RESEARCH ON BILEVEL TASK PLANNING METHOD FOR MULTI-UAV LOGISTICS DISTRIBUTION
/
面向多农业无人机物流配送的双层任务规划方法研究

Zhibo LI*), Yuan LIU
Business School, Chongqing Polytechnic University of Electronic Technology, Chongqing/China
Tel: +8617815380036; E-mail: Lizhibo68513@126.com
Corresponding author: Zhibo LI
DOI: https://doi.org/10.35633/inmateh-74-67

Keywords: *Agricultural UAV, Bilevel planning model, Improved PSO algorithm, Path planning, Task allocation*

ABSTRACT
Multi-unmanned aerial vehicle (UAV) collaborative task planning and distribution path planning are the core content of agricultural UAV logistics distribution. In this study, the multi-UAV collaborative task planning and the distribution path planning were discussed, and such constraint conditions as UAV load capacity, battery capacity and flight time were comprehensively considered, aiming to reduce the number of UAVs and their power consumption. To ensure the safe and efficient completion of multi-UAV logistics distribution tasks, 3D agricultural ultralow space was subjected to environment modeling, and a bilevel planning model for collaborative planning of UAV distribution route and flight path was constructed. Then, an improved particle swarm optimization (PSO) algorithm with the improved learning factor and inertia coefficient was designed on the basis of PSO framework, and the global optimal solution in the current iteration was improved using variable neighborhood descent search. The feasibility of the proposed algorithm was verified by analyzing a practical case. With the central city area of XX City as the study area, 1 logistics & freight transportation center was taken as the central warehouse (coordinates: 50, 50, unit: km) and 50 intelligent express cabinets as the express cabinets of UAVs. The obtained results were comparatively analyzed with those acquired through the basic PSO algorithm. The results manifest that the proposed algorithm performs better than the compared algorithms. The improved PSO algorithm is superior to the basic PSO algorithm in aspects of total UAV flight distance, number of UAVs used and algorithm convergence time, indicating that the model and algorithm established in this study are feasible and effective.

摘要
多无人机任务协同规划与配送路径规划是农业无人机物流配送的核心内容，探讨多无人机任务协同规划与配送路径规划的农业无人机群配送路径的规划问题，综合考虑无人机载重量、无人机电池容量、无人机飞行时间等约束条件，目标为降低无人机数量及耗电量。为保障安全、高效完成多农业无人机物流配送任务，首先对三维农业超低空间进行环境建模，构建了一种无人机配送线路以及航迹协同规划的双层规划模型。基于粒子群算法框架设计了一种改进学习因子与惯性系数的改进粒子群算法，利用变邻域下降搜索对当前迭代中的全局最优解进行改进。通过实际案例分析，验证了该算法的可行性，以 XX 市中心城区为研究区域。选取 1 个物流货运中心作为中心仓库位置坐标(50,50)，单位(km)、50 个智能快递柜作为无人机快递柜位置。将所得结果与基础粒子群算法进行对比分析，结果表明，本算法性能优于对比算法，改进 PSO 得到的无人机飞行总距离，启用无人机数量和算法收敛时间等方面均优于基础粒子群算法，说明本文构建的模型与算法是可行的和有效的。

INTRODUCTION
Comprehensively driven by unmanned technological progress, policy assistance and market demand, unmanned aerial vehicles (UAVs) have been widely used in agricultural plant protection, traffic monitoring, logistics and transportation, bringing new opportunities to urban logistics *(Liu et al., 2024)*. UAV logistics enterprises are actively promoting the pilot of UAV in medical treatment and food delivery, but due to the limitation of endurance, the current research and practice focus on the terminal distribution of UAVs and the vehicle-aircraft joint distribution mode, which still faces cohesion and technical problems in practical application *(Li et al., 2024)*. Although the existing pure UAV distribution can meet certain needs, it is difficult to cope with the challenges in large-scale commercialization and complex scenarios in the future.

Therefore, it is more critical and necessary to explore the logistics UAV distribution mode in complex environments *(Wei et al., 2024)*.

The rapid development of urban residents' consumption power has contributed to the rapid development of e-commerce and the explosive growth of the logistics industry, yet also accompanied by urban traffic congestion, express delivery delay, etc. *(Fan et al., 2024)*. UAVs have the advantages of strong mobility, high flexibility and low cost, providing a new path to solve the "one kilometer at the terminal" of urban logistics, and exploratory practice has been carried out in lots of cities in China and abroad *(Zhang et al., 2023)*. The core task of multi-UAV logistics distribution is manifested in two aspects: allocation of distribution tasks, i.e., giving the order of goods delivery according to customer needs; distribution path planning, also called trajectory planning or route planning, namely, giving the flight path of UAVs to each task point *(Xu et al., 2024)*.

The current research on UAV logistics distribution mostly focuses on small-scale terminal delivery scenarios, and UAV charging factors have been fully considered in some studies. In terms of safety flight and UAV distribution task allocation, *Zhao et al. (2019)* comprehensively considered such constraint conditions as the operational reliability and flight performance of UAVs and established a multi-UAV collaborative task allocation model in logistics transportation with the minimum safety risk and logistics cost as the objective functions. *Li et al. (2015)* built a UAV task allocation model fully considering flight range, task revenue and task completion time window. *Zhang et al. (2018)* applied the particle swarm optimization (PSO) algorithm to solve the multi-UAV task allocation problem after realizing the discretization of UAVs through binary matrix encoding. With the minimum number of UAVs distributed and the shortest total range as the objectives, *Shao et al. (2020)* constructed a multi-objective function to solve the path collaboration problem in the cruising process of UAVs and solved it through the multi-objective evolutionary algorithm.

