Research on the Optimization Problem of Agricultural Product Logistics based on Genetic Algorithm under the Background of Sharing Economy

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***Abstract*—China's national development and reform commission issued the "logistics industry adjustment and revitalization plan" in 2009 to support the development of agricultural product logistics and distribution centers. China's agricultural product logistics and distribution have entered a stage of rapid development. With the rise of the sharing economy, logistics has become a bottleneck restricting the further development of agricultural product distribution. In order to realize the effective cooperation among the main body of agricultural product logistics distribution, improve the distribution efficiency and reduce the distribution cost, a logistics distribution optimization model based on the two-layer planning idea and genetic algorithm is proposed. A two-level programming model is constructed by combining qualitative and quantitative methods, theory and examples, and insertion and deletion operators are introduced to optimize the genetic algorithm. The research results show that the optimized genetic algorithm has a 54.55% increase in convergence speed, 1.08% in performance, and a 54.231% reduction in path length compared to the benchmark algorithm. It effectively improves the efficiency of path planning and saves the planning cost, and the final target value is reduced by 48.19%.**

***Keywords*—Sharing economy; two-level programming; genetic algorithm; path optimization**

I. Introduction

With the rise of the sharing economy, urban residents in my country have higher requirements for the distribution of perishable agricultural products, and relevant online platforms need to have more professional logistics and distribution planning [1]. Due to the late start of the perishable agricultural product distribution network in China, the lack of infrastructure and equipment, and the lack of relevant technical and legal support are discussed in [2]. In addition to strengthening the construction of perishable agricultural product distribution infrastructure and improving relevant laws, it is also necessary to establish an efficient logistics network system for the distribution of perishable agricultural products [3]. In China, the distribution network of perishable agricultural products usually adopts the network model of a single economy. The production base is directly connected with the sales terminal, and the merchant arranges the delivery order according to the user's order delivery time. The lack of overall planning in each link of this model will not only result in waste of transport capacity, but once traffic congestion and other problems occur midway, the goods may not be delivered in time. In order to build a more reasonable logistics network and solve the problems existing in the layout of the existing logistics network, a genetic algorithm (GA) optimization logistics distribution model for two-level planning is proposed. The upper model is to determine the optimal location of logistics distribution nodes, and the lower model is to determine the best path for logistics distribution. For the optimization of the genetic algorithm, insertion operator and deletion operator are introduced to increase the coherence constraint of path planning and reduce the path mutation before and after the current planning. The combination of node location selection and distribution path optimization in the logistics distribution network can fundamentally realize the coordination and cooperation of various subjects, so as to improve logistics distribution efficiency, reduce distribution costs, and meet consumer demand for quality, time and price.

II. Related Work

The State Information Center of China mentioned in the "China Sharing Economy Development Report (2019)" released on February 28, 2019 that the transaction volume of China's sharing economy market exceeded three trillion yuan, a year-on-year increase of 41.6%, and the number of relevant participants was close to 800 million. The "sharing economy" has become a new economic growth point with huge potential in China [4]. The transaction scale of fresh agricultural products is about 162 billion yuan, maintaining a steady growth of 29.2% [5].

In order to solve the problems of high cost and low resource utilization in the process of logistics distribution under the sharing economy, many domestic and foreign scholars have carried out related research. Scholars such as Lv proposed a linear multi-objective bi-level programming method, the core of which is to replace the lower-level problem with optimal conditions, and use the complementary constraint as the penalty term for the upper-level objective. And introduce the concept of problem equilibrium point and analyze its characteristics, and propose an equilibrium point algorithm based on the penalty method [6]. Scholars such as Zeng proposed a two-level programming model with equilibrium constraints to optimize the planning and design of renewable energy electric vehicle charging stations. The lower-level problem is used to confirm the user's charging strategy [7].

Scholars such as Moon K proposed a two-level programming model to find a single minimum genetic variation by studying the logical reasoning of Boolean networks, and developed a branching and constraint algorithm, which can effectively find all the minimum mutations. The effectiveness of this model is validated through computational studies on a variety of Boolean networks [8]. Song et al. constructed an energy optimal scheduling model based on uncertain two-level programming. The upper model takes the transition matrix of the energy hub as the upper decision maker, and the minimum operating cost in the form of confidence as the objective function; the lower model uses the power subnet, the optimal operation scheme of the thermal energy sub-network and the gas sub-network is the lower-level decision-maker, aiming at the operation economy of each sub-network and taking its operation as a necessary constraint [9]. Aboelnaga Y and other scholars proposed an improved genetic algorithm and chaotic search to solve the two-layer programming problem, which improved the performance and convergence speed of the algorithm, and successfully got rid of the local optimum, allowing the algorithm to solve the global optimum [10].

