RESEARCH ON AGRICULTURAL LOGISTICS DISTRIBUTION PATH PLANNING CONSIDERING UAV ENDURANCE MILEAGE LIMIT
/
考虑无人机续航里程限制的农业物流配送路径规划研究

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ABSTRACT
To address the difficulties in logistics distribution in remote rural areas, a systematic planning of agricultural logistics distribution for UAV distribution was performed in this study. Considering the limit of cruising range, from the perspective of green routing, a multi-package distribution path planning model of UAV agricultural logistics considering the limitation of cruising range of unmanned aerial vehicle (UAV) was established to minimize total energy consumption. The task allocation was conducted according to the actual number of UAVs. Meanwhile, a mixed integer nonlinear programming model of task allocation was established. The improved ant colony algorithm was employed to solve the problem. The core idea was to exchange the pheromones of each ant subgroup, and subsequently to apply the insertion-based heuristic method and crossover and inversion operations to optimize the path. For the cases of remote areas in western China, the agricultural UAV distribution path planning considering the mileage limit contributes to saving resources and obtaining the lowest energy consumption distribution path. In addition, for the problem of agricultural logistics distribution path planning considering the mileage limit of UAV, the improved ant colony algorithm exhibits higher solution accuracy than the traditional ant colony algorithm.

摘要
为解决偏远农村地区物流配送存在的困难,对无人机配送进行农业物流配送系统性规划,考虑到续航里程限度,从绿色路由的角度,以最小化总能耗作为目标,建立了考虑无人机续航里程限制的无人机农业物流多包裹配送路径规划模型；根据实际无人机数量进行任务分配,建立了任务分配混合整数非线性规划模型,采用改进蚁群算法求解,其核心思想是将各个蚂蚁子群的信息素进行交换,再采用基于插入的启发式方法和交叉、反转操作进行路径优化,经过对照实验。对于我国西部偏远地区的案例,考虑续航里程限制的农业无人机配送路径规划有利于节约资源,能得到能耗最低的配送路径；对于考虑无人机续航里程限制的农业物流配送路径规划问题,本文设计的改进蚁群算法与传统蚁群算法相比,本文改进蚁群算法具有较高的求解精确度。

INTRODUCTION
Agricultural logistics distribution path planning has its own particularity. Agricultural products are fresh and seasonal, and are more sensitive to distribution distance and distribution efficiency. The allocation of goods in agricultural products warehouses should not be too frequent, and the profits of agricultural products themselves are not high. To ensure the interests of farmers, the cost of warehouse construction and distribution should be reduced as much as possible (*Li et al., 2021*). Recently, drone delivery has attracted considerable attention in the logistics industry. Numerous e-commerce companies and logistics suppliers have begun to test the application of drones to deliver packages. In China, Shunfeng and Jingdong took the lead in applying drones to deliver parcels to remote rural areas in places including Jiangxi and Shaanxi, and received government support. With the continuous improvement of civil unmanned aerial vehicle (UAV) control policies, UAVs will exert a vital role in distribution and emergency distribution in remote areas. Owing to the particularity of agricultural logistics distribution, refrigeration was needed to control the temperature during storage and transportation, which would produce a large amount of carbon dioxide *(Dorling et al., 2017)*. Agricultural logistics distribution was characterized by high energy consumption and carbon emissions. Economic benefits and environmental impacts needed to be considered in this study.

Increasing attention had been paid to agricultural logistics distribution *(Cheng et al., 2020)*. Therefore, reducing the cost of agricultural logistics distribution through agricultural logistics distribution path planning has been a focus of research.

An UAV is an aircraft that does not carry a pilot and is equipped with an autonomous flight control system. It has the characteristics of small size, low risk and easy to use, and is widely applied in military and civil fields. With the rapid development of the e-commerce industry, the pressure of logistics terminal distribution has also increased. Especially in mountainous areas, factors like scattered population and complex terrain lead to high logistics costs and long delivery time. In view of this situation, logistics drones came into being *(Torabbeigi et al., 2020)*. However, China's UAV logistics is still in its infancy, and there have been some problems in the marketization of UAV logistics, bringing many challenges to the sustainable development of UAV agricultural logistics. By applying the emerging thing of drones to the field of agricultural logistics that was closely associated with life, the public inevitably questioned and worried about the safety of this new technology *(Figliozzi et al., 2017)*. In addition, the high investment in technology research and development, personnel training and supporting system establishment of UAV agricultural logistics distribution also sets a higher threshold for enterprises to carry out UAV agricultural logistics business. The relevant policies and regulations and supervision mechanism system of UAV logistics are still in the stage of exploration and improvement. This study investigates the path planning of UAV agricultural logistics distribution from two aspects including the development of UAV technology and the standardized operation of UAV logistics.