As for multi-UAV distribution path planning, specific research results have been achieved regarding multi-UAV collaborative path planning based on single-UAV path planning research. *Ma et al. (2021)* combined PSO with Hook-Jeeves search algorithm, first solved the path information of single UAVs, and then coordinated the arrival time through the centralized path planning layer, thus realizing the cooperative path planning of multiple UAVs; when coping with the needs of multiple UAVs to execute multi-target reconnaissance tasks in the military field, *Liu et al. (2022)* improved the traditional A* algorithm, K-means algorithm and depth traversal method and dynamically adjusted the task allocation according to real-time changes. *Liu et al. (2023)* proposed a hybrid differential crow search algorithm based on Levy flight strategy, which added pruning and Logistic chaotic mapping mechanism to the fast traversal random tree algorithm, and initialized the path through the improved rapidly exploring random tree (RRT), so as to improve the efficiency of heterogeneous UAV path planning.

When it comes to the research on the integration of task allocation and path planning, *Yuan et al. (2020),* designed a two-layer mutual coupling task planning solution strategy, and used a nested two-layer model to solve the task allocation, attack sequence and path planning problems of multiple military UAVs in a two-dimensional environment. *Wu et al. (2021)* designed a two-stage hybrid algorithm based on Deep Reinforcement Learning (DRL). In the first stage, DRL algorithm was used to generate the distribution routes of multiple UAVs visiting customers in sequence, and in the second stage, A* algorithm was applied to search the shortest path of each UAV. The current research on multi-UAV collaborative path planning focuses on 2D space, while urban 3D spatial environments have been rarely involved. *Hwang et al. (2015)* put forward the concept of "the last mile of UAV delivery" earlier. *Tassone et al. (2016)* raised the FSTSP problem, distinguished the distribution nodes of UAVs and trucks, carried out distribution with a truck carrying a UAV, and constructed a hybrid integer planning model and heuristic algorithm for solving. *Chen et al. (2021)* proposed the TSP-D problem, which made the UAV and the truck exist in the same distribution network, and the UAV could start from the same location and return to the truck. *Zhou et al. (2018)* further studied the TSP-D problem, improved the hybrid integer planning model and solved it by designing the simulated annealing algorithm. *Yang et al. (2020)* designed a dynamic planning algorithm for TS-D problem, which could solve larger-scale problems. *Zhang et al. (2022)* put forward the VRP-D problem with the objective of minimizing the completion time of distribution, which included multiple trucks and multiple UAVs. *Agha et al. (2023)* added effective inequations to the proposed model, allowed UAVs to implement closed-loop flight, and designed a heuristic algorithm to solve large-scale examples. Another application scenario widely concerned in the academic circles is the distribution of emergency medical materials using UAVs.

Ma et al. (2021) studied the distribution of drugs for chronic diseases and the recovery of test samples in rural areas using UAVs, and used decomposition method and Lagrange relaxation algorithm to accurately solve the problem. *Hao et al. (2017)* proposed a UAV path model based on the minimization of time and cost.

Hu et al. (2020) studied the scheduling optimization of UAVs, considered the battery energy consumption rate related to the load capacity of UAVs, established a hybrid integer planning model and used the boundary generation algorithm of the original problem and the dual problem to speed up the solving process. *Han et al. (2021)* explored the drug distribution problem of UAVs in the last mile of the disaster-stricken area, and established a mixed integer planning model considering the energy consumption of UAVs related to load capacity and flight distance.

In this study, environment modeling was performed using the grid method in an urban ultralow (<120 m) 3D environment. Considering the constraints of obstacles, a bilevel planning model for UAV task allocation and collaborative path planning was proposed. The problems at the upper and lower levels were mutually nested and influenced each other. Given that both levels of the model belonged to NP-hard problem, the upper-level model was solved by introducing the genetic algorithm, and an improved PSO algorithm was designed to solve the bottom-level model problem. Finally, the effectiveness of the algorithm and model was analyzed by means of simulation.

MATERIALS AND METHODS

Problem description

The path planning problem of logistics UAVs can be defined as an undirected complete graph $G=(V,A)$, where V represents the set of vertexes, including customer point information set, warehouse point 0 and obstacle information set; *A* denotes the set of arcs. All customer points are distributed on the transportation network. UAV k fully loaded with cargoes starts from warehouse point 0, arrive at the customer point i to be served, each customer point i has a receipt demand B_i, the service time of the UAV at customer point i is τ_i, within which the UAV can complete unloading work by default, and after serving customer point i, the UAV continues to fly to the next customer point until the residual load capacity C_{ik} or residual battery capacity of UAV k is not enough to arrive at the next customer point (in this case, the residual battery capacity of the UAV can support the UAV to return to warehouse point 0 from the current location), and then returns to warehouse point 0.

