IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 3 January 2023, accepted 16 January 2023, date of publication 20 January 2023, date of current version 28 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3238464

RESEARCH ARTICLE

Logistics UAV Air Route Network Capacity Evaluation Method Based on Traffic Flow Allocation

JIA YI[1], HONGHAI ZHANG[1,2], SHAN LI[1], OUGE FENG[1], GANG ZHONG[1], AND HAO LIU[3]
[1]College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China
[2]College of General Aviation and Flight, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China
[3]College of Mathematics, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China

Corresponding author: Honghai Zhang (honghaizhang@nuaa.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 71971114, and in part by the Fundamental Research Funds for the Central Universities under Grant NQ2022012.

ABSTRACT A bi-level optimization model for the logistics UAV air route network capacity evaluation based on traffic flow allocation is designed in order to meet the future trend of large-scale and normalized operation of logistics UAVs. The maximum sorties of logistics UAVs that can be served by the air route network are the upper-bound model objective, namely, the maximum flow of the logistics UAV air route network. The impedance function is constructed by considering safety and efficiency factors, and the lower-bound model objective function with the minimum logistics UAV air route network impedance value. An improved particle swarm optimization(PSO) algorithm is combined with the method of the successive algorithm(MSA) for solving the bi-level optimization model. To verify the effectiveness of the proposed model and algorithm, a simplified logistics UAV air route network is built. The results show that the proposed algorithm obtains reliable results after 26 iterations, and most segments capacity utilization rate is more than 70%. Parametric analysis of safe separation and algorithm population size shows that the capacity of logistics UAV air route network decreases with the increase of safe separation and the decreasing trend is gradually slowed down, and the optimal algorithm population size corresponding to different safe separations also varies. Based on the study described above, a logistics UAV air route network based on actual geographic information data is constructed, and the experimental results demonstrate that the suggested technique could be used to a specific scale of logistics UAV route network capacity evaluation and had validity.

INDEX TERMS Air traffic management, urban air mobility, UAV logistics, airspace capacity.

I. INTRODUCTION

The worldwide civil aviation sector has had an unprecedented impact since the onset of COVID-19, with people's travel habits altering, flight numbers plummeting, and several carriers declaring bankruptcy. Entering the post-epidemic period, countries' prevention efforts are uneven, and although the civil aviation industry is increasingly recovering, it is difficult to return to its peak, but it creates development opportunities for Urban Air Mobility(UAM) and Unmanned Aerial Vehicle(UAV) industry. The United States, Europe, Japan, and South Korea have successively proposed urban low-altitude airspace management and UAV operation control planning strategies. National Aeronautics and Space Administration(NASA) spearheads Advanced Air Mobility(AAM) program to integrate air cabs, UAV delivery, and other advanced aircraft concepts into the national airspace system [1]. The European Single Sky program jointly related companies to release the U-Space design blueprint will provide a new intelligent service program for the future of large-scale UAV hybrid operations. Among the industries related to UAM and UAVs, UAVs logistics is one of the most focused research fields. Amazon analyzed the weight of parcels, and the statistics showed that about 86% of the parcels can meet

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

the requirements of UAV logistics capacity [2]. NASA proposed that UAV logistics is expected to undertake 500 million orders of parcel delivery services in 2030 [3]. Other multinational enterprises with global influence, such as DHL and ZipLine, also have made breakthroughs in logistics UAV manufacturing and pilot applications, and continue to explore and promote the UAV logistics scale development. In terms of core technologies, Kuru et al. developed an intelligent delivery platform for logistics UAVs, which compares multiple delivery methods [4].

The development of UAV logistics and other emerging industries has put new demands on low-altitude airspace management. Airspace capacity evaluation, as a core element of air traffic management, is an important prerequisite for the rational allocation of airspace resources. Airspace capacity evaluation originated in the 1940s [5]. The main methods commonly used today are mathematical model-based methods [6], controller workload-based methods [7], computer simulation-based methods [8], and data-driven methods [9]. Cheung et al. proposed a Mixed Integer Programming (MIP) airport scheduling optimization model considering runway capacity to address the problem of capacity-demand imbalance during peak hours, and verified the advantages of dynamic airport capacity and dynamic runway configuration over fixed capacity [10]. Mohamed et al. developed a dynamic neural network model based on the workload of air traffic controllers for terminal area capacity evaluation and adjusted the model parameters using Neural Partial Differentiation (NPD) equation [11]. Wang considered two factors: controller workload and acceptable delay level, summarized the process of airspace capacity evaluation based on computer simulation and elaborated the simulation principle, and reproduced the real airspace environment to verify the effectiveness of the proposed method [12].

However, low-altitude airspace is complex and variable, and there are limitations in applying existing typical airspace capacity evaluation methods to low-altitude airspace. Since the research on low-altitude airspace capacity evaluation technology is still in the early stage, a unified definition of low-altitude airspace capacity has not yet been formed. The Cal Unmanned Lab at the University of California believes that intelligent aircraft such as UAVs will be the main operating vehicle in the future low-altitude airspace, and with the emergence of Unmanned Aircraft Systems(UAS), the capacity of low-altitude airspace can be defined as the maximum number of aircraft that can be accommodated in the airspace under an acceptable level of conflict to ensure operational safety [13]. On the other hand, the change in airspace capacity can also be characterized by a sudden change in a specific index, when the number of aircraft in the airspace exceeds its capacity due to a sharp change in a specific index caused by the addition of an aircraft to the airspace [14]. The low-altitude airspace environment is complex and volatile, and flying according to pre-planned flight paths can effectively improve the supervisability and safety of the low-altitude airspace operating environment, Nanyang Technological University (NT) of Singapore proposed a low altitude capacity evaluation method based on the flight path network and defined the low altitude flight path network capacity as the maximum number of aircraft that can be carried by the whole air route network in specific airspace at a specified time [15].

In recent years, research scholars have gradually carried out research on the low-altitude airspace capacity evaluation method according to the operational characteristics and airspace management rules. The exploration of low-altitude airspace capacity evaluation techniques at the University of California, Berkeley, USA sprang from the estimation of air traffic complexity in an unmanned environment. In 2016, Bulusu et al. argued that in the future low-altitude environment, UAVs will present an organized free flight state, and proposed two air traffic complexity measures, Conflict Cluster Size and Normalized Time Spent in Conflict (NTSC), respectively, to build a simulation platform using the San Francisco Bay Area as a prototype, and based on simulation experiments, it was concluded that the future San Francisco Bay Area can carry an average of 100,000 daily UAV flights [13]. On this basis, motivated by the study of the impact of UAS on the operation of low-altitude airspace, Bulusu et al. clarified the definition of low-altitude airspace capacity and realized the evaluation of low-altitude airspace capacity using mathematical methods [14]. Since then, Bulusu and his team have gradually established the research route of 'constructing specific metrics - simulating experiments - locking threshold mutation - determining airspace capacity', measuring safety in terms of Total Loss of Flight per Flight Hour and performance in terms of Change in Direct Operating Cost, and comparing airspace capacity under two modes of UAV operation: cooperative and non-cooperative [14], [16]. Subsequently, a throughput-based capacity evaluation method for low-altitude airspace is proposed, in which three conflict detection and deconfliction algorithms and two minimum spacing requirements are evaluated by simulating unmanned aerial vehicle traffic in the airspace, considering the variability of traffic flow, and analyzing their impact on throughput. The results show that the throughput tends to decrease before the system security decreases, and this index has reference meaning for low altitude airspace capacity evaluation [18]. These studies take the future airspace operation characteristics as the background, weaken the consideration of controller factors, more consideration of the aircraft's conflict avoidance ability, and is not limited by the airspace structure, oriented to the future free flight setting, with a certain degree of foresight.

Sunil et al. at Delft University predict a large number of small UAVs to operate in urban airspace in the future. In this context, the Metropolis project, in which Sunil is involved, investigates the impact of airspace structure on the capacity, complexity, safety, and efficiency of high-density operational airspace. Therefore, four concepts of airspace structure are proposed, including full mix, layers, zones, and tubes. Simulation experiments show that the layers structure has the best performance considering capacity, safety, and efficiency, and can better adapt to the future high-density urban air traffic operation [2]. This study proposes four airspace structures with different degrees of freedom, and the simulations verify the performance characteristics of different types of airspace. The simulations consider different traffic densities, tidal characteristics of urban traffic, and the effects of stochastic factors such as wind and rogue aircrafts.