Currently, few studies focus on the trajectory planning of logistics UAVs. UAV path planning was a satisfactory space flight path for UAV to successfully complete the flight mission by comprehensively considering topography, various threats, energy and fuel consumption and many other factors *(Bug et al., 2018)*. At present, there were various path planning optimization algorithms, such as particle swarm optimization *(Hong et al., 2021)*, ant colony algorithm *(Buzzega et al., 2022)*, fish swarm algorithm *(Song et al., 2021)*, and artificial potential field method *(Chang et al., 2018)*. Among them, ant colony optimization (ACO) was widely used due to its strong robustness and fast search speed, while it revealed the disadvantages of low search efficiency, making it easy to fall into local optimum *(Choi et al., 2017)*. To address the problem of path smoothing, *Freitas et al.* (2018) considered the influence of the number of UAV turns in the heuristic function, enhancing the global search ability of the algorithm and improving the smoothness of the path. However, the improved algorithm still has the disadvantages of slow initial convergence speed, making it easy to fall into local optimum *(Freitas et al., 2018)*. *Yang et al. (2015)* proposed an ant colony algorithm with improved pheromone update rules based on the shortest path target. The performance of the algorithm is improved regarding running time and convergence speed. Nevertheless, only the shortest path is considered, and other factors including the safety and smoothness of the UAV track are not taken into consideration. *Freitas* et al. *(2020)* proposed a guiding factor considering the distance from the node to the target node and the distance from the node to the starting node. Through improving the guiding factor of the algorithm, the guiding effect of the heuristic function is enhanced. However, the algorithm is easy to fall into local optimum due to the influence of the initial distribution of pheromones *(Freitas et al., 2020)*. *Petrovska et al. (2013)* proposed a method using geometric optimization. The adaptive parameter adjustment method is employed to improve the search ability of the ant colony algorithm and the interaction ability between individuals, effectively improving the traditional ant colony algorithm. *Petrovska et al. (2013)* proposed a geometric optimization method and adopted adaptive parameter adjustment method for improving the search ability and interaction ability of ant colony algorithm, which effectively improved the traditional ant colony algorithm's slow convergence speed, making it easy to fall into local optimality. However, the problem of slow search speed still existed in the initial stage of the algorithm. *Williams et al. (2012)* plan drone delivery within a fixed service radius from the warehouse. Each package has a customized delivery time and deadline. To minimize the number of drones, the scheduling decision support model and genetic algorithm are used to solve. *Dell'Amico et al. (2021)* considered the economic cost, delay penalty, safety and reliability, carried out the task allocation planning of multi-UAV cooperative distribution, and improved the quantum particle swarm optimization algorithm to solve the problem. The research on improving ant colony algorithm mainly includes: *Wang et al. (2023)* initialized the initial number of agricultural handling robots by scanning method, and the geometric center of the sub-path node was set as a virtual node. Then, the improved ant colony algorithm with embedded genetic operator was applied to solve the optimal path of connecting virtual nodes and the optimal result of sub-paths. *Chu* (2023) improved the problem that the classical artificial potential field method failed to reach the end point and local lock-in in agriculture through introducing the method of intermediate point and target relative distance.

Subsequently, the improved artificial potential field method was combined with the traditional ant colony algorithm, and the ant colony algorithm exerted a major role in the later period with the increasing pheromone concentration. *Fan* (2023) proposed an improved PSO algorithm based on A* algorithm, introduced a nonlinear convergence factor balance algorithm with global search and local development capabilities into the traditional PSO algorithm, and adopted population initialization for enhancing population diversity, and thus the improved PSO algorithm exhibited stronger model solving capabilities.

Considering the establishment of the energy consumption formula, restricting UAV cruising range and so on, *Ke et al. (2014)* established a drone delivery model from the perspective of time and budget, considered energy consumption and load constraints, and applied simulated annealing algorithm to solve the model. *Zhou et al. (2019)* applied the nonlinear energy consumption function to the modelling of multi-trip UAV routing problem with time windows, and designed a branch cutting algorithm to solve the problem. *Jung et al. (2021)* obtained the formula of UAV battery energy consumption by testing UAVs, and applied the formula to path constraints to address the multi-package delivery problem, aiming to minimize the number of UAVs. *Agatz et al. (2018)* performed targeted research on the MD4-3000 series of drones and applied them to solve distribution problems many times. *Zheng et al. (2020)* established a maximum coverage model of a limited charging point, uniquely allocating the demand point to the nearest charging facility, and constraining the flight path between the charging points, and thus the generated distribution network is topological. *Boccia et al. (2021)* established a multi-level location model for warehouses and charging facilities in order to minimize the total cost, and improved the genetic algorithm with greedy search to solve the model. *Liu et al.* (2016) applied the maximum coverage model of limited facility points to the scenario of UAV rescue material delivery, and established a three-stage heuristic (3SH) model to address the facility center location problem, material allocation problem, and the number of required UAVs in stages. *Bouman et al.* (2018) developed a UAV distribution optimization model for medical items, including charging station location, medical item supplier assignment for suburban clinics, and scheduling trips and distribution routes for drones to minimize the total service time. *Boysen et al.* (*2021*) aimed at maximizing the coverage demand point and performed the location of UAV charging facilities in two steps.

Concerning the shortcomings of the above research, this study further carried out research and established an agricultural logistics distribution route planning model considering the mileage limit of drones. To evaluate and make full use of battery energy, the energy consumption formula is established. The path planning is conducted with the lowest energy consumption as the goal. Considering that the weight of general express parcels is within 5 kg, and the load of drones commonly used in terminal distribution is 20 kg, this study investigates multi-package distribution considering the mileage limit of drones. This model improves the actual loading rate of drones, which contributes to saving space and resources and improving distribution efficiency.

MATERIALS AND METHODS

Problem Description

This study describes the scene of remote agricultural logistics distribution services in places including mountainous areas, islands, and grasslands and other places. In actual operation, agricultural logistics service providers provide drone distribution services for remote rural areas, with towns as distribution centers and villages as receiving units. Starting from the distribution center, the drone delivers the goods to the designated collection point in each village (hereinafter referred to as the demand point). In this study, the problem of agricultural logistics distribution path planning considering the limitation of UAV cruising range is investigated. Under the requirement that all demand points are covered, the total energy consumption of distribution is the lowest, and multiple UAV distribution tasks are obtained after solving the problem.

Problem hypothesis and parameter description

Problem hypothesis

(1) Only a single distribution center is considered to provide agricultural logistics distribution services for multiple demand points within the distribution range.

(2) All UAV models remain the same, and the battery weight does not change during the flight of the UAV.

(3) This study only considers the energy consumption of UAV under ideal conditions, without considering the influence of weather and other factors.