Scholars such as Zhu believe that a genetic algorithm model based on the attention mechanism is proposed, and the attention mechanism is used to assign different weights to each feature, so that the model can focus more attention on key features. And through the genetic algorithm to optimize the structure of the model and the parameter selection of the data, the global search ability of the model is improved [11]. Wang et al. proposed a multi-objective trajectory planning method based on an improved elite non-dominant sorting genetic algorithm. The trajectory function is composed of a quintic polynomial and a cubic Bezier curve, and then three genetic operators are introduced: sorting group selection, direction-based crossover and mutation with adaptive precision control. The optimal solution of the algorithm is determined through fuzzy comprehensive evaluation to obtain the optimal trajectory [12]. Huang et al. (2022) proposed an adaptive optics technique based on genetic algorithm to detect the twisted wavefront of a laser beam, and then perform aberration correction, which has optimized the performance of two-photon fluorescence microscopy. With the spatial light modulator acting as a wavefront controller, the corrected phase is obtained through a signal feedback loop and a natural selection process [13]. Scholars such as Zemliak (2022) introduced the generalized optimization idea of circuit into the optimization of genetic algorithm, changing the control vector that determines the method of calculating the fitting function makes it possible to bypass the local minimum and find the global minimum, and the accuracy is high, and the central processing unit Time is also greatly reduced [14]. Scholars such as Al-Obaidi et al. (2021) incorporated the developed and validated process model into an optimization framework based on species conservation genetic algorithms to optimize the design and operating parameters of the process. And a multi-objective function is proposed to optimize the membrane design parameters, xylenol repulsion and required energy consumption [15]. Scholars at home and abroad have used two-level programming and genetic algorithm in the field of path planning, and achieved certain results. However, in terms of genetic algorithm optimization, only the smoothness of a single planned path is considered, but the coherence of multiple planned paths is not considered, and it is impossible to guarantee that the planned path has no mutation [16]. Aiming at the incoherence problem of common genetic algorithms in path planning, this paper proposes an optimization method that introduces insertion operator and deletion operator, and adds coherence constraints in the fitness function, in order to reduce the probability of path mutation and ensure the path Coherence and smoothness of planning.

III. Genetic Algorithm Optimization and Two-layer Model Construction

A. *Eight-neighborhood Path Selection Genetic Algorithm with Insertion Operator and Deletion Operator*

The GA algorithm is an optimization algorithm based on a biological optimization mechanism. It has strong global search ability and scalability, but has problems such as weak local search ability and high randomness [17]. In order to reduce the path length of the transport vehicle, and improve the stability of the vehicle during driving. The research introduces genetic operators such as deletion and insertion on the basis of standard GA algorithm, and correlates with the last path planning result. The main idea is to compare the angle difference between candidate paths. The larger the difference, the lower the weight given to the path and the smaller the probability of being selected. Assume that each path is a chromosome, and each individual in the population corresponds to only one chromosome, and the genes on the chromosome are path grounding singles. Compared with the coordinates, the grid number of the grid is simpler in form, which is convenient for the operation of the genetic operator, so the sequence number of the grid is used to encode the chromosome. Let any $P=[p_1,p_2,\cdots,p_n]$ path be a node on the path. $p_i\,(i=1,2,\cdots,n)$ As shown in Fig. 1.

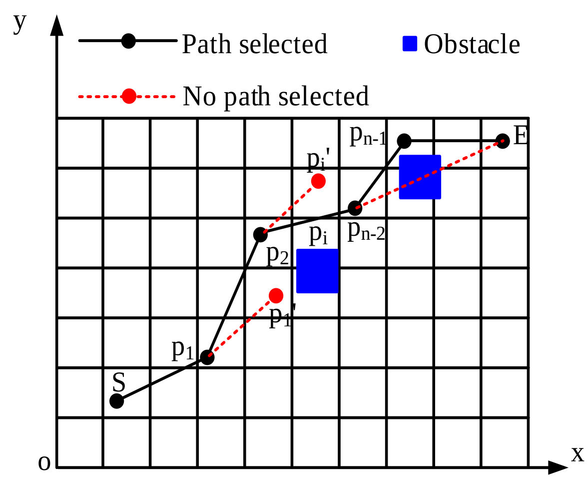


Fig. 1. Path coding of improved genetic algorithm.