During the flight process, UAVs will be affected by weather, environment and other external factors. This study mainly focuses on path planning. Assuming that UAVs fly under ideal environment, greater attention is then paid to the constraints of UAVs themselves. The flight time and mileage of UAVs are directly influenced by their power consumption, which, in turn, is closely related to their load capacity. To be more practical, the influence of cargo load capacity on the residual battery capacity of UAVs is taken into account. *Song et al. (2018)* put forward a flight time weight function based on the present load capacity and proved that the battery power consumption is linearly correlated with the load capacity.

Then, the power consumption based on the current residual load capacity of UAVs can be calculated as follows (1) and (2):

$$f(C_{ik})=1+\left(\frac{U-1}{Q}\right)C_{ik},\forall i\in\Omega_J,k\in\Omega_K \tag{1}$$

$$E(i,j,C_{ik})=f(C_{ik})e\left(d_{ij}/S_{\mathrm{p}}\right),\forall i\in\Omega_J,j\in\Omega_J,k\in\Omega_K \tag{2}$$

where k is UAV number; *i* and *j* are customer point numbers, $i,j\in\{1,2,3,\dots,N\}$; *N* denotes the total number of customer points. $i,j=0$ indicates the warehouse point; represents the residual load capacity of UAV k when starting from customer point i; Q is the maximum load capacity of UAVs; U is a proportionality factor; $f(C_{ik})$ means the power consumption factor under load capacity of C_{ik}; *e* is the power consumption of UAVs within unit time; S_p is the flight speed of UAVs; d_{ij} is the distance from customer point i to j; $E(i,j,C_{ik})$ is the battery power consumption when UAVs fly from customer point i to j under load capacity of C_{ik}; *E* represents the total battery capacity of UAVs; Ω_J is the set of customer points; Ω_k is the UAV number set. When calculating the power consumption of a UAV when unloading cargoes at one customer point, the residual load capacity is calculated according to the load capacity before unloading at the current customer point.

Model hypotheses

The model hypotheses are described as follows:

(1) Each customer point is served and only once;
(2) The flight loop of each UAV is completed within the limited duration of the battery;
(3) It is assumed that only one distribution center exists in this area;
(4) All UAVs are of the same model but different speeds, load capacities and ranges;
(5) UAVs unload cargoes at each customer point within the same time;
(6) The weights of cargoes to be distributed by UAVs to each customer are different, and the unloading time is also different.

Modeling

The objective functions and constraint conditions of the bilevel task planning problem facing multi-UAV logistics distribution are as below:

$$F_{\mathrm{U}}=\alpha \sum_{k\in\Omega_K}\sum_{j\in\Omega_J} X_{ojk}+\beta\sum_{k\in\Omega_K}\sum_{i\in\Omega_F}\sum_{j\in\Omega_F} f\,(C_{ik})(d_{ij}/S_{\mathrm{p}}+\tau_j) \tag{3}$$

$$\sum_{j\in\Omega_F}\sum_{k\in\Omega_K} X_{ijk}=1, \forall j\in\Omega_J \tag{4}$$

$$\sum_{i\in\Omega_F}\sum_{k\in\Omega_K} X_{ijk}=1, \forall j\in\Omega_J \tag{5}$$

$$\sum_{j\in\Omega_j} X_{0jk}=\sum_{i\in\Omega_j} X_{i0k}, \forall k\in\Omega_K \tag{6}$$

$$\sum_{i\in\Omega_J}\sum_{j\in\Omega_F} B_i\, X_{ijk}\leqslant Q, \forall k\in\Omega_K \tag{7}$$

$$\sum_{i\in\Omega_F} X_{ijk}=\sum_{i\in\Omega_F} X_{jik}, \forall j\in\Omega_J, \forall k\in\Omega_K \tag{8}$$

$$T_{jk}\geqslant T_{ik}+d_{ij}/S_{\mathrm{p}}+\tau_j-M(1-X_{ijk}), \forall i\in\Omega_F, \forall j\in\Omega_F, \forall k\in\Omega_k \tag{9}$$

$$C_{ik}\geqslant C_{jk}+B_j-M(1-X_{ijk}), \forall i\in\Omega_F, \forall j\in\Omega_F, \forall k\in\Omega_k \tag{10}$$

$$O_{ik}\geqslant O_{jk}+f(C_{ik})\left(d_{ij}/S_{\mathrm{p}}+\tau_j\right)-M\left(1-X_{ijk}\right), \forall k\in\Omega_k \tag{11}$$

$$\sum_{i\in\Omega_F}\sum_{j\in\Omega_F} X_{ijk}\,(f(C_{ik})(d_{ij}/S_{\mathrm{p}}+\tau_j))\leqslant E, \forall k\in\Omega_k \tag{12}$$