Cho et al. analyzed the urban airspace capacity in terms of available airspace identification using two types of geofences: keep-out and keep-in. Define inaccessible boundaries for UAVs around static obstacles by using keep-out geofences, and identify available airspace using keep-out geofences in combination with an alpha-shaped method. The simulation results show that the available airspace identified by keep-in is the upper limit of keep-out. Meanwhile, geofence parameters should be decided according to the complexity of the geospatial and the purpose of the flight in practical applications, rather than relying on fixed values [19]. According to the above studies, a mature architecture has not yet been formed for the study of low-altitude airspace capacity evaluation, but it follows a combination of mathematical analysis models and simulation validation. This research combines geo-fencing technology for UAVs and airspace identification, utilizing the relevant technologies already applied to UAVs to make it more compatible with real-world conditions.

For the complex airspace environmental conditions at low altitude, most of the current research uses computer simulation methods. Most of the current simulation platforms for capacity evaluation lack the verification of actual operation data, and the parameters are mostly hypothetical, which cannot expose the airspace capacity regulation in the real low-altitude airspace in a three-dimensional environment, and have certain limitations. Based on the research presented above, this paper proposes a method for evaluating the capacity of logistics UAV air route networks based on traffic flow distribution, which includes optimization modeling and heuristic algorithms. This approach considers the safety and efficiency of logistics UAVs during operation, and can be applied to different sizes of logistics UAV air route networks.

Logistics UAV air route network capacity is defined as the maximum number of UAV sorties that the air route network can serve, namely, the maximum flow of the logistics UAV air route network. The main contributions are as follows:

1) A bi-level optimization model for evaluating the capacity of logistics UAV air route network based on traffic assignment is established, considering efficiency and safety factors.
2) A bi-level optimization model solving algorithm mixed improved particle swarm optimization algorithm with the method of the successive algorithm is designed.

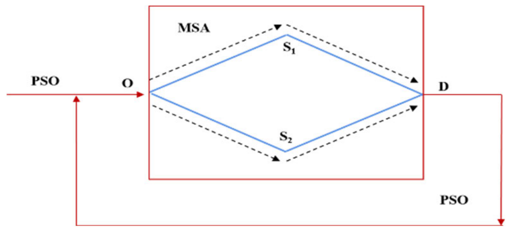

FIGURE 1. PSO-MSA algorithm operation mechanism schematic.

3) The simplified logistics UAV air route network is established, and several simulation experiments were carried out for parameters comparisons such as safe separation and algorithm population size, and the experimental results are analyzed.
4) Based on the real geographic information data, the logistics UAV air route network is built to verify the effectiveness of the proposed model and algorithm.

II. METHODOLOGIES

A bi-level logistics UAV capacity evaluation optimization model is developed in this study to address the trend of large-scale logistics UAV operation. The bi-level optimization model is a popular tool for studying urban transportation networks. With the development of UAV logistics, the operation scale is gradually expanded, the network structure is increasingly complex, and the factors to be considered are also increased, and these factors should be placed at different levels. The bi-level optimization model can construct a bi-level decision mechanism. The upper bound has the right of control and guidance over the lower-bound. The upper-bound makes a decision and passes it to the lower-bound. The lower-bound receives the decision, then makes appropriate decisions and feeds back to the upper-bound. The two different level models interact iteratively to find the optimal solution [23].

The improved particle swarm optimization algorithm is combined with the method of the successive algorithm to solve the model. The operation mechanism of the algorithm is shown in Figure 1. Suppose there is a simple logistics UAV air route network consisting of a starting point O, an end point D. There are two air routes available from O to D. The PSO algorithm will input a set of solutions, which is the flight flow between OD. According to the MSA algorithm, the flight flow will be allocated to different air routes. Then, the PSO algorithm evaluates the allocation results, and if the segment capacity requirement is satisfied it is a set of feasible solutions, if not, it is an invalid solution [22].

A. PROBLEM DESCRIPTION

This paper aims to propose a logistics UAV air route network capacity evaluation method, which provides support for future urban air mobility management. The logistics UAV air route network structure is known, including air route length, Origin-Destination (OD) pair location, etc. The vertical take-off and landing logistics UAV is used as the delivery tool to execute logistics distribution. On this basis, in order to better build the model, assuming:

1) Logistics UAVs must follow a fixed air route and are not allowed to change during flight.
2) Logistics UAVs fly at constant speed in the air route network, ignoring the influence of parcels' weight on flight speed.
3) The minimum safe separation must be maintained between logistics UAVs in the same flight segment.
4) Ignore the power consumption of logistics UAVs.
5) Ignore the impact of weather on the logistics UAVs operation.
6) Ignore the transmission signal delay and loss during the logistics UAVs operation.
7) Ignore the possible collisions and crashes of logistics UAVs in the operation process.

B. UPPER-BOUND MODEL ESTABLISHMENT

1) OBJECTIVE FUNCTION

According to the definition of the logistics UAV air route network capacity in Section I, the Upper-bound model objective function is set as the maximum sum of the logistics UAV air route network flow.

$$\mathrm{C} = \mathrm{Max}Q = \sum_{i}\sum_{j} f_{ij}, \quad \forall i \in I, \quad \forall j \in J \tag{1}$$

where, C is the capacity of logistics UAV air route network; Q is the total flow of the capacity of logistics UAV air route network; i is the origin node, namely, express station; I is the set of origin nodes, $i \in I$; j is the destination node, namely, receipt station; J is the set of destination nodes, $j \in J$; f_{ij} is the flow from the origin node i to destination node j.

2) CONSTRAINT CONDITIONS

The flow between the origin node i to the destination node j in the logistics UAV air route network cannot exceed its capacity and must be nonnegative integers.

$$0 \leq f_{ij} \leq C_{ij}, \quad \forall i \in I, \quad \forall j \in J \tag{2}$$

where C_{ij} is the capacity of the OD pair, the same OD pair has one or more air routes, C_{ij} is equal to the sum of all air routes between OD pairs; The air route capacity will be limited by the minimum segment capacity, therefore, the capacity of each air route is equal to the minimum capacity in the n segments. The specific formulas are:

$$C_{ij} = \sum_{i}\sum_{j} C_{ij}^{a}, \forall i \in I, \forall j \in J, \forall a \in A_{ij} \tag{3}$$

$$C_{ij}^{a} = Min\left\{C_{k_1}^{a}, C_{k_2}^{a}, \cdots, C_{k_n}^{a}\right\}, \forall i \in I, \forall j \in J, \forall a \in A_{ij}, \forall k \in K \tag{4}$$

In formula (3), where a is the air route between OD pairs, A_{ij} is the set of air routes, $a \in A_{ij}$; k represents the segment that constitutes the air route a, K is the set of segments, $k \in K$; C_{k_n} is the capacity of the nth segment k in the air route a, the calculation formula is as follows:

$$C_{k_n} = \frac{L_{k_n}}{d_u + d_s}, \quad \forall k \in K \tag{5}$$

where, L_{k_n} is the length of the segment k; d_u is the length of the logistics UAV; d_s is safe separation.

C. LOWER-BOUND MODEL ESTABLISHMENT

1) OBJECTIVE FUNCTION

When the OD pairs flight traffic input from the upper-bound model to the lower-bound model, the lower-bound model needs to allocate these flight traffic to different air routes according to impedance value. The lower-bound model objective function is set as the minimum sum of logistics UAV air route network impedance value. Considering the safety and efficiency factors, the total impedance function of the logistics UAV air route network w_{ij}^{a} is constructed.

$$\mathrm{Min}Z = \sum_{a \in A_{ij}} w_{ij}^{a} q_{ij}^{a}, \quad \forall i \in I, \quad \forall j \in J \tag{6}$$

where, q_{ij}^{a} is the flight flow between the origin node i to the destination node j; The sum of the air route flight flows is equal to the flight flows between the OD pairs, as shown in formula (7).

$$f_{ij} = \sum_{a \in A_{ij}} q_{ij}^{a}, \quad \forall i \in I, \quad \forall j \in J \tag{7}$$

w_{ij}^{a} is the impedance value of the air route a, which is summed by the impedance value of segment k, the calculation formula is as follows.

$$w_{ij}^{a} = \sum_{a \in A_{ij}} w_k, \quad \forall i \in I, \quad \forall j \in J, \quad \forall k \in a \tag{8}$$

where, w_k is the impedance value of the segment k, which is a combination of safety factors and efficiency factors, the calculation formula is as follows.

$$w_k = \sigma r_k + (1 - \sigma) t_k, \quad \forall k \in K \tag{9}$$

where, r_k is the safety sub-impedance function, which is calculated from formula (11). t_k is the efficiency sub-impedance function, which is calculated from formula (15).