In Fig. 1, S is the start point of the path and E is the end point of the path. On the node, the p_1 path is chosen $p_1 \to p_2$ instead $p_1 \to p_1^{'}$ of, because of $\angle Sp_1p_2 < \angle Sp_1p_1^{'}$. The quality of the initial population of the GA algorithm determines the quality of the final output of the GA algorithm, and the diversity and randomness of the initial population are important factors affecting the quality of the initial population [18]. The research uses two methods of directed search and random search to generate candidate paths, and the weights of the two methods are equal. When a path node is near the end, no new path nodes are generated and the current path is preserved. When there is an obstacle in front of the generated path node, the path is re-planned. As shown in formula (1) and formula (2).

$$\begin{aligned} x_{i+1} &= (x_G - x_i)\cdot rand + x_i \\ y_{i+1} &= (y_G - x_i)\cdot rand + y_i \end{aligned} \tag{1}$$

$$\begin{aligned} x_{i+1} &= N\cdot rand \\ y_{i+1} &= (y_G - y_i)\cdot rand + y_i \end{aligned} \tag{2}$$

In formula (1) and formula (2), (x_{i+1}, y_{i+1}) is the Cartesian coordinate of the candidate path node, is p_{i+1} the Cartesian coordinate (x_i, y_i) of the current path node p_i, (x_G, y_G) is the coordinate of the coordinate end point, and $rand$ is $0:\ 1$ a random number between. Genetic manipulation refers to the use of a series of genetic operators to perform operations [19]. Due to the randomness of path and path node generation, there is a probability of adjacent node breakpoints in the path, which is not conducive to genetic operations. And there are redundant path nodes in the randomly generated path, which is not the optimal path.

Research on adding an insert operator to connect breakpoint path nodes, and a new delete operator to delete redundant path nodes. In the GA algorithm, the roulette algorithm is a commonly used selection operation, but the roulette algorithm may lead to a large selection error due to its strong randomness, resulting in the frequent occurrence of individuals with large offspring fitness and falling into a local optimum [20]. The study introduces the deterministic sampling selection method to replace the roulette algorithm, and first calculates the expected survival number of the next generation of individuals, as shown in formula (3).

$$N_i = \frac{M_p f_i}{\sum_{i=1}^{M_p} f_i} \tag{3}$$

In formula (3), M_p is the number of individuals in the population, N_i where i is the expected survival number, f_i of the i th individual, and is the fitness value of the th individual. The integer part is taken N_i as the survival number of individuals in the next generation, the fractional part is sorted in descending order, and the top $M_p - \sum_{i=1}^{M_p}[N_i]$ individual is selected to join the next generation population, which $[N_i]$ is rounded.

In order to avoid the breakpoint path generated by the crossover operation, a single-point crossover method is used for crossover. When there are redundant path nodes in the path, a crossover is randomly selected, and when the path has no redundant path nodes, no crossover is performed. Compared with roulette algorithm, deterministic sampling selection method adopts single point crossing in the crossing process. The algorithm reduces the frequency of individuals with large fitness, effectively avoids falling into local optimum, and improves the local search ability of GA algorithm. In the GA algorithm, the most commonly used mutation method is the random mutation method. In practical problems, however, random variation may lead to poor or even impassable logistics paths. The study adopts the eight-neighbor random non-obstacle node method, as shown in Fig. 2.

In Fig. 2, the path nodes with higher fitness are selected in the eight neighborhoods near the mutation point. When the obtained path is better than the original path, it is replaced with the mutated path, otherwise the original path remains unchanged.

It should be noted that when there is an obstacle between the path node with higher fitness and the target node, another path node with higher fitness needs to be selected. Since the mutation operation will not produce a worse path, the research only performs mutation operation on the optimal path in each generation, which can greatly improve the efficiency and performance of the algorithm. When there is a breakpoint path, the insertion operator fills it with free grids to make it a feasible continuous path, as shown in formula (4).

$$\mathrm{V} = \max\{abs(x_{i+1} - x_i), abs(y_{i+1} - y_i)\} \tag{4}$$

In formula (4), at that time, it is determined that the two path nodes are continuous, otherwise it is determined to be discontinuous. $\mathrm{V}=1$ When the path is discontinuous, the average method is used to fill the discontinuous path, as shown in formula (5).

$$\begin{aligned} x'_{i+1} &= \frac{(x_{i+1} + x_i)}{2} \\ y'_{i+1} &= \frac{(y_{i+1} + y_i)}{2} \\ n_i &= x'_{i+1} + Ny'_{i+1} \end{aligned} \tag{5}$$

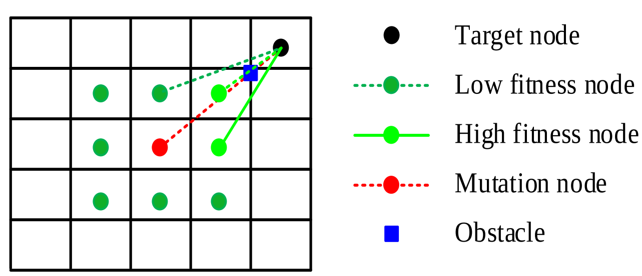


Fig. 2. Eight-neighborhood random non-obstacle node method.

