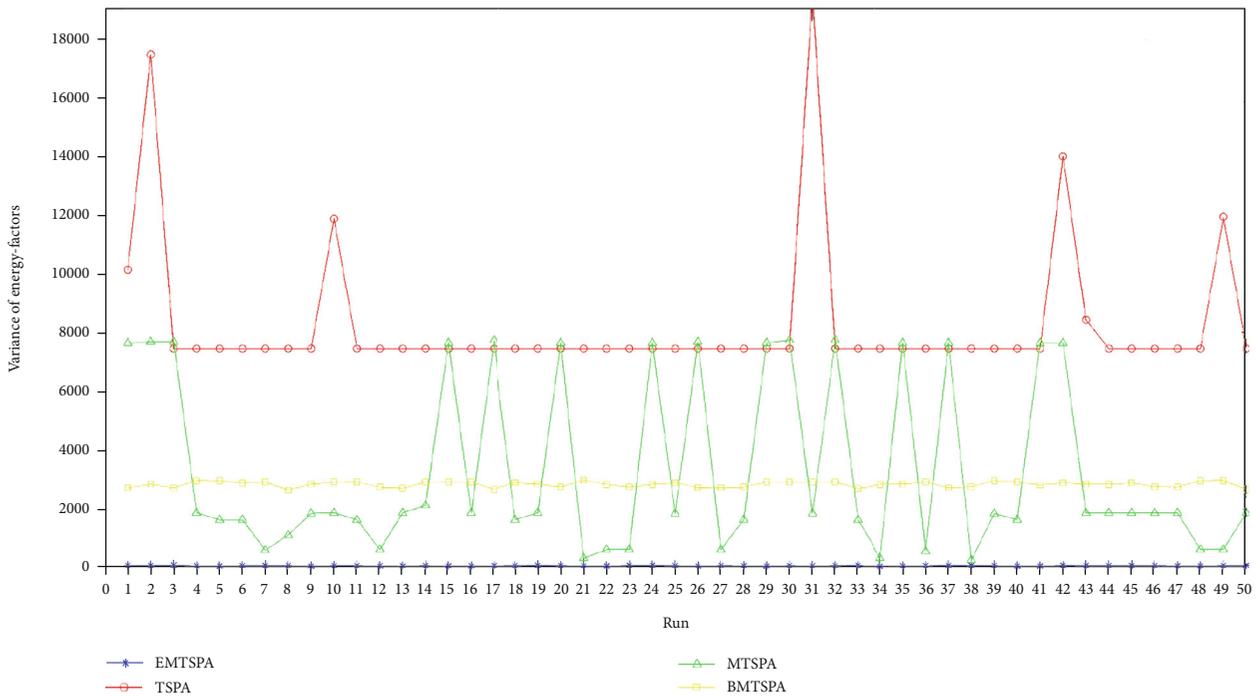


FIGURE 10: VEF in 50 rounds of test.

However, GMDR of EMTSPA is still greater than GMDR of TSPA and MTSPA

- (ii) Most of the time, GMDR of EMTSPA is greater than other algorithms. As test time increases, some ferrying UAVs may be energy-exhausted, then, these energy-exhausted ferrying UAVs can no longer ferry messages. While in EMTSPA, the ferrying UAVs with more energy are assigned longer PPL. In other words, ferrying UAVs with more energy can ferry more messages and ferry messages in longer time.

Undoubtedly, this will increase GMDR. The experimental results have verified this

- (iii) From the overall performance of GMDR, EMTSPA performed best, BMTSPA performed second, and MTSPA and TSPA performed poorly. The comparison is shown as Table 3. (The “+” means that EMTSPA’s performance is better while the “-” means that EMTSPA’s performance is worse. The default unit is %. For example, +925.9 in Table 3 means that EMTSPA’s GMDR is 925.9% of TSPA’s GMDR)

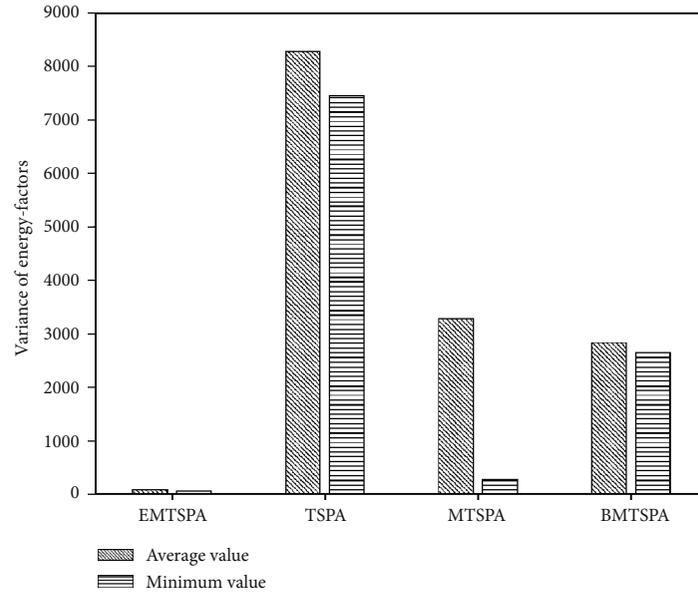


FIGURE 11: Comparison of EF.