(4) The power consumption of UAV rising and falling is not calculated, respectively. Considering the battery safety factor μ=1.25, the safe power of UAV is set to 80% of the maximum power that is: $Q = Q_{\max} / \mu$.

(5) Assuming that each demand point can only be delivered by one UAV, while one UAV can serve multiple demand points.

(6) The multi-package delivery model of UAV is defined by directed graph $G=(V, A)$, and the set of points is $V = D \cup C \cup R'$ and $(i, j) \epsilon V$. Distribution center $D=\{v_0\}$, and the set of demand points $C=\{v_1, v_2, ..., v_n\}$.

Parameter declaration

The relevant parameters of the agricultural logistics distribution path planning model considering the mileage limit of the UAV are shown in Table 1.

Table 1

Model parameter description

Parameter	Parameter definition	Parameter units
D	The set of distribution centers, denoted by the following index o in the decision variable	—
C	The set of demand points	—
R	Set of candidate charging points	—
y_j	If the candidate charging point j is determined to be the charging point, then y_j = 1, otherwise y_j = 0	—
x_{ij}	If the demand point i is uniquely assigned to the facility point j, $j \epsilon D \cup R$, then; x_{ij} =1, otherwise x_{ij} =0	
d_{ij}	The distance between points i and j	km
c_{i0}	The total distance of the path from the demand point i to the distribution center	km
H	Unmanned aerial vehicle full range	km
λ_1	The distance from the candidate facility point to the distribution center does not exceed λ_1 times of the full load range of the drone, $\lambda_1 = 0.8$	—
$\lambda 2$	The coverage of the facility point to the demand point is not more than λ_2 times the full range of the UAV, λ_2=0.4	—
f	The energy consumed per unit distance of horizontal flight	W.h
m_t	Net weight of UAV without battery and cargo	kg
m_b	Battery weight of UAV	kg
m_l	The weight of cargo carried by UAV	kg
g	acceleration of gravity	N/kg
d	unit distance	m
η	energy transfer efficiency	—
ϑ_v	The ratio of lift to drag is a function of flight speed.	—
$f(m_l)$	The energy consumed per unit distance in horizontal flight when the cargo weight is m_l	W.h
α	Formula parameters	—
β	Formula parameters	—
R'	The set of charging points and virtual charging points -	—
V	The set of all vertices, $V = D \cup C \cup R', (i, j) \in V$	—
K	The set of UAVs, $k \in K$	—
W_i	The demand for node i, $i \in C$	kg
m_{ik}	The weight of the cargo when the kth drone leaves point i, $i \in V, k \in K$	kg
q_{ik}	The remaining power of the kth drone when it leaves point i, $i \in V, k \in K$	W.h
t_{ij}	The flight time of UAV from node i to node j	h
T_k	Time spent on the delivery of the k^{th} drone	h
x_{ijk}	When the k^{th} UAV passes through node j from node i, x_{ijk} =1; otherwise x_{ijk} =0	—
N	Number of drones at distribution centers, $N = \lvert K \rvert$	—
W	Maximum load capacity of UAV	kg
Q_{max}	Maximum power of UAV	W.h
Q	Maximum safe power of UAV, $Q = Qmax / \mu$	W.h
μ	Battery safety factor, $\mu = 1.25$	—
τ	The residence time of the UAV at the demand point or the charging point	h
v	UAV constant flight speed	m/s

UAV agricultural logistics distribution model

UAV energy consumption formula

In this study, the energy consumption of UAV in horizontal flight state is defined as Equation (1):

$$f = \frac{(m_t + m_b + m_l)g}{3600\theta_v \eta} d \tag{1}$$

When the net weight and battery weight of the UAV are regarded as constant values, the energy consumption rate of the UAV per unit distance is only associated with the load capacity. The energy consumption Equation (1) is improved to obtain a new energy consumption Equation (2).

$$f = (\alpha m_1 + \beta)d = f(m_1)d \tag{2}$$

α is shown as Equation (3).

$$\alpha = g\frac{1}{3600J_v\eta}, \quad \beta = (m_t + m_b)g\frac{1}{3600J_v\eta} \tag{3}$$

UAV agricultural logistics distribution model considering endurance mileage

The combination of agricultural logistics distribution tasks is solved with the least total energy consumption and the delivery time of the corresponding tasks.

$$\mathrm{Min}\sum_{k\in K}\sum_{i\in V}\sum_{j\in V} f(m_{ik})d_{ij}x_{ijk} \tag{4}$$

The meaning of Equation (4) is to minimize the total energy consumption of distribution. Among them, $f(m_{ik})$ indicates the energy consumption per unit distance of flight when the load capacity of the UAV is m_{ik}.

Constraint conditions are shown as follows:

$$\sum_{k\in K}\sum_{j\in V} x_{ijk} = 1, \forall i \in C \tag{5}$$

$$\sum_{j\in V} x_{ijk} \le 1, \forall i \in R', \forall k \in K \tag{6}$$

$$\sum_{j\in V} x_{jik} - \sum_{j\in V} x_{ijk} = 0, \forall i \in V, \forall k \in K \tag{7}$$

$$\sum_{(i,j)\in E(U)} x_{ijk} \le |U| - 1, \forall U \subseteq R' \cup C, U \ne \varnothing, \forall k \in K \tag{8}$$

Equation (5) suggests any requirement point, and there is only one UAV to visit once. Equation (6) indicates that for any charging point, the same UAV is accessed at most once. Equation (7) indicates that for any node, the number of visits and departures of the same UAV is equal. Equation (8) represents the sub-loop constraint, that is, no loop can appear in any non-empty subset composed of charging points and demand points.