In formula (5), it (x'_{i+1}, y'_{i+1}) is the coordinates of the free grid, and when it n_i is an obstacle grid, it is n_i filled with the nearest grid grid. In order to reduce the length of chromosomes and improve the efficiency of the algorithm, a deletion operator is introduced. Retrieve all path nodes from the starting point. If the weak current path node and the end point are connected without obstacles, it means that the path nodes in between are redundant nodes. These redundant path nodes should be deleted and the path should be re-planned, as shown in Fig. 3.

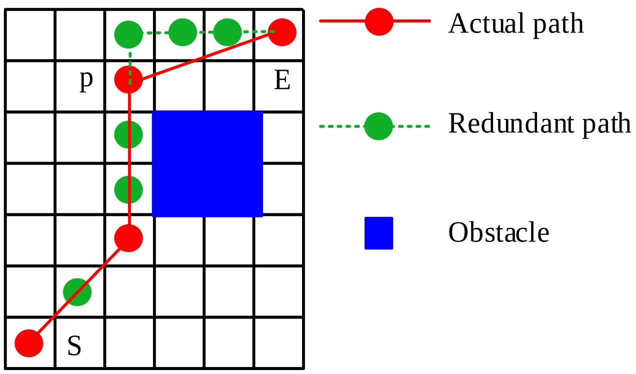


Fig. 3. Paths before and after deleting redundant nodes.

In Fig. 3, redundant path nodes are meaningless and only add computational burden to the algorithm. In particular p, the redundant path nodes between the path node and the end point not only reduce the operating efficiency of the algorithm, but also directly cause the algorithm to fail to select the optimal path. E The elite retention strategy is a commonly used strategy in GA algorithms to ensure that individuals with the highest fitness can be retained after each iteration. Assume that the individual with the highest fitness in the current candidate path is a, compare the fitness of the candidate path a with the fitness of the optimal path so far A, and then use it $a > A$ a instead A. The fitness function is a performance index to evaluate the fitness of an individual, which directly affects whether the final output of the GA algorithm is the optimal solution. The purpose of the research is to find the most suitable logistics distribution path and distribution node, so it is necessary to optimize the length and coherence of the path at the same time. The fitness function is shown in formula (6).

$$f(x) = Inf - w_1 \cdot f_1(p) - w_2 \cdot f_2(p) \tag{6}$$

In formula (6), Inf is a large enough real number, w is $f(p)$ the weight, $f_1(p)$ is the path length function, $f_2(p)$ is the path coherence function. As shown in formula (7) and formula (8).

$$f_1(p) = \sum_{i=0}^{L-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \tag{7}$$

$$f_2(p) = |\theta_k - \theta_{k-1}| \tag{8}$$

In Eq. (7), L is the number of all path nodes, in Equation (8), θ_k is the angle between the direction of the transportation vehicle at the current moment and the planned path, and θ_{k-1} is the angle between the direction of the transportation vehicle and the planned path at the previous moment. The research abstracts the transportation reserve as a mass point, which can θ also be regarded as the expected turning angle of the vehicle, as shown in Eq. (9).

$$\theta = arc\tan\left(\frac{x_1 - x_S}{y_1 - y_S}\right) \tag{9}$$

In formula (9), (x_1, y_1) is the first path node after the operator is deleted, and (x_S, y_S) is the starting point coordinate.

B. Construction of Upper Model and Lower Model

Agricultural products include products with simple storage conditions and long storage time, as well as perishable products. Under the sharing economy, the logistics and distribution of agricultural products in cities are mostly perishable products such as fresh and aquatic products, so such products are mainly considered when constructing a two-tier planning model. There are many kinds of perishable agricultural products, and it is difficult to unify the storage conditions of each logistics distribution node, so it is impossible to find suitable variables to calculate the real loss during transportation. All perishable products, even with the most advanced preservation techniques, have a limited shelf life and can be roughly divided into three stages, as shown in Fig. 4.

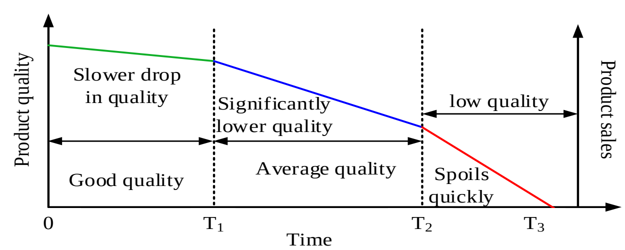


Fig. 4. Quality-time change of perishable agricultural products.