σ is the weighting parameter.

Due to the value range difference between these two sub-impedance functions, the min-max normalization method was used to standardize the data, the calculation formula is as follows.

$$f'(x) = \frac{f(x) - f(x)_{\min}}{f(x)_{\max} - f(x)_{\min}} \tag{10}$$

where, $f'(x)$ is the sub-impedance normalized value. $f(x)$ is the original sub-impedance value. $f(x)_{\min}$ and $f(x)_{\max}$ are the minimum and maximum values of the sub-impedance function respectively.

a: SAFETY SUB-IMPEDANCE FUNCTION

The logistics UAV crash causing injuries to ground personnel is considered as the main factor of the logistics UAV air route network safety sub-impedance function r_k.

$$r_k = P_{uav} N_{people} F_{die} \tag{11}$$

where, r_k is the safety impedance of the segment k. P_{uav} is the probability that logistics UAVs break down and crash on the ground. N_{people} is the number of fatalities after the logistics UAV crash. F_{die} is logistics UAV crash fatality rate [20], [21].

In formula (11), the number of fatalities after a logistics UAV crash on the ground N_{people} is calculated as follows:

$$N_{people} = A \rho_{people} \tag{12}$$

where, A is the area where logistics UAV crash on the ground; ρ_{people} is the population density on the ground in the segment k.

In formula (11), the logistics UAV crash fatality rate F_{die} is related to the logistics UAV state and ground environment. According to reference [20], F_{die} is calculated as follows:

$$F_{die} = \frac{1}{1 + \sqrt{\frac{\lambda}{\mu}} (\frac{\mu}{E})^{\frac{1}{4S}}} \tag{13}$$

In formula (13), S is sheltering parameter, $S \in (0, 1]$, namely, exposure of ground personnel in the logistics UAV air route area. λ is the energy required that the logistics UAV crash fatality rate reaches 50% when $S = 50$. μ is the energy threshold required for ground personnel to be injured when the sheltering parameter S approaches 0. E is the impact of kinetic energy, the calculation formula is as follows:

$$E = \frac{m^2 g \left[1 - \exp(-hqA\rho_A/m)\right]}{qA\rho_A} \tag{14}$$

In formula (14), m is the mass of logistics UAV and parcels; q is drag coefficient; ρ_A is air density; h is the logistics UAV flight altitude.

b: EFFICIENCY SUB-IMPEDANCE FUNCTION

The efficiency impedance t_k is related to the segment length and the logistics UAV flight speed the calculation formula is as follows:

$$t_k = \frac{L_k}{V}, \quad \forall k \in K \tag{15}$$

where, L_k is the length of the segment k; V is the speed of the logistics UAV.

2) CONSTRAINT CONDITIONS

The segment is the basic unit of the logistics UAV air route network, and the air routes have shared segments. Therefore, the flight flow assigned to the segment must be non-negative and less than or equal to its capacity.

$$0 \le x_k \le C_k, \quad \forall k \in K \tag{16}$$

where, C_k is the capacity of the segment k, the calculation method is shown in formula (5). x_k is the flow assigned to the segment k, an air route consists of one or more segments, K is the set of segments, $k \in K$.

$$x_k = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{kk} \end{pmatrix} \in R^k \tag{17}$$

The segment k flight flow is the flight flow between the origin node i to destination node j multiplied by the segment-air route relationship matrix, the calculation formula is as follows:

$$x_k = q_{ij}^a \delta_{ij}^k, \quad \forall i \in I, \quad \forall j \in J, \quad \forall a \in A_{ij} \tag{18}$$

where, x_k is the flight flow of segment k, q_{ij}^a is the flight flow of air route a, δ_{ij}^k is the segment-air route relationship matrix, which is a 0-1 matrix.

$$\delta_{ij}^k = \begin{pmatrix} & k_1 & k_2 & \cdots & k_n \\ a_1 & 1 & 0 & \cdots & 0 \\ a_2 & 0 & 1 & \cdots & 0 \\ \vdots & 0 & 0 & \cdots & 1 \\ a_k & 1 & 1 & \cdots & 1 \end{pmatrix} \tag{19}$$

where, 1 represents the air route a contains the corresponding segment k, 0 represents the air route a is not contains the corresponding segment k.

D. A BI-LEVEL LOGISTICS UAV AIR ROUTE NETWORK CAPACITY EVALUATION OPTIMIZATION MODEL

In this paper, logistics UAV air route network capacity is defined as the maximum number of UAV sorties that the air route network can serve, namely, the maximum flow of the logistics UAV air route network. There are many OD delivery pairs in the logistics UAV air route network, in other words, there are many air routes between the origin node i and the destination node j. The maximum flow of the air route network is the upper-bound model objective, namely, the maximum flow between the origin node i and the destination node j. Considering the safety and efficiency factors, the total impedance function is constructed. According to the Wardrop system optimization (SO) principle, the minimize the sum of logistics UAV air route network impedance value is lower-bound model objective. The bi-level logistics UAV air route network capacity evaluation optimization model proposed in this paper is shown as follows:

$$\begin{cases} \mathrm{Max}Q = \sum_i \sum_j f_{ij} \\ s.t.\ 0 \le f_{ij} \le C_{ij}, \forall i \in I, \forall j \in J \\ and\ \mathrm{MinZ} = \sum_{a \in A_{ij}} w_{ij}^a q_{ij}^a \\ s.t.\ f_{ij} = \sum_{a \in A_{ij}} q_{ij}^a, \forall i \in I, \forall j \in J \\ w_{ij}^a = \sum_{a \in A_{ij}} w_k, \forall i \in I, \forall j \in J, \forall k \in a \\ x_k = q_{ij}^a \delta_{ij}^k, \forall i \in I, \forall j \in J, \forall a \in A_{ij} \\ x_k \le C_k, \forall k \in K \\ w_k = \sigma r_k + (1-\sigma) t_k, \forall k \in K \\ r_k = P_{uav} N_{people} F_{die}, \forall k \in K \\ t_k = \dfrac{L_k}{V}, \forall k \in K \end{cases} \tag{20}$$

E. ALGORITHM SOLUTION

To solve the bi-level logistics UAV air route network capacity assessment optimization model, the modified particle swarm optimization technique is paired with the successive algorithm method (MSA). The particle swarm optimization (PSO) algorithm originated from research on the birds' foraging behavior. The core idea is to establish an effective individual information sharing and cooperation mechanism in the group and to find the optimal solution by iteratively updating the particles' velocity and position [24]. PSO algorithm has become a typical swarm intelligence algorithm, which is widely used in optimization model solving [25]. The method of the successive algorithm is a typical method for traffic flow allocation. The main idea is to average a series of auxiliary points in the iterative process, where each iteration is obtained by solving the auxiliary planning problem, which in turn is based on the auxiliary points in the previous iterative process. The advantage of MSA in comparison with the Frank Wolf algorithm is that the iteration steps obtained by solving the linear search problem are not required in each iteration. The basic idea is to solve the probability of route selection by the Logit function, and continuously update the flow allocated iteratively to each segment until it is close to the balanced flow allocation result in the route network. In this paper, the PSO algorithm is used to solve the upper-bound model, and the method of the successive algorithm is used to solve the lower-bound model.

The specific steps are as follows:

Step 0: Algorithm initialization. In the PSO algorithm based on linear decreasing inertia weight, a particle represents a set of solutions of the upper-bound model, and the dimension of the particle is the number of independent variables of the upper-bound model, namely, the number of OD delivery pairs. The fitness value corresponds to the upper-bound model value Q. In the initialization of the algorithm, the number of particles, the number of iterations, and other parameters should be set. The linear decreasing inertia weight calculation formula is as follows:

$$\omega_m = (\omega_{start} - \omega_{end}) \times \frac{(T_{\max} - T_m)}{T_{\max}} + \omega_{end} \tag{21}$$

where, ω_m is the inertia weight at the mth iteration; ω_{start} is the initial inertia weight, it is usually set to 0.9; ω_{end} is the final inertia weight, it is usually set to 0.4; $T_{\max}$ is the maximum iterations; T_m is the current iterations. Setting the inertia weight can be conducive to getting out of the local optimal solution.