The number of UAV departures is constrained to be:

$$\sum_{j\in R'\cup C} x_{ojk} \le 1, \forall k \in K \tag{9}$$

Equation (9) limits the number of departures of each UAV to at most 1. The bearing weight constraint is presented as follows:

$$m_{ok} = \sum_{i\in V}\sum_{j\in C} w_j x_{ijk}, \forall k \in K \tag{10}$$

$$m_{ok} \le W, \forall k \in K \tag{11}$$

$$m_{jk} = (1 - x_{ijk})m_{jk} + x_{ijk}(m_{ik} - w_j), \forall i \in V, \forall j \in C \cup R' \tag{12}$$

Equation (10) calculates the weight of each UAV 's cargo when it departs from the distribution center. Equation (11) constrains the weight of each drone's cargo when it departs from the distribution center. Equation (12) indicates that for any node j ($j \in C \cup R'$), the UAV flies from node i to node j, and the weight of the cargo when starting from node j is equal to the weight of the cargo when starting from node i minus the demand for node j.

The aim of this study is that the flight distance of the agricultural distribution UAV is affected by the power of the UAV, and the flight distance constraint is:

$$q_{jk} = (1 - x_{ijk})q_{jk} + x_{ijk}(q_{ik} - f(m_{ik})d_{ij}), \forall i \in V, \forall j \in C, \forall k \in K \tag{13}$$

$$q_{ik} = Q, \forall j \in D \cup R^{'}, \forall k \in K \tag{14}$$

$$x_{ijk}(q_{ik} - f(m_{ik})d_{ij} - f(m_{ik} - w_j)d_{jr}) \geq 0, \forall i \in V, \forall j \in C \cup R^{'}, \forall k \in K \tag{15}$$

Equation (13) indicates that for any demand point j, if the UAV flies from node i to node j, the electric quantity when starting from node j is equal to the electric quantity when starting from node i minus the flight energy consumption between nodes i and j. Equation (14) suggests that for any facility point, the electric quantity when the UAV leaves is equal to the maximum safe electric quantity. Equation (15) indicates that if the k^{th} UAV flies from node i to node j, the power of the UAV leaving node i should be enough to support the UAV to fly from node i to node j, and then from node j to the nearest facility point r from j. When j is a demand point, there must be a corresponding nearest facility point r. When the node j is a charging point, the nearest facility point r is the node j itself.

Equation (16) presents the calculation of the total flight time of each UAV:

$$T_k = \sum_{i \in V} \sum_{j \in V} (t_{ij} + \tau) x_{ijk}, \forall i \in V, \forall j \in V, \forall k \in K \tag{16}$$

Algorithm Design

Ant colony algorithm is a heuristic algorithm, which is essentially an iterative algorithm based on the positive feedback. There are two key node steps in the ant colony algorithm. One is the selection of the next node, and the other is the pheromone update rule. The common strategies for node selection include random selection, and roulette. In addition, the pheromone update strategy also has different methods. The original ant colony algorithm basically uses the global update strategy, that is, when all ants complete the search, the pheromone is updated. Subsequently, the elite strategy is introduced into the elite ant colony algorithm to improve the convergence. Under the elite strategy, there is no need to wait for all ants to complete the search, and only the pheromone is updated on the path of the optimal ants in each loop. Based on the basic ant colony algorithm, the maximum and minimum ant colony algorithm limits the concentration range of pheromone to a certain range, therefore increasing the possibility of searching for the optimal solution.

The core mechanism of ant colony algorithm

The basic ant colony algorithm is a kind of swarm intelligence bionic algorithm inspired by the path finding during the process of ant foraging. The basic idea of the algorithm is that the path of the ant indicates the feasible solution of the problem to be optimized, and all the paths of the whole ant population constitute the solution space of the problem to be optimized. The content of pheromone is determined by the length of the path. It indicates the longer the path, the lower the content of pheromone. The path selection of ants depends on the content of pheromone. Besides, it suggests the higher the content, the greater the probability that the path is selected. With the passage of time, most of the ants will eventually concentrate on a shorter path. Then, the path is the optimal solution of the optimization problem. The direction of each ant 's progress is mainly related to two factors. One is pheromone, and the other is heuristic information. It shows the higher the content of pheromone on the path, the greater the possibility of ants choosing the path; the heuristic information is to guide each ant to determine the direction of the next step. Therefore, the key of ant colony algorithm lies in the construction of pheromone update model and heuristic function. The ant determines the direction of the next step according to the transition probability, which is expressed as following:

$$p_{i,j}^{m}(t) = \begin{cases} \dfrac{\left[\tau_{i,j}(t)\right]^{\alpha}\left[\eta_{i,j}(t)\right]^{\beta}}{\sum\limits_{s \in allowed_i}\left[\tau_{i,s}(t)\right]^{\alpha}\left[\eta_{i,s}(t)\right]^{\beta}}, & j \in \text{allowed}_i \\ 0, & j \notin \text{allowed}_i \end{cases} \tag{17}$$

$$\tau_{i,j}(t+1) = (1-\rho)\tau_{i,j}(t) + \sum_{m=1}^{M} \Delta\tau_{i,j}^{m}(t) \tag{18}$$

where $\eta_{i,j}(t)$ is the heuristic function, usually taking $\eta_{i,j}(t) = 1/d_{ij}$ (d refers to the Euclidean distance of the center of two nodes i, j). $\tau_{i,j}(t)$ is a pheromone. $allowed_i$ is the set of feasible adjacent nodes at node i; m is the ant label; i denotes the current position node label; j is the node label of the next position to be transferred; t suggests the current number of iterations; α and β suggest the relative importance of pheromone and heuristic factors, respectively.