$$T_{ck}\geqslant 0 \tag{13}$$

$$C_{ik}\geqslant 0 \tag{14}$$

$$O_{ik}\geqslant 0 \tag{15}$$

$$X_{ijk}\in\{0,1\} \tag{16}$$

Formula (3) is the optimized objective function, including reducing the number of UAVs and their total power consumption. α represents the weight coefficient for the number of UAVs; β denotes the weight coefficient for power consumption. When α=1 and β=0, the only optimization objective is to reduce the number of UAVs; when α=0 and β=1, the only optimization objective is to reduce the power consumption of UAVs. Another weight method is adopted, a very great positive integer M is taken, and when α is close to 1, β is the reciprocal of M. To ensure that value range of the part after the plus sign on the right side of Formula (3) is 0-1, $M>2E$ should be satisfied; As the change in the number of UAVs before the plus sign on the right side of Formula (3) is an integer variable, Formula (3) indicates that the main optimization objective is to reduce the number of UAVs while the secondary objective is to reduce the power consumption of UAVs. Formula (4) means that for any customer point, the corresponding backward node can only be a point, i.e., ensuring that each customer point will be served only once. Formula (5) indicates that for any customer point, the corresponding forward node can only be a point, i.e., ensuring that each customer point will be served only once. Formula (6) ensures that each UAV starts from the warehouse point and finally returns to this point. Formula (7) manifests that the load capacity of UAVs during one flight should not exceed the maximum load capacity of UAVs. Formula (8) means that if UAV *k* works at customer point *i*, it must be UAV *k* that leaves after completing the work, i.e., ensuring that each customer point can only be served by one UAV simultaneously. Formula (9) indicates the flight time change when a UAV flies from customer point i to customer point *j*. Formula (10) denotes the change of the residual load capacity when UAV *k* flies from customer point *i* to customer point *j*. Formula (11) constrains that when UAV k flies from customer point *i* to customer point *j*, the residual battery capacity when leaving customer point *i* should be greater than the residual battery capacity when leaving customer point *j*. Formula (12) ensures that the total power consumption for a UAV to complete one loop should be greater than or equal to the total battery capacity of this UAV. Formula (13) ensures that the residual time of UAVs is a positive value.

Formula (14) ensures that the residual load capacity of UAVs is positive. Formula (15) ensures that the residual battery capacity of UAVs is positive. Formula (15) is a decision variable, when UAV *k* flies from customer point *i* to customer point *j*, $X_{ijk} = 1$, otherwise, it is equal to 0.

How to solve the path optimization problem accurately and efficiently has always been a major problem. In the existing research, heuristic algorithm is generally used to solve similar problems. As a heuristic algorithm, whale optimization algorithm has been widely developed and applied because of its simple mechanism, few parameters and strong optimization ability. By improving the standard PSO algorithm, models can be solved faster and more effectively.

PSO algorithm

The PSO algorithm assumes that every member of the population is a particle with no mass and the same volume, and each particle has a memory and moves at a specific speed. Each particle is extended to form an n-dimensional structure, and all particles are given the fitness value of the function. When the PSO algorithm is started, the particles will be distributed at any position in space, that is, initializing the random solution set. In the subsequent iterative evolution, the particles will not only remember their own "best experience" but also learn from other particles' "best experience", and then constantly adjust the direction and speed of movement to move to the destination with "best experience". The particle moves in the space limited by the optimization condition, and its movement direction is influenced by three factors: the movement speed of the particle, the best position of itself and the best position of the whole population.

The PSO algorithm model is described as follows: Assuming an E-dimensional search space, the particle swarm P consists of *m* particles, and all particles therein move at a specific speed. The position of the *m* particles is expressed as $X = \{x_1, x_2, x_3, \dots, x_n\}$, their speed as $V = \{v_1, v_2, v_3, \dots, v_n\}$, and their position in the space as E -dimensional vector X. $X = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{iE}), (i = 1,2,3, \dots, n)$. For instance, the L -dimensional position of the i -th particle is X_{iL}. During algorithm operation, the particles will share information with other particles according to their own path memory, the position of each particle is continuously adjusted as per its movement speed, and the speed of the i -th particle is $V = (v_{i1}, v_{i2}, v_{i3}, K, v_{iE}), (i = 1,2,3, K, n)$. Assuming that the best historical position reached by one particle is expressed as $p_i = (p_{i1}, p_{i2,} p_{i3}, \cdots, p_{iE}), (i = 1,2,3, \dots, n)$, the best position obtained by all particles in the particle swarm is $g_i = (g_{i1}, g_{i2}, g_{i3}, \cdots, g_{iE}), (i = 1,2,3, \dots, n)$. Each particle is slightly correlated with the objective function and fitness value, and the particle position X is substituted into the objective function to obtain the corresponding function fitness value. By comparing fitness values, their matching degree with the objective function can be judged, and finally particles will continuously adjust their speed and position to find out the optimal solution of the objective function.

During algorithm operation, particles share information with other particles based on their own path memory. The position of each particle is continuously adjusted according to their movement speed, and the speed of the i-th particle is expressed as $V = (v_{i1}, v_{i2}, v_{i3}, K, v_{iE}), (i = 1,2,3, K, n)$. Assuming that the best historical position reached by one particle is denoted as $p_i = (p_{i1}, p_{i2,} p_{i3}, \cdots, p_{iE}), (i = 1,2,3, \dots, n)$, the best position obtained by all particles in the particle swarm is $g_i = (g_{i1}, g_{i2}, g_{i3}, \cdots, g_{iE}), (i = 1,2,3, \dots, n)$. Each particle is slightly correlated with the objective function and fitness value, and the particle position X is substituted into the objective function to obtain the corresponding function fitness value. By comparing fitness values, their matching degree with the objective function can be judged, and finally particles will continuously adjust their speed and position to find out the optimal solution of the objective function.