Step 1: The initial velocity and position of each particle are randomly generated according to the constraint conditions of formula (2).

Step 2: Update particles' velocity and position. The update formula is shown as follows:

$$\begin{aligned} V_{nd}^{m+1} &= w_m v_{nd}^m + c_1 rand_1 (P_{nd,pbest}^m \\ &\quad - L_{nd}^m) + c_2 rand_2 (P_{nd,gbest}^m - L_{nd}^m) \end{aligned} \tag{22}$$

$$L_{nd}^{m+1} = L_{nd}^m + V_{nd}^{m+1} \tag{23}$$

where, V_{nd}^{m+1} is the update speed of d-dimensional particle n at the $(m+1)th$ iteration; w_m is the inertia weight at the mth iteration; v_{nd}^m is the update speed of n at the mth iteration; c_1 is the particle's individual acceleration coefficient; $rand_1$ and $rand_2$ are random numbers in the range (0,1); $P_{nd,pbest}^m$ is the best individual position of n at the mth iteration; L_{nd}^m is the position of n at the mth iteration; L_{nd}^{m+1} is the position of n at the $(m+1)th$ iteration, c_2 is the particle's group acceleration coefficient; $P_{nd,gbest}^m$ is the best group position of n at the mth iteration; At the first iteration. $P_{nd,pbest}^m$ and $P_{nd,gbest}^m$ are set to 0. Acceleration coefficients also named learning factors, which are critical to the PSO algorithm's ability to search. The acceleration coefficients will be related to the speed of particle motion and algorithm convergence.

Step 3-1: Start the MSA algorithm. Bring L_{nd}^{m+1} into the lower-bound model. The dimension of the particle corresponds to the OD delivery pair, namely, $L_{nd}^{m+1} = (f_{11}, f_{12}, f_{13}, \cdots, f_{\mathrm{ij}})$. According to formula (7), the initial air route flight flow q_{ij}^a is generated.

Step 3-2: Calculate air route impedance value w_{ij}^a, the calculation method is shown in formula (8).

Step 3-3: Logit function was used to calculate the iteration direction of the lower-bound model $d_{(I)a}^{ij}$, the calculation formula is as follows:

$$d_{(I)a}^{ij} = P_{ij}^a \times q_{ij}^a \tag{24}$$

where, P_{ij}^a is the probability that the logistics UAV chooses air route a. Logit function is used to solve the probability of air route selection, the calculation formula is as follows:

$$P_{ij}^a = \frac{\exp(-\theta w_{ij}^a)}{\sum_{a \in A_{ij}} \exp(-\theta w_{ij}^a)} \tag{25}$$

where, θ is the Grumbel distribution, θ is set to 0.1 in this paper.

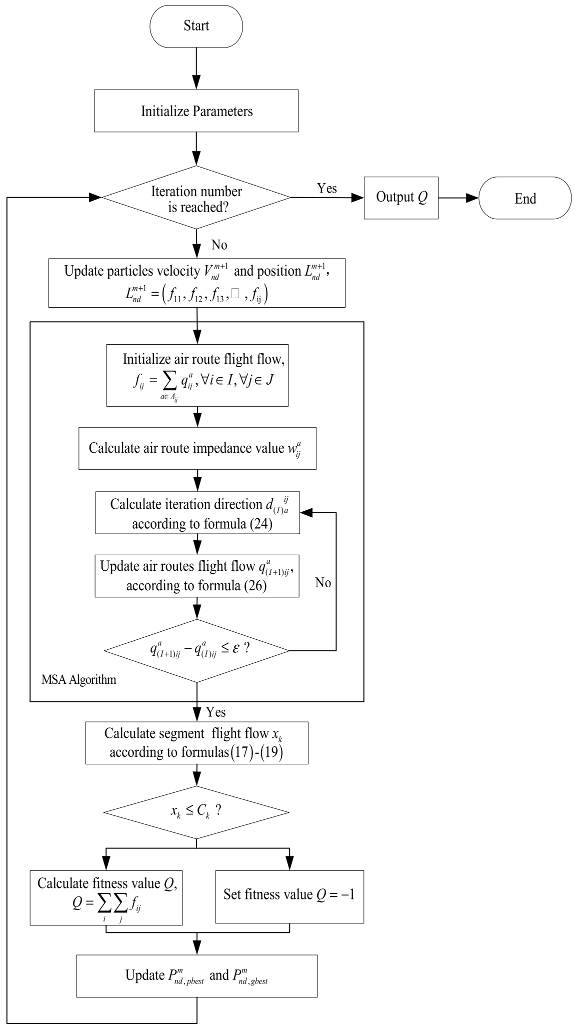

FIGURE 2. PSO-MSA algorithm flow chart.

Step 3-4: Update flight flow $q_{(I+1)a}^{ij}$, the calculation formula is as follows:

$$q_{(I+1)ij}^{a}=q_{(I)ij}^{a}+\frac{1}{I}(d_{(I)ij}^{a}-q_{(I)ij}^{a}) \tag{26}$$

Step 3-5: If the difference between $q_{(I+1)ij}^{a}$ and $q_{(I)ij}^{a}$ is less than the threshold ε, as shown in formula (27), the iteration will be stopped, and Step 4 is entered. If the difference between $q_{(I+1)ij}^{a}$ and $q_{(I)ij}^{a}$ is not reached ε, Step 3-3 is returned.

$$q_{(I+1)ij}^{a}-q_{(I)ij}^{a}\le\varepsilon \tag{27}$$

Step 4: Calculate the fitness value of each particle, namely, the upper-bound objective function Q. Then, calculate the flight flow x_k assigned to the segment according to formulas (17) - (19). If $x_k > C_k$, set Q to a negative number, indicates this result is invalid.

Step 5: Update the best individual position $P_{nd,pbest}^{m}$.

Step 6: Update the best group position $P_{nd,gbest}^{m}$.

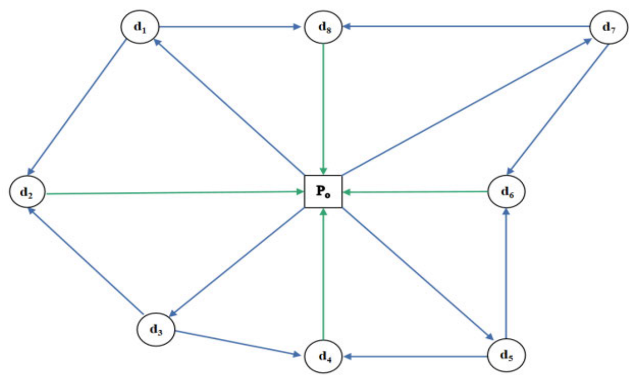

FIGURE 3. Logistics UAV air route network.

Step 7: If the upper limit of iterations set in Step 0 is reached, the result will be output; if not, Step 2 will be returned.

The specific PSO-MSA algorithm flow is shown in Figure 2.

III. EXAMPLE ANALYSIS

A. PARAMETER SETTINGS

Python was used as an experimental tool to verify the effectiveness of the proposed model and algorithm. The logistics UAV air route network as shown in Figure 3 is adopted, which includes 9 nodes, 16 OD delivery pairs, 16 segments, and 24 air routes. Each segment has only one flight direction, and two-way flight is not allowed. P_0 is the express station, $d_1 \sim d_8$ are the receipt station. The logistics UAV will deliver the parcels from P_0 to different receipt stations, and return according to the prescribed air route. The air route parameters are shown in Table 2, and the segment parameters are shown in Table 1.

EHang Falcon B logistics UAV is selected for parcel delivery in this paper. Basic parameter settings are shown in Table 3 [21], [27].

B. RESULT ANALYSIS

1) CAPACITY ANALYSIS

Based on the parameter settings, the POS-MSA algorithm is used to solve the bi-level logistics UAV air route network capacity evaluation optimization model. The simulation experiment was repeated 50 times, and the result with the largest fitness value was used to draw the algorithm iteration curve, as shown in Figure 4. The algorithm iteration curve rose quickly at the beginning and reached the optimal result after 26 iterations, which means the algorithm has a strong searchability. The fitness value, namely, the proposed logistics UAV air route network capacity value, is 211 sorties. The flows of 16 OD pairs from a_1 to a_{24} are 10, 27, 3, 20, 11, 20, 4, 25, 17, 11, 25, 5, 4, 5, 19, 5.