In Fig. 4, the perishable agricultural products are divided into three stages. The first stage is when the initial time 0 arrives T_1, the product is in a state of good quality, and the quality of the product declines slowly; in the second stage, the quality of the product is relatively obvious. In this process, the speed of quality decline is accelerated; in the third stage, the quality of the product deteriorates, and the speed of quality decline increases sharply, and it is T_3 no longer suitable for consumption at any time. In the entire logistics network, the investment and construction of distribution nodes is the focus of optimization, and reasonable distribution node construction can greatly improve the ability to collect and disperse goods. Build the upper-level model for decision-making of distribution nodes, and the cost is shown in formula (10).

$$
\begin{aligned}
&H=\min\sum_{r\in G}C_{pr}d_{pr}Z_r+\sum_{r\in G}F_rZ_r+\theta_1\sum_{r\in G}\left(t_{pr}Z_r\right)^2\\
&\sum_{r\in G}Z_r\ge 1\\
&\sum_{r\in G}Q_rZ_r\ge\sum_{j\in H}q_j\\
&Z_r=\begin{cases}1,\text{Create a distribution node at } r\\ 0,\text{else}\end{cases}
\end{aligned}
\tag{10}
$$

In formula (10), $\sum_{r\in G}C_{pr}d_{pr}Z_r$, $\sum_{r\in G}F_rZ_r$ and $\theta_1\sum_{r\in G}\left(t_{pr}Z_r\right)^2$ represent the transportation cost of perishable agricultural products from the supplier p to the distribution node r, the construction and operation cost of the distribution node, and the consumption cost of perishable agricultural products in the distribution process, respectively. $\sum_{r\in G}Z_r\ge 1$ Indicates that at least one distribution node must be established, $\sum_{r\in G}Q_rZ_r\ge\sum_{j\in H}q_j$ indicating that the carrying capacity of the distribution node is greater than the demand of the terminal retailer. In actual distribution, the collection and distribution of goods need to be flexibly changed according to the specific requirements of customers. Considering the storage capacity, transportation capacity and time requirements of customers, the lower-level model of distribution path decision-making is constructed, as shown in formula (11).

$$
\begin{aligned}
&U=\min\sum_{i\in S}\sum_{j\in H}\sum_{k\in V}C_{ij}X_{ijk}d_{ij}+\sum_{k\in V}C_kX_k+\sum_{j\in H}R_jE_j+\theta\sum_{k\in V}\left(\sum_{i\in S}\sum_{j\in H}X_{ijk}t_{ij}\right)^2\\
&\sum_{k\in V}\sum_{j\in H}C_{ij}X_{ijk}=1;\ j\in H\\
&\sum_{j\in H}\sum_{i\in S}q_{ij}X_{ijk}\le Q_k;k\in V\\
&\sum_{i\in S}X_{ijk}-\sum_{i\in S}X_{pjk}=1;k\in V,p\in S\\
&\sum_{k\in V}X_{rmk}+Z_r+Z_m\le 2;r\in G,m\in G\\
&\sum_{i\in S}\sum_{j\in H}X_{ijk}\le 1,k\in V\\
&E_{ij}\le T_j\le L_{ij}\\
&X_k=\begin{cases}1,\text{vehicle } k \text{ is used}\\ 0,\text{else}\end{cases}\\
&X_{rjk}=\begin{cases}1,\text{the } k\text{-th vehicle delivers from } r \text{ to } j\\ 0,\text{else}\end{cases},k\in V,j\in H\\
&Y_{rj}=\begin{cases}1,j\text{ deliver from } r\\ 0,\text{else}\end{cases},r\in G,j\in H\\
&R_j=\begin{cases}1,\text{time window met}\\ 0,\text{else}\end{cases},j\in H
\end{aligned}
\tag{11}
$$

In Eq. (11), $\sum_{i\in S}\sum_{j\in H}\sum_{k\in V}C_{ij}X_{ijk}d_{ij}$, $\sum_{k\in V}C_kX_k$, $\sum_{j\in H}R_jE_j$ and $\theta\sum_{k\in V}\left(\sum_{i\in S}\sum_{j\in H}X_{ijk}t_{ij}\right)^2$ points are represented by the distribution cost of the distribution node to the retailer, the use cost of the vehicle, the penalty cost of overtime and the loss cost on the way. $\sum_{k\in V}\sum_{j\in H}C_{ij}X_{ijk}=1;\ j\in H$ Indicates that each retailer has only one vehicle for distribution, $\sum_{j\in H}\sum_{i\in S}q_{ij}X_{ijk}\le Q_k;k\in V$ indicates that the total amount of goods in each distribution route does not exceed the maximum capacity of each vehicle, $\sum_{i\in S}X_{ijk}-\sum_{i\in S}X_{pjk}=1;k\in V,p\in S$ indicates that each distribution process is continuous, and $\sum_{k\in V}X_{rmk}+Z_r+Z_m\le 2;r\in G,m\in G$ indicates that there is no distribution relationship between the two distribution nodes., which $\sum_{i\in S}\sum_{j\in H}X_{ijk}\le 1,k\in V$ means that each vehicle belongs to at most one distribution node, which $E_{ij}\le T_j\le L_{ij}$ is the time constraint of the retailer. It can be seen that, whether it is the upper-level distribution node decision-making model or the lower-level distribution path arrangement model, the cost of the entire logistics activity is required to be the lowest. By changing the location class of distribution nodes, the choice of distribution path is affected, and the continuous optimization of the distribution path in turn affects the choice of the location of distribution nodes. This process is a process of mutual influence. The process of solving the model is shown in Fig. 5.