Taking seeking for the minimum value in the structure for example, the individual iterative formula is shown in Formula (17):

$$p_i^{\vec{n}+1} = \begin{cases} f(X_i^{-n+1}), if \quad \mathrm{f}(X_i^{-n+1}) < p_i^{-n} \\ p_i^{-n}, else \end{cases} \tag{17}$$

Particles operate with the algorithm, and their speed and position changes are expressed by Formulas (18) and (19):

$$v_{ie}^{K+1} = v_{ie}^{K} + c_1 r_1 (p_{ie}^{K} - x_{ie}^{K}) + c_2 r_2 \left(p_{ge}^{K} - x_{ie}^{K}\right) \tag{18}$$

$$x_{ie}^{K+1} = x_{ie}^{K} + v_{ie}^{K+1} \tag{19}$$

In the above formula, $i = 1,2,3 \cdots, K; e = 1,2,3, \cdots, K$; c_1 and c_2 generally fluctuate within 0-4, usually taken as 2; r_1 and r_2 are random numbers within [0,1]. x_{ie}^{K} indicates the present e-dimensional position of particle *i* in the *K*-the iteration.

Improved PSO algorithm

Given the abovementioned advantages and disadvantages of PSO algorithm and in order to overcome the proneness of PSO algorithm to local optimum and realize the stronger optimization ability and the higher convergence rate, algorithm parameters were first improved, and learning factors c_1 and c_2 and inertia weight ω were subjected to algorithm optimization. The learning factors c_1 and c_2 were improved as follows: Self-learning factor c_1 and social learning factor c_2 tended to change synchronously in the running process of the improved PSO algorithm, and the two continuously changed within $[c_{\min}, c_{\max}]$ with time during the whole optimization process. This optimization measure improved the learning ability of particles before algorithm operation, and particles were searched globally; after algorithm improvement, the social learning ability of particles was relatively weak but their self-learning ability was strong, which could accelerate convergence to obtain the optimal solution faster. The value of the learning factor upon the *t*-th iteration is solved as per Formula (20):

$$c_1 = c_2 = c_{\max} - \frac{c_{\max} - c_{\min}}{t_{\max}} \times t \tag{20}$$

The inertia weight ω was improved as below: The linear decrease in ω could easily lead to the local optimum of the PSO algorithm. To avoid this circumstance, in the improved PSO algorithm, ω was set to a variable number randomly distributed with movement during operation. First, at the initial evolution stage with the gradual closeness to the optimal point, relatively efficient values might be randomly generated to accelerate the algorithm convergence rate; then, if the algorithm failed to search the optimal value in the initial stage, values would be randomly generated according to the specific circumstance to overcome the local optimum induced by linear decrease. The calculation formula for ω is as shown in Formula (21).

$$\begin{cases} \omega = \mu + \sigma * N(0,1) \\ \mu = \mu_{\min} + (\mu_{\max} - \mu_{\min}) * rand(0,1) \end{cases} \tag{21}$$

Where $N(0,1)$ represents the variable number following a quasi-normal distribution; $rand(0,1)$ denotes a variable number within 0-1. In addition to the improvement of learning factors c_1 and c_2 and inertia weight ω, the model results could reach the optimum if relevant parameters were adjusted according to the established model in this study.

RESULTS

Hardware environment and parameter settings

To verify the effectiveness of the model and algorithm under different scales, the central city area of XX City was taken as the study area. Taking the location distribution as the standard, several nodes whose distribution relatively conform to the problem description were screened out, including 1 logistics & freight transportation center as the central warehouse (position coordinate: 50,50, unit: km) and 50 intelligent express delivery cabinets as the UAV express delivery cabinets plus the quantity demanded, as shown in Table 1.

Table 1

Position coordinates of UAV express delivery cabinets and quantity demanded

No.	X (km)	Y (km)	Quantity demanded (kg)	No.	X (km)	Y (km)	Quantity demanded (kg)
1	37	30	1	26	46	46	2
2	57	79	3	27	78	72	2
3	78	21	1	28	37	11	1
4	18	62	1	29	98	23	1
5	67	50	1	30	83	37	1
6	55	76	2	31	10	49	2
7	32	58	2	32	28	100	3
8	54	76	2	33	58	30	1

No.	X (km)	Y (km)	Quantity demanded (kg)	No.	X (km)	Y (km)	Quantity demanded (kg)
9	10	53	1	34	66	18	4
10	33	61	1	35	4	78	4
11	78	45	1	36	4	68	2
12	59	12	2	37	37	42	2
13	16	11	3	38	64	74	1
14	76	55	1	39	79	30	1
15	80	2	4	40	79	68	1
16	13	43	4	41	28	8	2
17	37	54	2	42	38	30	3
18	55	18	2	43	44	100	1
19	32	29	1	44	25	1	4
20	68	40	1	45	78	26	4
21	75	94	2	46	33	74	2
22	60	89	2	47	27	79	2
23	65	33	1	48	76	79	1
24	58	7	1	49	35	61	1
25	77	69	1	50	67	95	1

The battery capacity of UAVs was, 6.48×106C, the power consumption within unit time was 70.4C/s, the maximum load capacity was 15 kg, the no-load duration of flight was 120 min, the full-load duration of flight was 30 min, the flight speed was 20 m/s, the hovering time was 30 s, and the proportionality coefficient was U=1.5. This example was solved using the improved PSO algorithm. The population size of the algorithm was designed as 100, the number of VND iterations as 100, and the cycle index as 100. The duration of flight was taken as the mean value (120 min) of full-load duration and no-load duration, i.e., $\alpha = 1, M = 50000, \beta = 1/M$.