The logistics UAV air route network capacity evaluation method proposed in this paper is to assign OD pair flow to air routes, then, assigned air routes flow to segments through

TABLE 1. Air routes parameters.

	OD delivery pairs	Air routes
Delivery:		
a_1	$P_0 \rightarrow d_1$	$P_0 \rightarrow d_1$
a_2	$P_0 \rightarrow d_2$	$P_0 \rightarrow d_1 \rightarrow d_2$
a_3		$P_0 \rightarrow d_3 \rightarrow d_2$
a_4	$P_0 \rightarrow d_3$	$P_0 \rightarrow d_3$
a_5	$P_0 \rightarrow d_4$	$P_0 \rightarrow d_3 \rightarrow d_4$
a_6		$P_0 \rightarrow d_5 \rightarrow d_4$
a_7	$P_0 \rightarrow d_5$	$P_0 \rightarrow d_5$
a_8	$P_0 \rightarrow d_6$	$P_0 \rightarrow d_5 \rightarrow d_6$
a_9		$P_0 \rightarrow d_7 \rightarrow d_6$
a_{10}	$P_0 \rightarrow d_7$	$P_0 \rightarrow d_7$
a_{11}	$P_0 \rightarrow d_8$	$P_0 \rightarrow d_7 \rightarrow d_8$
a_{12}		$P_0 \rightarrow d_1 \rightarrow d_8$
Return:		
a_{13}	$d_1 \rightarrow P_0$	$d_1 \rightarrow d_2 \rightarrow P_0$
a_{14}		$d_1 \rightarrow d_8 \rightarrow P_0$
a_{15}	$d_2 \rightarrow P_0$	$d_2 \rightarrow P_0$
a_{16}	$d_3 \rightarrow P_0$	$d_3 \rightarrow d_2 \rightarrow P_0$
a_{17}		$d_3 \rightarrow d_4 \rightarrow P_0$
a_{18}	$d_4 \rightarrow P_0$	$d_4 \rightarrow P_0$
a_{19}	$d_5 \rightarrow P_0$	$d_5 \rightarrow d_4 \rightarrow P_0$
a_{20}		$d_5 \rightarrow d_6 \rightarrow P_0$
a_{21}	$d_6 \rightarrow P_0$	$d_6 \rightarrow P_0$
a_{22}	$d_7 \rightarrow P_0$	$d_7 \rightarrow d_6 \rightarrow P_0$
a_{23}		$d_7 \rightarrow d_8 \rightarrow P_0$
a_{24}	$d_8 \rightarrow P_0$	$d_8 \rightarrow P_0$

TABLE 2. Segments parameters.

	Segments	Length(m)		Segments	Length(m)
k_1	$P_0 \rightarrow d_1$	800	k_9	$d_1 \rightarrow d_2$	650
k_2	$P_0 \rightarrow d_3$	600	k_{10}	$d_1 \rightarrow d_8$	500
k_3	$P_0 \rightarrow d_5$	650	k_{11}	$d_3 \rightarrow d_2$	600
k_4	$P_0 \rightarrow d_7$	1000	k_{12}	$d_3 \rightarrow d_4$	450
k_5	$d_2 \rightarrow P_0$	950	k_{13}	$d_5 \rightarrow d_4$	500
k_6	$d_4 \rightarrow P_0$	500	k_{14}	$d_5 \rightarrow d_6$	500
k_7	$d_6 \rightarrow P_0$	450	k_{15}	$d_7 \rightarrow d_6$	700
k_8	$d_8 \rightarrow P_0$	500	k_{16}	$d_7 \rightarrow d_8$	950

the segment-air route relationship matrix. Whether the flow assigned to each segment exceeds its capacity is an important constraint of this method. The segment flow under the optimal experimental results is shown in Table 5. The segment capacity utilization ratio was calculated according to the formula (28).

$$k_{utilization} = \frac{k_{flow}}{k_{capacity}} \times 100\% \tag{28}$$

TABLE 3. Model basic parameters [21], [27].

Parameters	Value	Parameters	Value
P_{uav}	6.04×10^{-5}h	A	0.0188m^2
λ	10^6J	q	0.3
μ	100J	σ	0.5
m	1.38kg	S	0.5
ρ_A	1.225kg/m^3	d_s	20m

TABLE 4. Algorithm basic parameters.

Parameters	Value
the number of particles	50
the dimension of particles	16
the limit of iterations	100
the initial inertia weight	0.8
individual acceleration coefficient: c_1	0.5
group acceleration coefficient: c_2	0.5
MSA algorithm iteration threshold	1
the final inertia weight	0.1

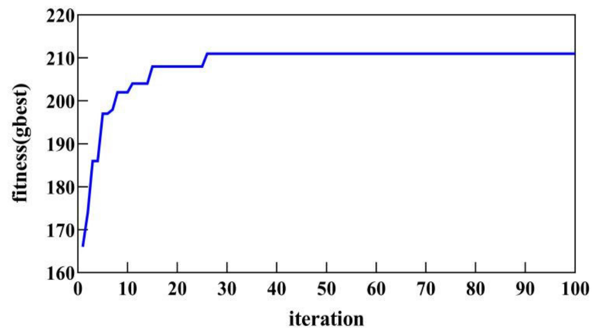

FIGURE 4. Algorithm iteration curve.

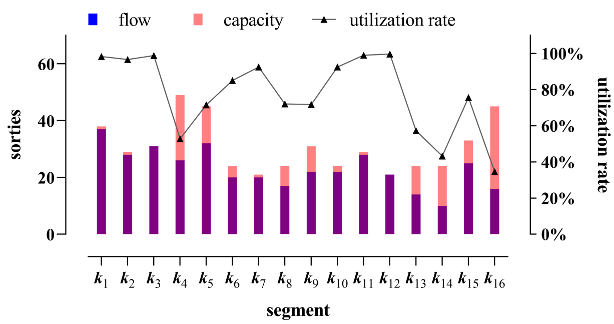

FIGURE 5. The flow assigned to segments.

where, $k_{utilization}$ is the segment capacity utilization ratio; k_{flow} is the flow assigned to segments; $k_{capacity}$ is segments capacity. The calculation results are shown in Figure 5 and Table 5. Most segments' capacity utilization is more than 70%, among them, the segment capacity utilization ratio of the segment k_1, k_2, k_3, k_7, k_{10}, k_{11}, k_{12} exceeds 90%, the lowest is segment k_{16}, only 34.53%.

2) PARAMETER ANALYSIS

a: SAFE SEPARATION

The safe separation proposed in this paper refers to the minimum space that must be maintained between the front

TABLE 5. Algorithm basic parameter Segment capacity utilization ratio.

segment	k_{flow}	$k_{capacity}$	$k_{utilization}$
k_1	37	38	98.32%
k_2	28	29	96.65%
k_3	31	31	98.90%
k_4	26	49	52.85%
k_5	32	45	71.61%
k_6	20	24	85.09%
k_7	20	21	92.50%
k_8	17	24	72.13%
k_9	22	31	71.75%
k_{10}	22	24	92.49%
k_{11}	28	29	99.02%
k_{12}	21	21	99.73%
k_{13}	14	24	57.23%
k_{14}	10	24	43.24%
k_{15}	25	33	75.58%
k_{16}	16	45	34.53%

and rear logistics UAVs in the air route network. According to formula (5), the safe separation is directly related to the segment capacity, and then affects the capacity level of the entire logistics UAV air route network capacity. Some scholars have studied the UAV safe separation demarcation method [26], but no unified standard has been formed. In this paper, the safe separation is the most important parameter, the calculation of the segment capacity is based on the safety separation, which is a highly significant constraint in the model, and the safety separation has the most direct impact on the capacity. In order to explore the influence of safe separation on logistics UAV air route network capacity, set the safe separation to 5m, 10m, 15m, 20m, 25m, and 30m respectively Adopting the experimental results before when $d_s = 20m$, the other safe separations are carried out 50 times, and the optimal value was used to draw the iteration curve. The results are shown in Figure 6.