Pheromone is the key to the construction of ant colony algorithm. It indicates the shorter the path of ants, the higher the pheromone concentration, and the more it can play a guiding role for ants. With the passage of time, the pheromone will also evaporate, and thus it is essential to establish a pheromone update model. Common pheromone update models include ant week model, ant quantity model and ant density model.

$$\tau_{i,j}(t+1)=(1-\rho)\tau_{i,j}(t)+\sum_{m=1}^{M}\Delta\tau_{i,j}^{m}(t) \tag{19}$$

$$\Delta\tau_{i,j}^{m}(t)=\begin{cases}Q/L_m, \textit{ If m ants go through the path } (i,j)\\ 0, \textit{ others}\end{cases} \tag{20}$$

where ρ is the pheromone volatilization factor, Q refers to a pheromone constant, L_m is the total length of the path passed by the m ant in this cycle, and m represents the total number of ants.

Generally, the ant colony algorithm program design is composed of two nested loops. The external cycle is a cycle of iterations, which is used to simulate the multiple explorations of the ant colony system. The internal loop is the loop of the single ant search process in the ant colony system, as displayed in Fig. 1.

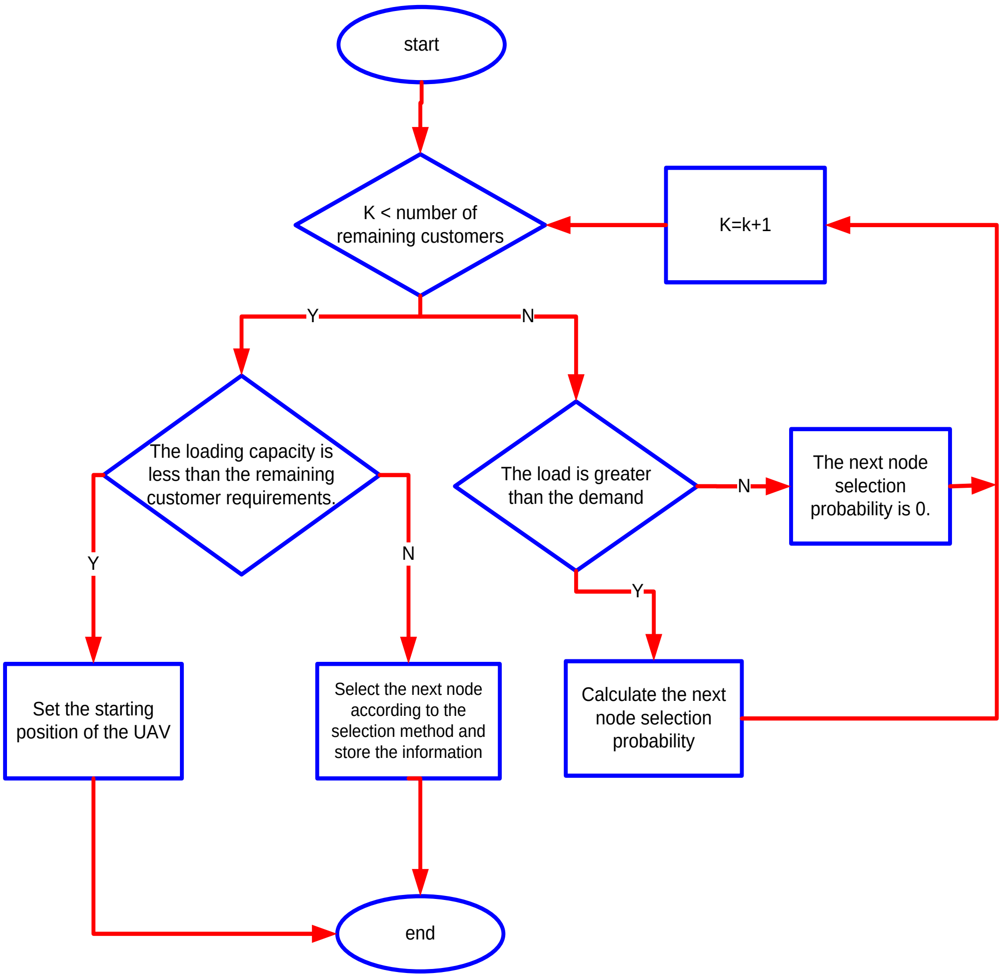

Fig. 1 – The basic process of ant colony algorithm

Considering the limitation of UAV load, when the cargo capacity of a single UAV fails to satisfy the needs of the next target customer, the UAV needs to return to the distribution center halfway. Its internal contains a cycle, that is, whether the UAV completes the traversal of all target customer nodes. The rule of UAV traversing the target customer is displayed in Fig. 2.