The process of solving the two-layer model is shown in formula (12).

$$
p_{ij}^k\left(t\right)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}\left(t\right)\eta_{ij}^{\beta}\left(t\right)}{\sum_{s\in allowed_k}\tau_{is}^{\alpha}\left(t\right)\eta_{is}^{\beta}\left(t\right)},j\in allowed_k\\ 0,\text{else}\end{cases}
\tag{12}
$$

In Eq. (12), the α sum β score is denoted by the weight of the distance-influenced heuristic factor. α The larger the value, the more inclined the shorter distance is when planning the path, the β larger the more inclined the path with fewer obstacles. $allowed_k$ Indicates k the path nodes that can be selected in the next planning of the path, τ_{ij} and η_{ij} is the amount of information obtained by the two weights when planning the path. The update of information is shown in formula (13).

$$
\begin{aligned}
&\tau_{ij}\left(t+n\right)=\rho\tau_{ij}\left(t\right)+\Delta\tau_{ij}\\
&\Delta\tau_{ij}=\sum_{k=1}^{n}\tau_{ij}^k
\end{aligned}
\tag{13}
$$

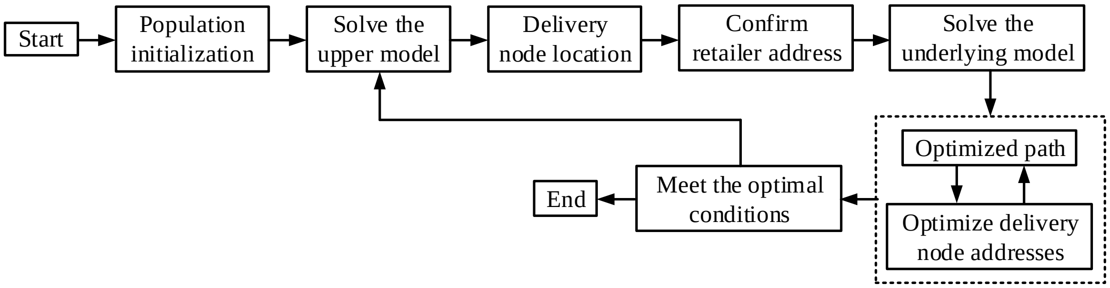


Fig. 5. Genetic algorithm to solve the two-layer model.

In formula (13), it $\rho(0<\rho<1)$ is the residual coefficient of information, and η_{ij} the update is the same as formula (13), so it is omitted. This process is repeated continuously, and the iteration is stopped when the end condition is satisfied. If it is not satisfied, a new round of optimization is started after jumping to the initialized population.

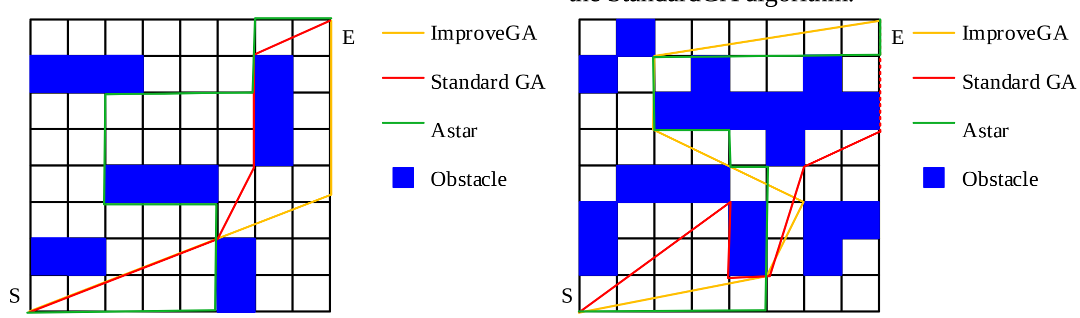
IV. Path Planning Model Training and Examples

A. *Path Planning using Different Genetic Algorithms in Simple and Complex Environments*

Two training scenarios are constructed. The first environment is relatively simple, and the second environment is relatively complex. Assuming that the length of each fence grid is 1, the evaluation indicators are the path length and the number of corners. The comparison algorithms are the A-Star algorithm and the GA algorithm commonly used in path planning, and the results are shown in Fig. 6.