According to Figure 6, $d_s = 5m$, $C = 763$ sorties; $d_s = 10m$, $C = 406$ sorties, $d_s = 15m$, $C = 276$ sorties; $d_s = 20m$, $C = 211$ sorties, $d_s = 25m$, $C = 164$ sorties; $d_s = 30m$, $C = 146$ sorties. With the increase in safe separation d_s, the capacity of the logistics UAV air route network C gradually decreases. The capacity decreases rate is calculated, and the results are shown in Table 4. According to Table 4, with the increase of safe separation, the sensitivity of capacity to safe separation decreases gradually, when safe separation d_s increase from 5m to 10m, the decrease rate is 46.79%. When safe separation d_s increase from 25m to 30m, the decrease rate is 10.98%.

The computation times of the 6 optimal solutions are 44.89s, 44.31s, 43.57s, 43.38s, 43.72s, 43.29s. It can be seen that the computation time for different safe separation

TABLE 6. The capacity decreases rate.

d_s	C	decrease sorties	decrease rate
5m	763	-	-
10m	406	357	46.79%
15m	276	130	32.02%
20m	211	65	23.55%
25m	164	47	22.27%
30m	146	18	10.98%

does not show large differences, and as the safe separation increases, there is a very slight but not significant downward trend in the computation time.

In order to study the relationship between safe separations and air route capacity of logistics UAV, the following experiment is designed: the safe separation was gradually increased from 5m to 30m according to the step size of every 0.5m. The experiment was repeated 20 times for each safe separations and the average value was taken. The results are shown in the following figure 7. According to the figure 7, there is an obvious linear relationship between safe separations and logistics UAV air route capacity. The least square method was used to perform univariate linear fitting, binary linear fitting and ternary linear fitting respectively, and the resulting functional equations are shown in figure 7.

b: ALGORITHM POPULATION SIZE

The algorithm population size is one of the most important parameters in PSO algorithm. If the population size is set too small, it is likely to result in a local optimal solution, and if the population size is too large, the algorithm complexity will increase. In this paper, algorithm population size selection and safety separation are integrated. Safe separation is an important parameter affecting the logistics UAV air route network capacity. On this basis, the effect of algorithm population size on logistics UAV air route network capacity is considered. Except for the safe separation and algorithm population size, other parameters in Table 3 and Table 4 remain unchanged. Under different safe separations, the population size of the PSO-MSA algorithm was successively increased from 25 to 300. Each experiment was repeated 20 times and the average value is obtained, and the results were shown in figure 8.

According to Figure 8, with the increase of algorithm population size, the logistics UAV air route network capacity also increases and tends to be stable. Therefore, expanding the algorithm population size is an effective method to improve the logistics UAV air route capacity and the optimal algorithm population size corresponding to various safe separations is also different. The consumption time also shows a significant linear increasing trend. When the particle quantity increases from 25 to 300, the computation time increases by a factor of 5 accordingly. Considering the performance and complexity of the algorithm, the optimal algorithm population size N_{best} is obtained under different safe separations: $d_s = 5m$,

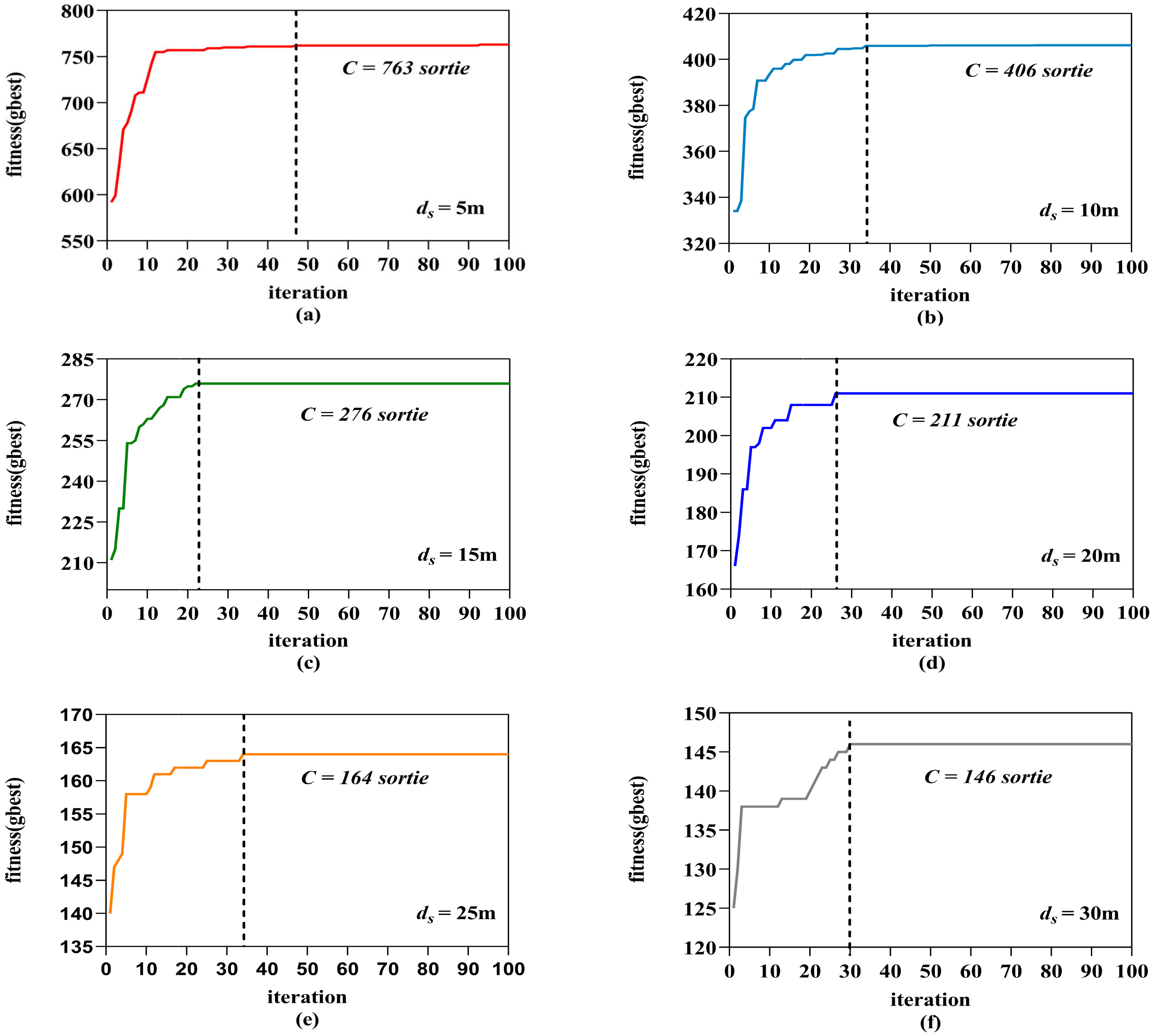

FIGURE 6. **Logistics UAV air route network capacity at different safe separations.**

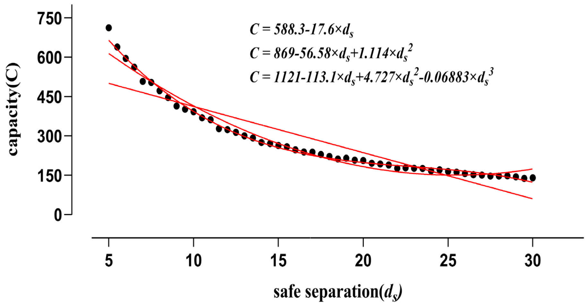

FIGURE 7. **Relationship between safe separations and Logistics UAV air route network capacity.**

$N_{best} = 225$, $d_s = 10m$, $N_{best} = 125$, $d_s = 15m$, $N_{best} = 200$, $d_s = 20m$, $N_{best} = 150$; $d_s = 25m$, $N_{best} = 175$, $d_s = 30m$, $N_{best} = 175$.