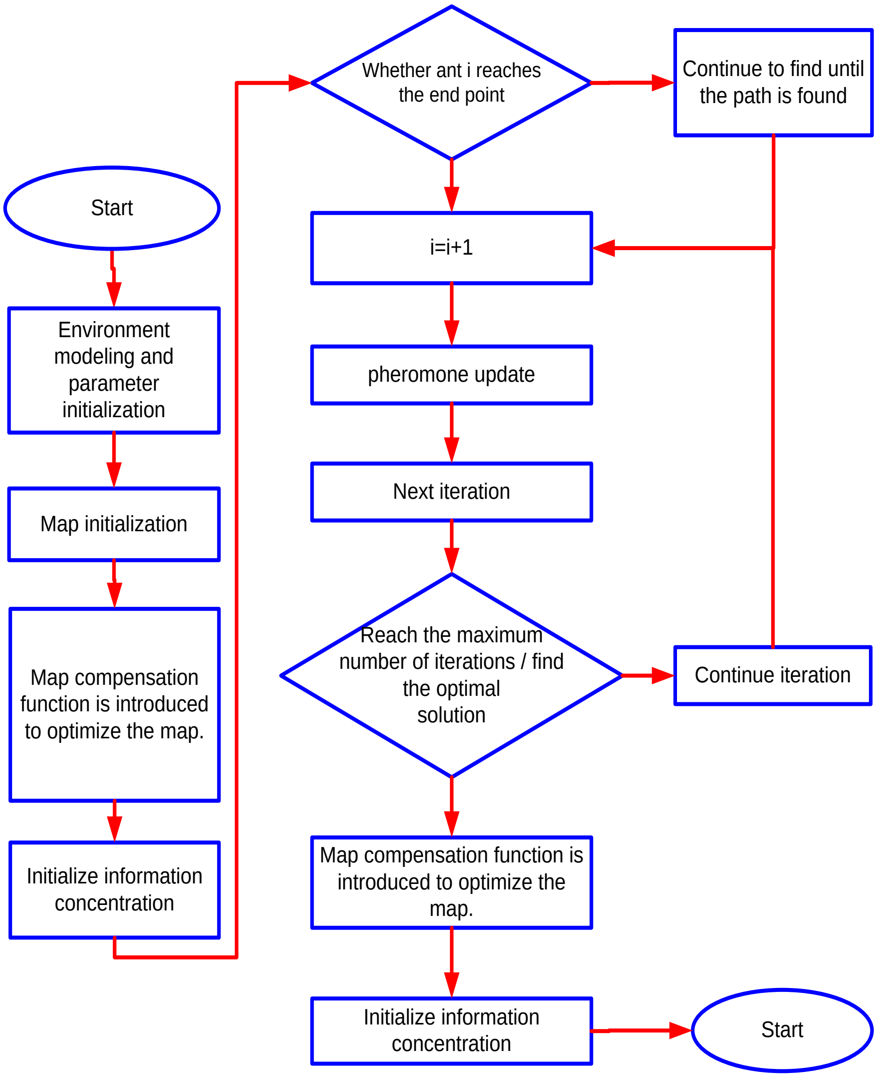

Fig. 2 – Traversal rules of agricultural logistics distribution UAV

Parameter design of improved ant colony algorithm

The optimization performance of ant colony algorithm is affected by key parameters including heuristic factors and pheromone volatilization rate. The parameters are closely related and exert a decisive role in the global search ability and solution efficiency of the ant colony algorithm. The ant colony algorithm uses fixed parameters, which has certain limitations. The information heuristic factor is set to α, and the empirical value range of the expected heuristic factor β is [0,5]. The value interval of pheromone volatilization rate ρ is [0,1]. The parameters are coupled with each other and are associated with the research problem. When the scale of the problem to be dealt with is relatively large and the pheromone volatilization rate ρ is small, the random performance and global search ability of the algorithm will increase, and the overall convergence of the algorithm will be weakened. If ρ increases, the random performance and global search ability of the algorithm will be reduced, and the convergence speed of the algorithm will be slowed down. If the information heuristic factor α is too large, the randomness of the search is weakened, making the ants' search prematurely limited to local optimum. With the increase of the expected heuristic factor β, the ants are more likely to choose the local shortest path at a local point, which leads to the weakening of the randomness of the ants' search for the optimal path, making it easy to fall into local optimum. By contrast, it indicates the smaller the heuristic factor, the stronger the search ability, but the convergence decreases.

The idea of variable parameter has been widely used in control engineering including piecewise PID control, and parameter adaptive control. In summary, a simple idea is proposed, that is to ensure its search ability at the beginning of the algorithm iteration, maintain equilibrium in the middle of the algorithm iteration, and ensure its convergence performance at the end of the iteration. To realize the above ideas, the hyperbolic tangent function is introduced, and its mathematical expression is:

$$\tanh(x) = \left(e^{x} - e^{-x}\right) / \left(e^{x} + e^{-x}\right) \tag{21}$$

In the initial stage of the loop search, to search the global optimum in a wider range, ρ is controlled at a lower level. The pheromone on the path is low, and thus the information heuristic factor α is at a low level. In order to prevent directly falling into local optimum, the expected heuristic factor β is also at a low level. At the end of the loop search, both ρ and β are controlled at a higher level, maintaining a faster convergence speed.

The specific mathematical expression is shown in Equations (22)-(24):

$$\alpha = \alpha_{\max} - (\alpha_{\max} - \alpha_{\min})\tanh[c_{\alpha}(Nc_{\max} - Nc)] \tag{22}$$

$$\beta = \beta_{\min} + (\beta_{\max} - \beta_{\min})\tanh[c_{\beta}(Nc_{\max} - Nc)) \tag{23}$$

$$\rho = \rho_{\min} + (\rho_{\max} - \rho_{\min})\tanh[c_{\rho}(Nc_{\max} - Nc)) \tag{24}$$

where c_{α} , c_{β} and c_{ρ} are adjustable parameters to control the range of α , β and ρ , Nc_{max} is the set maximum number of iterations, Nc refers to the current number of iterations, $\alpha_{\max}$ and $\alpha_{\min}$ are the upper and lower limits of α , $\beta_{\max}$ and $\beta_{\min}$ represent the upper and lower limits of β ; $\rho_{\max}$ and $\rho_{\min}$ are the upper and lower limits of ρ .

To lower the computational pressure, the information heuristic factor α and the expected heuristic factor β are rounded. The rounding rules can be rounded or intercepted based on the rounding rules. After the rounding rules are introduced, the mathematical expressions of Eqs. 22 and 23 are shown in Eqs. 25 and 26, respectively:

$$\alpha = \text{Round}(\alpha_{\max} - (\alpha_{\max} - \alpha_{\min})\tanh[c_{\alpha}(Nc_{\max} - Nc)]\} \tag{25}$$

$$\beta = \text{Round}\{\beta_{\max} - (\beta_{\max} - \beta_{\min})\tanh[c_{\beta}(Nc_{\max} - Nc)]\} \tag{26}$$

RESULTS

Experimental environment and parameter settings

In this study, Intel i7 processor and Matlab2014 b are used for experiments. The mutation probability of genetic algorithm is 0.1, the crossover probability is 0.9, and the genetic generation gap is 0.7. In the ant colony algorithm, the important factor of pheromone is 1, the constant coefficient Q is 1, the volatilization factor of information is 0.1, and the important factor of heuristic function is 5. The discount coefficient of the reinforcement learning algorithm is 0.9, and the learning rate is 0.2.