In the simple scenario of Fig. 6(a), all three algorithms successfully plan paths. Among them, the path length of the ImproveGA algorithm is about 13.544 and the number of corners is one. The path length of the StandardGA algorithm is 12.857, and the number of corners is three. The path length of Astar algorithm is 22, and the number of corners is 6. In the complex scene of Fig. 6(b), the path length of the ImproveGA algorithm is about 17.890, and the number of corners is 4. The StandardGA algorithm falls into a local optimal solution and fails to plan a path. The path length of Astar algorithm is 22, and the number of corners is 7. In a simple scene, the path length of the StandardGA algorithm is 5.72% shorter than that of the ImproveGA algorithm, but the number of corners is three times. In a complex scene, the path cannot be planned because it falls into a local optimal solution. The ImproveGA algorithm can successfully plan paths in both simple and complex environments. Compared with the Astar algorithm, the paths in the two environments are 38.44% and 18.68% shorter, respectively, and the number of corners is much lower than that of the Astar algorithm. In order to further study the performance of the algorithm, the traveling salesman problem dataset maintained by Heidelberg University is used to train the algorithm, and the results are shown in Table I.

In Table I, the path length of the ImproveGA algorithm is optimized by 54.231% and 25.554% compared with the other two algorithms, the maximum yaw angle is optimized by 39.939% and 18.257%, and the sum of the absolute value of the turning angle is optimized by 46.713% and 25.779%. Combining Fig. 6 and Table I, it can be concluded that compared with the Astar algorithm, the GA algorithm has certain advantages, and it can plan the path more flexibly, reduce the turning angle, reduce the path length and the calculation amount of the algorithm, but the StandardGA algorithm is easy to fall into in the face of complexity. The ImproveGA algorithm can not only deal with complex environments, but also has better performance indicators than the StandardGA algorithm.



(a)Simple scene (b)Complex scene

Fig. 6. Simulation results of path planning scenarios.

TABLE I. Path Planning Training Results

Algorithm	Path length	Maximum yaw angle change	The sum of the absolute values of the corners
Astar	27.18km	32.8°	371.2°
StandardGA	16.71km	24.1°	266.5°
ImproveGA	12.44km	19.7°	197.8°

B. Practical Application of Two-level Planning Model to Logistics Network Optimization

In order to test the optimization effect of the two-level planning model on the logistics network, an example containing five potential distribution nodes and 20 demand points is used for testing. An enterprise selects two out of five alternative distribution nodes to serve 20 demand points, numbers the five alternative distribution nodes as A, B, C, D, E, and the 20 demand points as 1, 2, 3,..., 20. There are a total of five delivery vehicles, all of the same model, and the demand at each demand node is shown in Table II.

For the convenience of calculation, the unit transportation cost is set at 10 yuan per ton per kilometer, and the cost of using vehicles is 50 yuan per vehicle. The average driving speed of the vehicle is 20 kilometers per hour, the load capacity of the vehicle is 20 tons, and the consumption cost of perishable agricultural products is 1 yuan per hour. Since the relative positions of delivery nodes and demand nodes are fixed, unit price and vehicle cost will not affect the results no matter how they are chosen. The total demand of all demand nodes is 370, and the coordinates and capacities of potential distribution nodes are shown in Table III.

In Table III, the total supply of any two nodes is required to be greater than or equal to 370, so the only combinations considered are point A, any point, and CD. The research uses Matlab to solve the model. Since the problem is not complicated, the fixed value method is used instead of the adaptive probability method in parameter setting. In order to better find the global solution, the initial population size is set to 100. In order to prevent falling into local optimum, the crossover probability is set to 0.5, and the mutation probability is set to 0.05. Due to the large initial population size and low mutation probability, the number of iterations is set to 500 to ensure that the optimal solution can be found. Using fitness as the evaluation index, the change trajectory of the optimal target value is shown in Fig. 7.

TABLE II. C COORDINATES AND DEMAND QUANTITY OF DEMAND NODES

Numbering	X coordinate	Y coordinate	Time window upper limit	Lower time window	Service hours	Demand
1	Twenty-three	28	0	110	10	20
2	52	34	0	120	10	30
3	27	6	0	120	10	15
4	95	38	0	100	10	25
5	64	Twenty-four	0	115	10	10
6	Twenty-three	15	0	120	10	10
7	6	16	0	140	10	15
8	41	10	0	160	10	20
9	38	26	0	105	10	30
10	91	32	0	120	10	10
11	82	14	0	110	10	10
12	64	Twenty-two	0	100	10	5
13	57	71	0	150	10	10
14	56	82	0	100	10	20
15	19	66	0	180	10	10
16	Twenty-two	9	0	105	10	25
17	13	18	0	115	10	25
18	41	35	0	110	10	15
19	69	32	0	115	10	30
20	32	91	0	155	10	35