C. REAL SCENARIO

A preliminary attempt is made to evaluate the efficacy of the suggested model and algorithm based on the geographic information data in accordance with the analysis presented above. Nanyang Technological University has proposed three types of urban air route networks include AirMatrix, Over-buildings, and Over-roads [14]. Over-roads air route network refers to the urban road as the basis, 45m and 60m above the ground road. One of the advantages of the Over-roads air route network is that it can avoid interference from the ground building distribution. The geographic information data of a region in Nanjing, China were collected, air route nodes were adjusted according to the location of buildings, and a logistics UAV air route network based on real geographic information data was built, as shown in Figure 9. The logistics UAV air route network is divided into four communities,

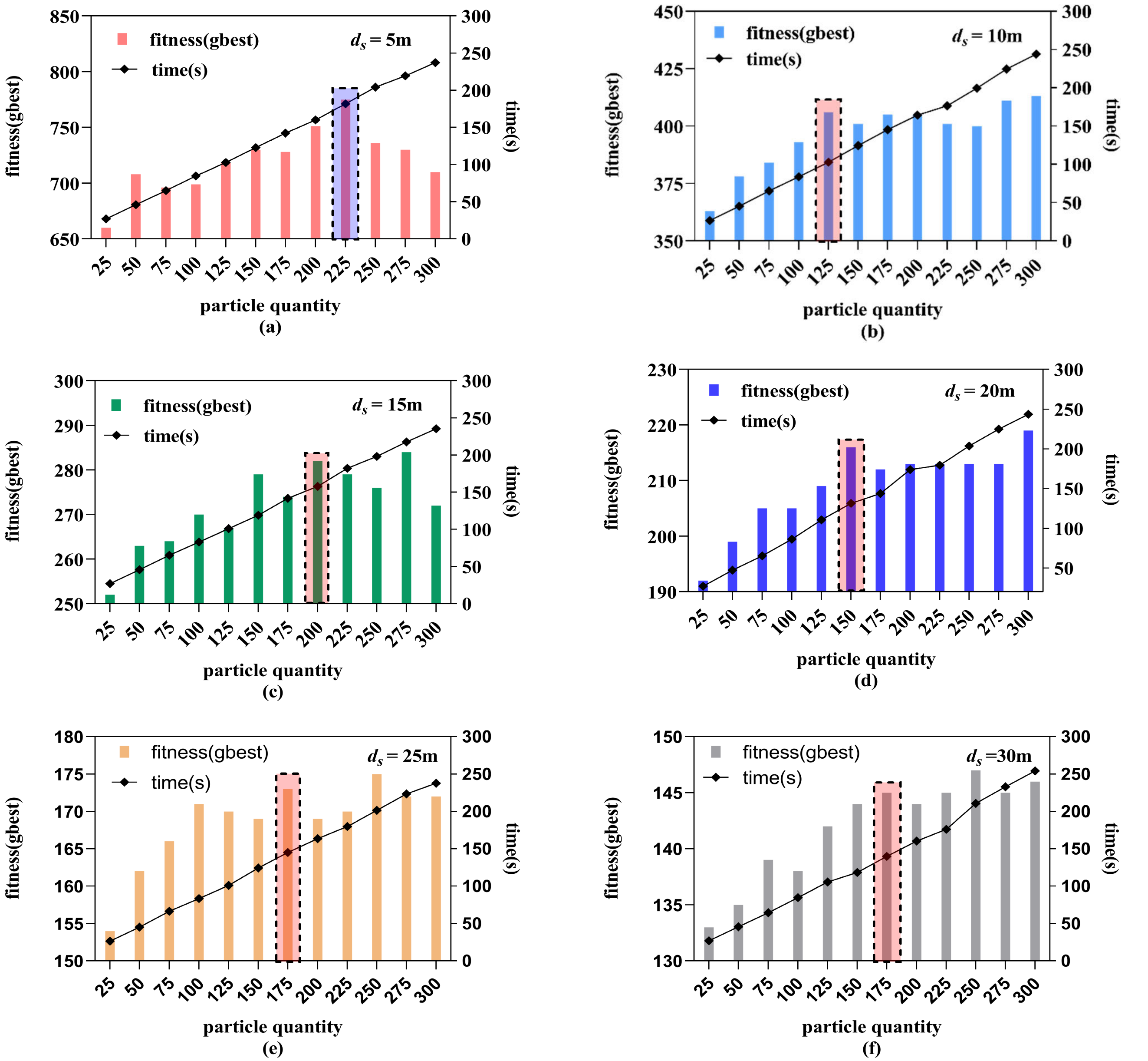

FIGURE 8. Logistics UAV air route network capacity at different population sizes.

and 4 logistics express stations and 42 receipt stations are randomly selected. Determine the air routes to ensure that the logistics UAVs can reach any receipt stations in its community, and return to express stations after completing delivery, as shown in Figure 10. This logistics UAV air route network has 46 nodes, 86 OD pairs, 64 segments, and 102 air routes.

Considering logistics UAV air route network is larger than the example in Section III-A, the algorithm population size is set to 200, and the iterations number is set to 200. Experiments are repeated for 20 times with different safe separations, and the result with the largest fitness value was used to draw the algorithm iteration curve, as shown in Figure. 11. According to Figure. 11, $d_s = 5m$, $C = 900$ sorties, $d_s = 10m$, $C = 498$ sorties, $d_s = 15m$, $C = 350$ sorties, $d_s = 20m$, $C = 261$ sorties, $d_s = 25m$, $C = 204$ sorties, $d_s = 30m$, $C = 175$ sorties. With the increase in safe separation, the algorithm reaches stability faster, the sensitivity of capacity to safe separation decreases gradually. The computation times of the 6 optimal solutions are 1513.29s, 1465.52s, 1422.23s, 1368.88s, 1387.49s, 1432.84s. As the logistics UAV air route network size increases, the computation time increases accordingly. The computation time for real scenario is almost 30 times longer than the example network, and the models and algorithms proposed in this paper can be applied to different sizes of logistics UAV air route networks.

FIGURE 9. Logistics UAV air route network in an area of Nanjing, China.

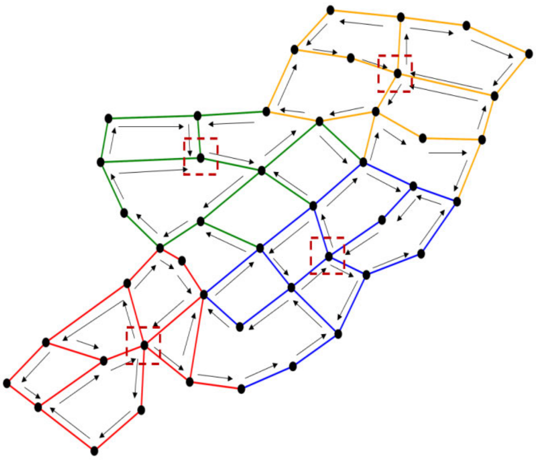

FIGURE 10. Topology of logistics UAV air route network in Nanjing, China.

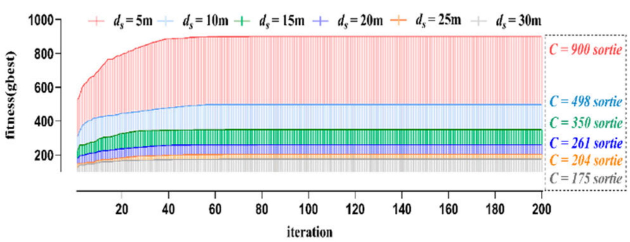

FIGURE 11. Algorithm iteration curve at different safe separations.

IV. CONCLUSION

To address the practical requirements of the large-scale operation of logistics UAVs, a technique for evaluating the air route network capacity of logistics UAVs is provided. The following are the key contributions:

1) The capacity of the logistics UAV route network is defined as the maximum number of UAV sorties that the air route network can serve, namely, the maximum flow of the logistics UAV air route network, and then bi-level logistics UAV air route network capacity evaluation optimization model is established. The Upper-bound model objective function is set as the maximum sum of the logistics UAV air route network flow. According to the Wardrop system optimization (SO) principle, the minimize the sum of logistics UAV air route network impedance value is lower-bound model objective.
2) The improved particle swarm optimization algorithm is combined with the method of the successive algorithm(MSA) to solve the bi-level logistics UAV air route network capacity evaluation optimization model. In order to verify the effectiveness of the proposed model and algorithm, a logistics UAV air route network consisting of 9 nodes, 16 OD pairs, 16 flight segments, and 24 air routes was built. The results show that the proposed algorithm achieves stable results after 26 iterations, and the capacity utilization rate of most segments is more than 70%.
3) Several groups of comparative experiments were designed respectively for safe separation and algorithm population size. With the increase in safe separation, the capacity of the logistics UAV air route network gradually decreases. and the sensitivity of capacity to safe separation decreases also gradually. The optimal algorithm population size corresponding to various safe separations is also different, and the corresponding algorithm population size should be selected according to the safe separation to reach the utility of the proposed model and algorithm.
4) The logistics UAV air route network based on real geographic information data was attempted to build, including 46 nodes, 86 OD pairs, 64 segments, and 102 air routes. The model parameters can be adjusted according to the real scene data, and according to the experimental results, the model and algorithm proposed in this paper can be applied to the capacity evaluation of logistics UAV air route network in real scenarios.