The three cost parameters are presented in Table 2.

Table 2

Cost parameter table

Parameter type check	Parameter name	Taking values
Underlying cost	The basic cost of sending UAVs	500 yuan
Transportation cost	Unit distance loss of UAV	6 yuan
	UAV running speed	200 m/min
Time cost	UAV loading and unloading time	5 min
	Maximum carrying capacity of UAV	20 kg

With Zhukou Town Center and other 20 villages in Taining County, Sanming City, Fujian Province as the research object. This study explores the problem of agricultural logistics distribution path planning considering the limitation of UAV endurance mileage. The location, demand, time window requirements, and basic demand information for the required service time of Zhukou Town Center and other 20 villages are shown in Table 3. Among them, '0' represents the distribution center, and '1 ~ 20' represents the village needing to be served.

Table 3

Customer basic needs information

Coding	Coordinate X (km)	Coordinate Y (km)	Coordinate Z (m)	Magnitude of demand (kg)	L*w*h (mm)	Expected time window (h)	Acceptable time window (h)	Service time (min)
A	0.000	0.000	0	0	0	0	0	0
B1	2.477	3.462	423	3	100*80*30	8:00-9:00	8:00-16:00	10
B2	1.119	3.301	291	2	100*60*30	9:00-10:00	8:00-16:00	10
B3	2.819	1.753	155	2	100*60*30	10:00-11:00	8:00-16:00	10
B4	4.711	3.044	497	2	100*60*30	10:00-11:00	8:00-16:00	10
B5	4.279	0.227	311	4	120*80*30	10:00-11:00	8:00-16:00	10
B6	0.181	3.264	325	1	80*40*30	8:00-9:00	8:00-16:00	10
B7	4.679	4.589	304	2	100*60*30	10:00-11:00	8:00-16:00	10
B8	0.662	0.380	54	4	120*80*30	9:00-10:00	8:00-16:00	10
B9	3.520	4.537	104	3	100*80*30	11:00-12:00	8:00-16:00	10
B10	1.434	2.430	308	4	120*80*30	10:00-11:00	8:00-16:00	10
B11	4.027	4.337	321	4	120*80*30	9:00-10:00	8:00-16:00	10
B12	4.960	4.313	489	2	100*60*30	11:00-12:00	8:00-16:00	10
B13	2.193	2.969	438	3	100*80*30	8:00-9:00	8:00-16:00	10
B14	0.063	4.726	485	4	120*80*30	11:00-12:00	8:00-16:00	10
B15	0.524	2.276	241	5	120*100*30	11:00-12:00	8:00-16:00	10
B16	3.336	2.250	397	5	120*100*30	9:00-10:00	8:00-16:00	10
B17	0.649	2.002	231	1	80*40*30	10:00-11:00	8:00-16:00	10
B18	2.043	4.915	365	4	120*80*30	8:00-9:00	8:00-16:00	10
B19	1.689	4.540	70	5	120*100*30	11:00-12:00	8:00-16:00	10
B20	2.073	4.743	431	3	100*80*30	9:00-10:00	8:00-16:00	10

The technical parameters of the agricultural logistics distribution UAV were presented as follows: the weight of the empty aircraft was 42.5 kg (excluding batteries), 65 kg (including double batteries), the large take-off weight was 85 kg (standard cargo box, near sea level), the shape size was 2000 mm, the wheelbase was 2200 mm, the shape size was 1590 mm, the width was 1900 mm, and the height was 947 mm (arm expansion, blade folding).

Experiment and comparative analysis

In this study, an improved ant colony algorithm was employed to solve the agricultural logistics distribution path planning model considering the limitation of UAV cruising range. The maximum number of iterations was set to 200, and the cost of agricultural handling UAV was 300 yuan. A satisfactory solution could be obtained by solving the model, that was, three mobile drones were needed to complete the storage and unloading tasks of agricultural products. The total travel distance of the drone was 55.086 km, and the total cost was 4055.09 yuan. The algorithm took 349.47 seconds. The improved ant colony algorithm path diagram was shown in Fig.3. The convergence curve of the improved ant colony algorithm embedded in the genetic algorithm was shown in Fig.4, and the calculation results were presented in Table 4.

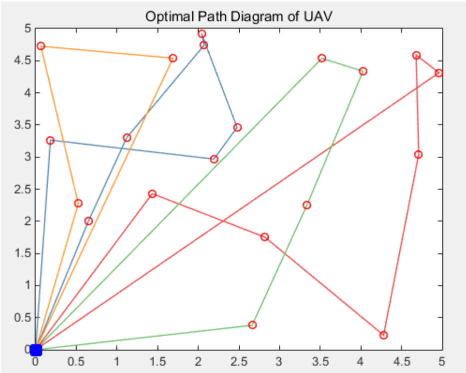

Fig. 3 – The path diagram of genetic algorithm

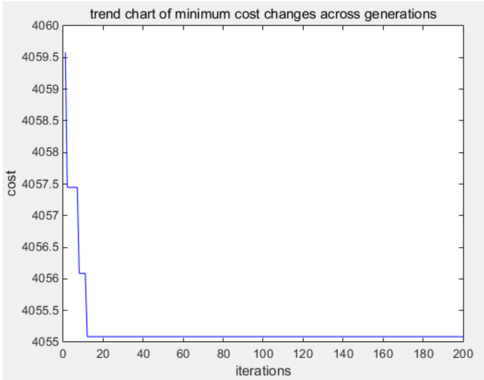

Fig.4 – Convergence curve of genetic algorithm

Table 4

Optimal service path.