Simulation results

Based on the above designed model, the example was solved using the improved PSO algorithm. The results show that a total of 6 UAVs are needed to serve all customer points as required, the algorithm convergence curve is displayed in Fig 1, and the customer points served by each UAV are exhibited in Fig 2.

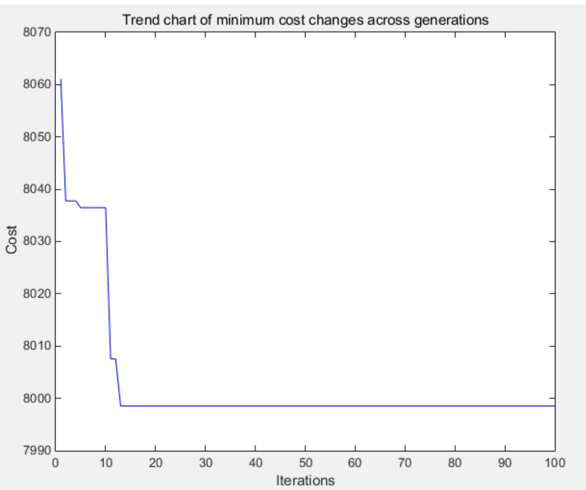

Fig. 1 – Convergence curve of improved PSO algorithm

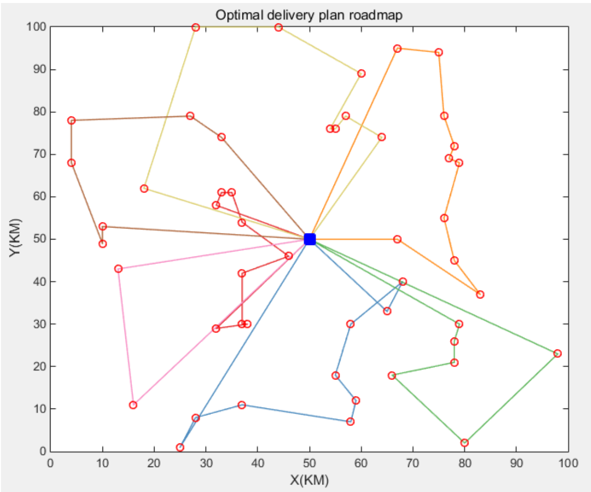

Fig. 2 – Optimal distribution path of improved PSO algorithm

The calculation example was solved using the improved PSO algorithm, and the UAV path results obtained by the improved PSO algorithm are displayed in Table 2.

In Table 4. No.1 represents UAV distribution station, and No.2-51 denote 50 demand points; a total of 7 UAVs return to the distribution station after completing the distribution task. The total flight distance is 998.56 km and the algorithm convergence time is 854.72 s.

Table 2

UAV path of improved PSO algorithm

S/N	UAV path
UAV1	0→7→10→49→17→26→37→1→42→19→0
UAV2	0→44→41→28→24→12→18→33→20→23→0
UAV3	0→39→45→3→34→15→29→0
UAV4	0→50→21→48→27→25→40→14→11→30→5→0
UAV5	0→38→2→6→8→22→43→32→4→0
UAV6	0→9→31→36→35→47→46→0
UAV7	0→16→13→0

Algorithm verification

To further verify the effectiveness of the algorithm, the basic PSO algorithm was adopted to test an example under the same simulation conditions. The difference between the basic PSO algorithm and the improved PSO algorithm is that the former lacks the optimization of learning factors and inertia weights. The experimental results obtained by the basic PSO algorithm based on repeated tests are shown in Table 3, the convergence curve of the algorithm is shown in Fig 3, and the path of the UAVs is shown in Fig 4. A total of 8 UAVs return to the distribution station after completing the distribution task. The total flight distance is 1074.12 km, and the convergence time of the algorithm is 992.56 s.

According to the experimental results in Table 2 and Table 3, the improved PSO is superior to the basic PSO algorithm in solving the bilevel task planning problem for multi-agricultural UAV logistics distribution. Besides, the improved PSO performs better than the basic PSO in terms of the total flight distance, the number of UAVs enabled and the convergence time of the algorithm. This shows that the optimization of learning factors and inertia weights by improved PSO ensures the diversity of particle swarm, enhances the local search ability of the algorithm, and improves the accuracy and quality of the solution. This manifests that PSO can better arrange the customer distribution order, meet the time window of customers to the greatest extent, and improve their consumption experience. Therefore, for the bilevel task planning problem of multi- UAV logistics distribution, the improved PSO algorithm has more advantages than the basic PSO algorithm, because particles have the characteristics of dynamically tracking extreme values and storing historical memories, and it is easier to detect changes in the external environment, so as to jump out of the previous environment to adapt to the new environmental conditions, making it easier to search for the global optimal solution to the problem.