This paper follows the development trend of the scale and normalization of logistics UAVs and focuses on the evaluation method of the capacity of logistics UAV air route network for the complex and changing airspace operation environment at low altitude. The validity of the proposed model and algorithm is verified through experiments. This method applies traffic flow allocation theory to low-altitude airspace capacity evaluation, complementing current related research. In the future, the dynamic influencing factors will be considered, and the simulation verification of logistics UAV air route network capacity will be realized by establishing a 3D low-altitude airspace simulation operating environment.

REFERENCES

[1] P. Kopardekar. (2017). *Urban Air Mobility: Initial Reflections*. [Online]. Available: https://ntrs.nasa.gov/api/citations/20170009886/downloads/20170009886.pdf

[2] E. Sunil, J. Hoekstra, J. Ellerbroek, F. Bussink, D. Nieuwenhuisen, A. Vidosavljevic, and S. Kern, "Metropolis: Relating airspace structure and capacity for extreme traffic densities," in *Proc. ATM Seminar, 11th USA/EUROPE Air Traffic Manag. R D Seminar*, 2015, pp. 1–11.

[3] C. Reiche. (2018). *Urban Air Mobility Market Study*. [Online]. Available: https://escholarship.org/uc/item/0fz0x1s2

[4] K. Kuru, D. Ansell, W. Khan, and H. Yetgin, "Analysis and optimization of unmanned aerial vehicle swarms in logistics: An intelligent delivery platform," *IEEE Access*, vol. 7, pp. 15804–15831, 2019.

[5] E. G. Bowen and T. Pearcey, "Delays in the flow of air traffic," *Aeronaut. J.*, vol. 52, no. 448, pp. 251–258, 1948.

[6] W. Swedish, "Upgraded FAA airfield capacity model. Volume 1. Supplemental user's guide," Federal Aviation Admin., USA, Tech. Rep. FAA-em-81-1-vol-1, 1981.

[7] M. Zhang, L. Shan, M. Zhang, K. Liu, H. Yu, and J. Yu, "Terminal airspace sector capacity estimation method based on the ATC dynamical model," *Kybernetes*, vol. 45, no. 6, pp. 884–899, Jun. 2016.

[8] K. Ramamoorthy and G. Hunter, "Simulation-based airport capacity estimation," in *Proc. Aviation Technol., Integr., Oper. Conf.*, Aug. 2013, p. 4354.

[9] Z. Lv, H. Song, P. Basanta-Val, A. Steed, and M. Jo, "Next-generation big data analytics: State of the art, challenges, and future research topics," *IEEE Trans. Ind. Informat.*, vol. 13, no. 4, pp. 1891–1899, Aug. 2017.

[10] W. L. Cheung, R. Piplani, S. Alam, and L. Bernard-Peyre, "Dynamic capacity and variable runway configurations in airport slot allocation," *Comput. Ind. Eng.*, vol. 159, Sep. 2021, Art. no. 107480.

[11] M. Mohamed and S. Rong, "Neural partial differentiation-based estimation of terminal airspace sector capacity," *SAE Int. J. Aerosp.*, vol. 14, no. 2, p. 203, Jul. 2021.

[12] Q. Wang, "Research and application of simulation technology in airspace capacity assessment," in *Proc. 5th China Aeronaut. Sci. Technol. Conf.* Singapore: Springer, 2022, pp. 120–127.

[13] V. Bulusu, R. Sengupta, V. Polishchuk, and L. Sedov, "Cooperative and non-cooperative UAS traffic volumes," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Miami, FL, USA, Jun. 2017, pp. 1673–1681.

[14] V. Bulusu and V. Polishchuk, "A threshold based airspace capacity estimation method for UAS traffic management," in *Proc. Annu. IEEE Int. Syst. Conf. (SysCon)*, Montreal, QC, Canada, Apr. 2017, pp. 1–7.

[15] M. F. B. M. Salleh, C. Wanchao, Z. Wang, S. Huang, D. Y. Tan, T. Huang, and K. H. Low, "Preliminary concept of adaptive urban airspace management for unmanned aircraft operations," in *Proc. Inf. Systems-AIAA Infotech Aerosp.*, Jan. 2018, p. 2260.

[16] V. Bulusu, R. Sengupta, and Z. Liu, "Unmanned aviation: To be free or not to be free?" in *Proc. 7th Int. Conf. Res. Air Transp.*, 2016, pp. 1–8.

[17] V. Bulusu, V. Polishchuk, R. Sengupta, and L. Sedov, "Capacity estimation for low altitude airspace," in *Proc. 17th AIAA Aviation Technol., Integr., Oper. Conf.*, Jun. 2017, p. 4266.

[18] V. Bulusu, R. Sengupta, E. R. Mueller, and M. Xue, "A throughput based capacity metric for low-altitude airspace," in *Proc. Aviation Technol., Integr., Oper. Conf.*, Jun. 2018, p. 3032.

[19] J. Cho and Y. Yoon, "How to assess the capacity of urban airspace: A topological approach using keep-in and keep-out geofence," *Transp. Res. C, Emerg. Technol.*, vol. 92, pp. 137–149, Jul. 2018.

[20] K. Dalamagkidis, K. P. Valavanis, and L. A. Piegl, "Evaluating the risk of unmanned aircraft ground impacts," in *Proc. 16th Medit. Conf. Control Autom.*, Ajaccio, France, Jun. 2008, pp. 709–716.

[21] S. Primatesta, A. Rizzo, and A. L. Cour-Harbo, "Ground risk map for unmanned aircraft in urban environments," *J. Intell. Robotic Syst.*, vol. 97, nos. 3–4, pp. 489–509, Mar. 2020.

[22] K. Lachhwani and A. Dwivedi, "Bi-level and multi-level programming problems: Taxonomy of literature review and research issues," *Arch. Comput. Methods Eng.*, vol. 25, no. 4, pp. 847–877, Nov. 2018.

[23] A. Sinha, P. Malo, and K. Deb, "A review on bilevel optimization: From classical to evolutionary approaches and applications," *IEEE Trans. Evol. Comput.*, vol. 22, no. 2, pp. 276–295, Apr. 2018.

[24] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. Int. Conf. Neural Netw.*, Perth, WA, Australia, 1995, pp. 1942–194.

[25] M. B. Abdelhalim, A. E. Salama, and S. E.-D. Habib, "Hardware software partitioning using particle swarm optimization technique," in *Proc. 6th Int. Workshop Syst. Chip Real Time Appl.*, Cairo, Egypt, Dec. 2006, pp. 189–194.

[26] Y. Zou, H. Zhang, G. Zhong, H. Liu, and D. Feng, "Collision probability estimation for small unmanned aircraft systems," *Rel. Eng. Syst. Saf.*, vol. 213, Sep. 2021, Art. no. 107619.

[27] A. Z. J. Chen and J. P. T. Mo, "Modelling of unmanned aerial vehicle deliveries in populated urban areas for risk management," in *Proc. 10th Int. Conf. Softw., Knowl., Inf. Manag. Appl. (SKIMA)*, Chengdu, China, 2016, pp. 61–66.

JIA YI is currently pursuing the Ph.D. degree with the College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing, China. Her interests include urban air mobility and airspace capacity evaluation.

HONGHAI ZHANG received the Ph.D. degree from the Nanjing University of Aeronautics and Astronautics, Nanjing, China. He is currently working with the College of General Aviation and Flight, Nanjing University of Aeronautics and Astronautics, Nanjing, China. His interests include air traffic management and urban air mobility.

SHAN LI is currently pursuing the Ph.D. degree with the College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing, China.

Her interests include urban air mobility and air route network planning.

OUGE FENG is currently pursuing the Ph.D. degree with the College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing, China. His interests include urban air mobility and air traffic management.

GANG ZHONG received the Ph.D. degree from Southeast University, Nanjing, China. He is currently working with the College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing. His interests include the intelligent transportation systems and transportation data mining.

HAO LIU received the Ph.D. degree from the Nanjing University of Aeronautics and Astronautics, Nanjing, China. He is currently working with the College of Mathematics, Nanjing University of Aeronautics and Astronautics. His interests include the intelligent transportation systems and intelligence algorithm.