Service path	Actual carrying capacity	Load limit	Capacity utilization
0→6→13→1→18→20→2→17→0	17	20	85%
0→10→3→5→4→7→12→0	15	20	75%
0→8→16→11→9→0	15	20	75%
0→19→14→15→0	14	20	70%

To further demonstrate the effectiveness of the improved ant colony algorithm, this study also designed a traditional ant colony algorithm to solve the model. In the case of constant initial cost and parameters, solving the agricultural UAV path optimization model required 5 mobile UAVs, and the total travel of the UAV was 59.85 km. The total cost was 5059.85 yuan, and the algorithm took 365.31 seconds. The path diagram of the traditional ant colony algorithm was shown in Fig.5. The convergence curve of the traditional ant colony algorithm was displayed in Fig. 6, and the calculation results were presented in Table 5.

Table 5

Optimal service path.

Service path	Actual carrying capacity	Load limit	Capacity utilization
0→6→18→1→13→10→0	15	20	75%
0→2→20→11→16→17→0	15	20	75%
0→3→5→4→7→12→9→0	15	20	75%
0→14→19→15→0	14	20	70%
0→8→0	4	20	20%

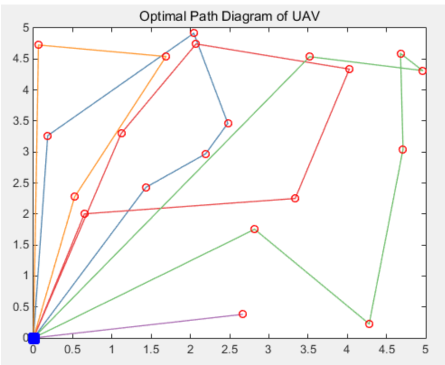

Fig. 5 – Path diagram of traditional algorithm

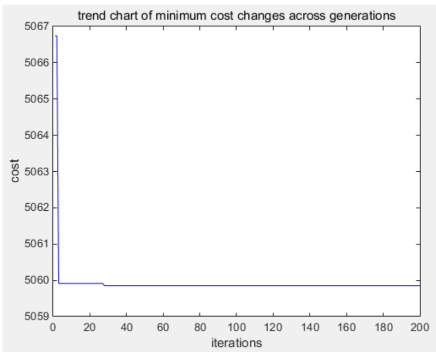

Fig. 6 – Convergence curve of traditional algorithm

Compared with the traditional ant colony algorithm, the improved ant colony algorithm embedded with genetic operator exhibited strong exploration and convergence, and the value of the objective function was better. The comparison of the two algorithms was shown in Table 6.

Table 6

Comparison of two algorithms.

Algorithm	Number of drones	Average full	Distance of run(km)	Total cost (yuan)	The algorithm takes time (s)
improved ant colony algorithm	4	76.25%	55.09	4055.09	349.47
traditional ant colony algorithm	5	63%	59.85	5059.85	365.31

It can be observed from Table 6 that the improved ant colony algorithm was superior to the traditional ant colony algorithm regarding the number of UAVs, average full load rate, driving distance, total cost and algorithm time. The traditional ant colony algorithm required 5 UAVs to complete the agricultural logistics distribution task considering the UAV 's cruising range limit, while the improved ant colony algorithm only needed 4 machines to complete the same task, with the efficiency being improved by 20%. Regarding full load rate, the average full load rate of the traditional ant colony algorithm agricultural UAV was 63 %, while the average full load rate of the improved ant colony algorithm to complete the same task was 76.25%, and the average full load rate was increased by 13.25%. Concerning the driving distance of the UAV, the total distance of the traditional ant colony algorithm agricultural UAV was 59.85 km, while the total distance of the improved ant colony algorithm to complete the same task was 55.09 km. In terms of the driving distance of the UAV, the total cost of the traditional ant colony algorithm agricultural UAV was 5059.85 yuan, while the total cost of the improved ant colony algorithm to complete the same task was 4055.09, regarding algorithm time, the convergence time of the traditional ant colony algorithm was 365.31 seconds, while the convergence time of the improved ant colony algorithm was 349.47 seconds.

CONCLUSIONS

To conclude, this study mainly investigated the path planning problem of agricultural logistics distribution for express parcel delivery by UAV in remote areas, and established the path planning model of agricultural logistics distribution considering the mileage limit of UAV. By comparing the optimal path of agricultural distribution without considering the mileage limit of drones and considering the mileage limit of drones, this study established a mathematical optimization model to minimize the total distribution cost of agricultural logistics under the constraints of customer demand for agricultural logistics, the maximum carrying capacity of agricultural drones, customer time window requirements, and drone endurance mileage restrictions. Aiming at the problems of slow convergence speed and the easiness to fall into local optimum of ant colony algorithm, the idea of variable parameters was introduced into ant colony algorithm. The parameters were automatically adjusted in the iterative process of the algorithm through hyperbolic tangent function to achieve the purpose of strong global search ability in the early stage of the algorithm and significant improvement of convergence speed in the later stage of the algorithm. Through simulation and comparative experiments, the effectiveness of the model and algorithm was verified, which could provide scientific method support for the cold chain logistics industry to achieve a win-win situation of economy and environmental protection. Additionally, the introduction of hyperbolic sine function was not only suitable for ant colony algorithm, but also could be introduced into optimization algorithms which were greatly affected by parameters. After introducing the hyperbolic sine function, the upper and lower limits of the algorithm parameters needed to be firstly determined. Therefore, how to quickly determine the upper and lower limits of the parameters was a work worthy of study. Meanwhile, the mechanism of the influence of ant colony algorithm parameters on its performance was still unclear and lacked systematic mathematical theoretical support. In the future, it is necessary to conduct more in-depth studies on the influencing mechanism of parameters on research results.

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