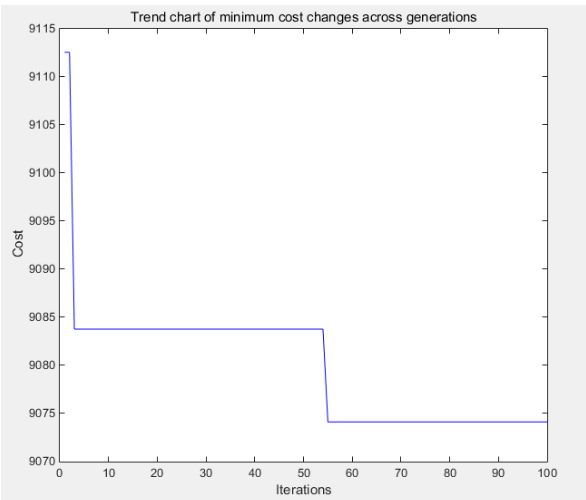

Fig. 3 – Convergence curve of basic PSO algorithm

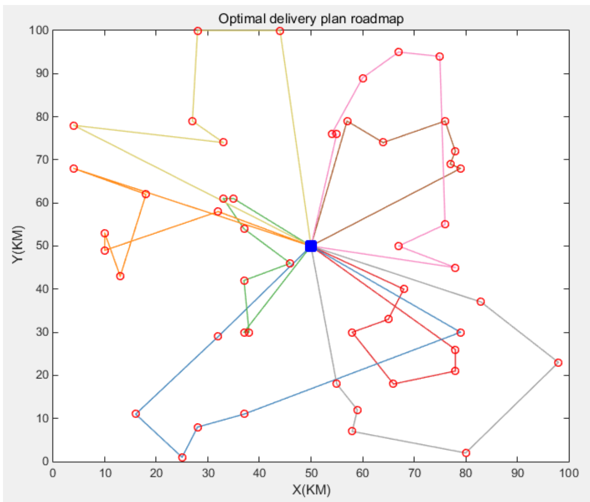

Fig. 4 – Optimal distribution path of basic PSO algorithm

Table 3

UAV path of basic PSO algorithm

S/N	UAV path
UAV1	0→20→23→33→34→3→45→0
UAV2	0→39→28→41→44→13→19→0
UAV3	0→1→42→37→26→17→10→49→0
UAV4	0→7→31→9→16→4→36→0
UAV5	0→35→46→47→32→43→0
UAV6	0→40→25→27→48→38→2→0
UAV7	0→6→8→22→50→21→14→5→11→0
UAV8	0→30→29→15→24→12→18→0

CONCLUSIONS

The bilevel task planning for multi-UAV logistics distribution is one of the hot topics in the academic circles in China and abroad at this stage. Multi-UAV task allocation and path planning do not exist independently, so their coupling relationship must be considered to carry out integrated research. Considering the factors of energy consumption and time window, UAV path problem modeling and solving algorithm were investigated in this study, which can not only provide decision-making reference for the R & D, application and promotion of logistics UAVs in relevant enterprises but also enrich and extend the theoretical research on vehicle paths in the academic circles. Specifically, the model was solved by designing the improved PSO algorithm, which could gain an effective task allocation and path planning scheme and provide theoretical guidance for practicing the bilevel task planning problem of multi-UAV logistics distribution. The established bilevel task planning model for multi-UAV logistics distribution and the adopted example can be referenced by other research work. In the follow-up research, accurate algorithms with better solving efficiency or heuristic algorithms with better solving effects can be searched for, and the modeling and solving algorithm for the extended problem of bilevel task planning for multi-UAV logistics distribution can also be explored. In addition, this article focuses on the flight path at the planning level and does not address the issue of flight conflicts at the operational level. In the future, the focus will be on solving this problem.

REFERENCES

[1] Agha, K., & Vojdani, A. (2023). Adaptive Path Planning for UAVs in GPS-Denied Environments. *Aerospace Science and Technology,* Vol. 118, pp. 107892, France.

[2] Chen, W., & Wu, X. (2021). Autonomous UAV path planning in dynamic environments using an algorithm and fast marching method. *Robotics and Autonomous Systems*, Vol. 139, pp. 103747, Netherlands.

[3] Fan, H.M., Gan, L., Zhang, Y.G., & Bai, X. (2024). Optimization of collaborative distribution path between time-dependent vehicles and UAVs with no-fly zone (有禁飞区的时间依赖型车辆与无人机协同配送路径优化). *Control Theory & Application*, Vol. 41, pp. 321-330, Guangdong/China.

[4] Han, P., & Zhao, Y. F. (2021). An air route planning model of unmanned aerial vehicles under constraints of ground safety. *Transactions of Nanjing University of Aeronautics and Astronautics*, Vol. 38, pp. 298-305, Nanjing/China.

[5] Hao, L., Tang, J., Wang, Q., Tao, H., Ma, X., Ma, D., & Ji, H. (2017). Fractal characteristics of tight sandstone reservoirs: A case from the Upper Triassic Yanchang Formation, Ordos Basin, China. *Journal of Petroleum Science and Engineering*, Vol. 158, pp. 243-252, Beijing/China.