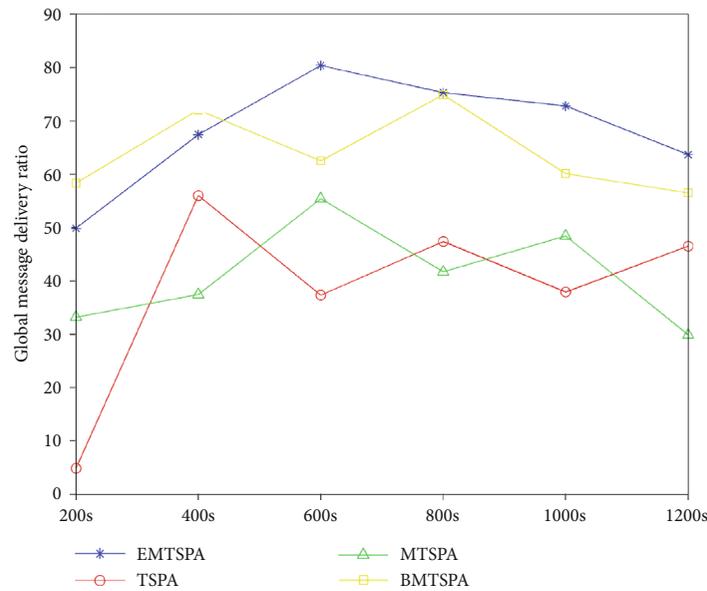


FIGURE 12: GMDR in different test time.

TABLE 3: Comparison of GMDR.

	200 s	400 s	600 s	800 s	1000s	1200 s
TSPA	+925.9	+20.4	+115.2	+58.9	+92.1	+36.9
MTSPA	+50.1	+80.0	+45.1	+80.6	+50.5	+113.0
BMTSPA	-14.5	-6.4	+28.6	+0.6	+17.5	+11.3
EMTSPA	/	/	/	/	/	/

5.2.5. *Global Message Delay.* When test time is different, the result of the global message delay in different test time is shown in Figure 13. As can be seen from Figure 13, GMD of TSPA is much larger than other algorithms, and GMD of

EMTSPA is close to BMTSPA's. The PPL of MTSPA is the smallest, and GMD of MTSPA is the smallest. It can be found that GMD has a positive correlation with the PPL. The results also verify the correctness of Theorem 10 in Section 3. Specifically, EMTSPA's GMD is only 50% of TSPA's.

6. Conclusions

In this paper, we considered the path planning problem in search and rescue scenarios using UAV networks. In particular, we have noticed such a problem that the existing path planning methods for ferrying UAVs usually focus on shortening the path length and ignore the different initial energy

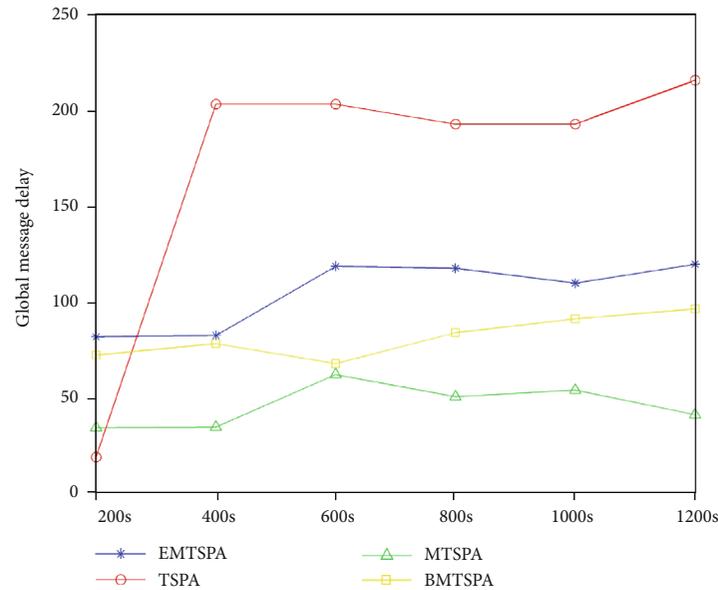


FIGURE 13: Results of GMD.

of ferrying UAVs, and with ignoring this problem, the next problem will arise: low-energy ferry UAV is assigned a longer path, and this low-energy ferry UAV may be no longer deliver messages successfully. To solve the mismatch between the planned path length and the initial energy, we propose a new concept named energy-factor for the ferrying UAV, and use the variance of all ferrying UAVs' energy-factor to measure the balance between the planned path length and the initial energy. Based on multiobject optimization method, we propose a novel method named EMTSPA to deal with this problem. We have completed the modeling, algorithm design, analysis, and experimental verification; the results show that EMTSPA has a significant improvement in global message delivery ratio and global message delay compared to other algorithms. However, because the algorithm in this study uses weight coefficients to superimpose two optimization goals, the choice of weight coefficients is subjective. The algorithm can be further optimized based on Pareto solution which finally get a set of solutions.

Data Availability

If need any information about the paper, please contact the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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