TABLE III. C COORDINATES AND SUPPLY VOLUME OF EACH DISTRIBUTION NODE

Numbering	X coordinate	Y coordinate	Capacity	Construction Cost
A	3	38	22 0	100
B	54	32	1 70	50
C	41	7	1 90	70
D	50	80	1 80	90
E	25	71	1 70	60

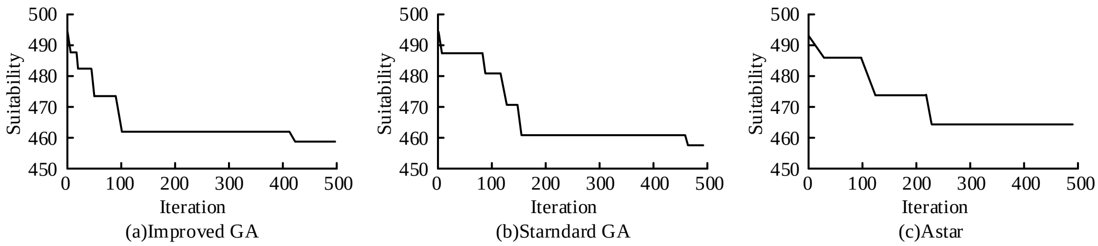


Fig. 7. Trajectory of optimal target value change.

In Fig. 7(a), the two-level programming model using the ImproveGA optimization algorithm tends to converge after about 100 iterations. When the number of iterations is less than 100, the fitness value decreases rapidly. After convergence, the fitness value is 462. The value converges to 459. In Fig. 7(b), the two-level programming model using the StamdardGA algorithm tends to converge at about 150 iterations, but the adaptation value will be slower before the 80 iterations. After convergence, the adaptation value is around 461, and the optimal target The value converges to 458. In Fig. 7(c), the two-level programming model using the Aster algorithm tends to converge after about 220 iterations, the adaptive value after convergence is about 464, and the optimal target value converges to 464. Compared with the Asters algorithm, the ImproveGA algorithm improves the performance by 1.08% and the convergence speed by 54.55%. It can be seen that although the other two algorithms are not much worse than ImproveGA in terms of optimal target value when used in bi-level programming, there is a large gap in stability and optimization speed. It cannot meet the needs of timeliness in the distribution route planning of perishable agricultural products. The optimal distribution node location and distribution path are shown in Fig. 8.

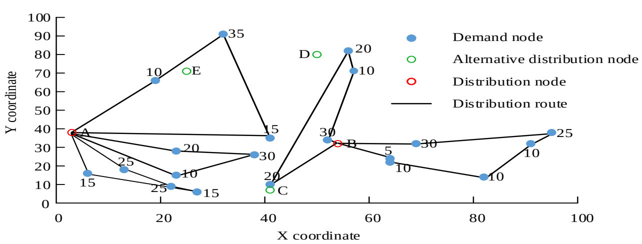


Fig. 8. Optimal distribution node and distribution path.

Combining Table II, Table III and Fig. 8, it can be seen that if only the optimization of distribution nodes is considered, the selected distribution nodes are also points A and B. Since the distribution is not carried out in a roving manner, the total logistics cost is as high as 1072. However, if only the delivery route is considered and the delivery nodes are not considered, the final target value is 884. The bi-level programming model considers both the distribution node and the distribution route, and the final target value is only 458, which is 57.28% and 48.19% lower than the single problem.

V. CONCLUSION

On the basis of consulting relevant literature and referring to domestic and foreign research results, the distribution network of perishable agricultural products is optimized. The main optimization direction is to establish a two-level planning model to optimize the distribution node location and route planning of the logistics network. And improve the genetic algorithm in the two-level programming model to improve its path planning ability. Compared with the standard GA, the improved GA introduces insertion and deletion operators in the crossover stage. The improved genetic algorithm, Astar algorithm and standard genetic algorithm are tested for path planning. The performance of the improved genetic algorithm is increased by 18.68% and 38.44% respectively. The maximum yaw angle decreased by 18.257% and 39.939%, respectively, and the sum of absolute angles decreased by 25.554% and 46.713%, respectively. Then, the constructed bi-level programming model is tested, and the improved genetic algorithm can plan the optimal configuration faster than the other two comparison algorithms. Speed increased by 54.55%. Finally, comparing the bi-level programming model with the single-planning model, it is found that the cost of the bi-level planning is reduced by 57.28% compared with only considering the distribution node optimization. Compared with only considering the distribution route optimization, the cost of bi-level planning is reduced by 48.19%. This model can effectively save planning costs and improve delivery efficiency. The limitation of this study is that it simplifies the calculation of consumption cost, which is not enough to fully simulate the actual situation. Therefore, future research will consider adding the loss cost in the calculation to make the experiment more realistic.

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