[6] Hwang, Y. H., & Agha, K. (2015). Path Planning and Navigation for Autonomous UAVs in Unknown Environments. *Journal of Intelligent & Robotic Systems*, Vol. 78, pp. 227-239, Netherlands.

[7] Hu, Y., Guo, Y., Shangguan, J., Zhang, J., & Song, Y. (2020). Fractal characteristics and model applicability for pores in tight gas sandstone reservoirs: A case study of the Upper Paleozoic in Ordos Basin. *Energy & Fuels*, Vol. 34, pp. 16059-16072, United States.

[8] Li, N., & Xin, C. Y. (2024). "Vehicle + UAV" urban logistics distribution path optimization based on clustering-Floyd-genetic algorithm (基于聚类-Floyd-遗传算法的"车辆+无人机"城市物流配送路径优化). *Science Technology and Engineering*, Vol. 24, pp. 141-150, Beijing/China.

[9] Li, X., Liu, L., & Ding, Z. (2015). A Hybrid Particle Swarm Optimization for Multi-UAV Path Planning. Computers. *Environment and Urban Systems*, Vol. 53, pp. 62-75, United Kingdom.
[10] Liu, S., & Zhang, L. (2023). Dynamic and Adaptive Path Optimization for Autonomous Drone Delivery Systems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 53, pp. 3592-3605, United States.
[11] Liu, X. X., Xu, Z. F., Li X. L., & Xu, J. H. (2024). Research on the Path of Vehicle+UAV Delivery Model Based on a Two-stage Approach (基于两阶段法的车+无人机配送模式路径研究). *Journal of Taiyuan University of Science and Technology*, Vol. 45, pp. 409-414+420, Shanxi/China.
[12] Liu, Z., & He, Z. (2022). Energy-Efficient Path Planning for UAV-Based Delivery Systems. *International Journal of Environmental Research and Public Health*, Vol. 16, pp. 7907, Switzerland.
[13] Ma, J., & Hu, S. (2021). Multi-UAV Path Planning in Urban Environments for Package Delivery: A Review. *International Journal of Robotics and Automation*, Vol. 36, pp. 14-25, United States.
[14] Shao, S., Peng, Y., He, C., & Du, Y. (2020). Efficient path planning for UAV formation via comprehensively improved particle swarm optimization. *ISA transactions*, Vol. 97, pp. 415-430, United States.
[15] Song, B. D., Park, K., & Kim, J. (2018). Persistent UAV Delivery Logistics: MILP Formulation and Efficient Heuristic. *Computers & Industrial Engineering*, Vol. 120, pp. 418-428, United States.
[16] Tassone, D., & Amato, N. (2016). A Review on UAV Path Planning Algorithms and Applications. *In Proceedings of the 2016 IEEE International Conference on Robotics and Automation* (ICRA), pp. 3999-4004, United States.
[17] Wei, M., Wu, L., & Sun, B. (2024). An optimization model of emergency distribution path for UAVs with multiple material types (一类多物资类型无人机应急配送路径优化模型). *Mathematics in Practice and Theory*, Vol. 54, pp. 215-218, Beijing/China.
[18] Wu, X., Yin, Y., Xu, L., Wu, X., Meng, F., & Zhen, R. (2021). Multi-UAV task allocation based on improved genetic algorithm. *IEEE Access*, Vol. 9, pp. 100369-100379, United States.
[19] Xu, L., Yang, L. C., Zhu, W. X., & Zhong, S. J. (2024). Research on optimization of collaborative distribution path between UAVs and vehicles under rural E-commerce logistics (农村电商物流下无人机与车辆协同配送路径优化研究). *Computer Engineering and Applications*, Vol. 60, pp. 310-318, Beijing/China.
[20] Yang, J., & Wang, Y. (2020). Task Scheduling and Path Planning for Autonomous UAVs in Large-Scale Networks. *International Journal of Robotics and Automation*, Vol. 35, pp. 104-113, United States.
[21] Yuan, J., & Zhang, D. (2020). A Review on Path Planning for UAVs: Key Issues and Solutions. *Aerospace Science and Technology*, 99, 105721. China
[22] Zhang, X., & Zhang, X. (2018). Drone Delivery System: Optimal Path Planning with Multiple Depots and Uncertain Demand. *Computers and Industrial Engineering*, Vol. 116, pp. 383-398, United Kingdom.
[23] Zhang, Y., & Li, W. (2022). Deep Reinforcement Learning for UAV Path Planning in Complex Environments. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 52, pp. 5730-5741, United States.
[24] Zhang, Y., & Wei, D. C. (2023). Automatic optimization method of UAV logistics distribution path based on improved genetic algorithm (基于改进遗传算法的无人机物流配送路径自动优化方法). *Modern Computers*, Vol. 29, pp. 72-74, Shandong/China.
[25] Zhao, J., Liu, W., & Wang, H. (2019). Optimization of Drone Delivery Path Using Genetic Algorithm and Ant Colony Optimization. *Journal of Intelligent & Robotic Systems*, Vol. 95, pp. 479-491.
[26] Zhou, H., & Shi, P. (2018). Path Planning for UAVs in Urban Environments with Mission Constraints. *Journal of Intelligent & Robotic Systems*, Vol. 92, pp. 297-310, Netherlands.