Logistics Path Planning Method using NSGA-II Algorithm and BP Neural Network in the Era of Logistics 4.0

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***Abstract*—The distribution of fresh food is affected by its perishable characteristics, and compared with ordinary logistics distribution, the distribution path needs to be very reasonably planned. However, the complexity of the actual road network and the time variation of traffic conditions are not considered in the existing food logistics planning methods. In order to solve this problem, this study takes road section travel prediction as the starting point, and uses the non-dominant ranking genetic algorithm II and the backpropagation network to construct a new logistics path planning model. Firstly, the road condition information detected by the retainer detection and the floating vehicle technology is integrated, and the travel time prediction is input into the backpropagation network model. In order to make the prediction model perform better, it is improved using a whale optimization algorithm. Then, according to the prediction results, the non-dominant ranking genetic algorithm II is used for distribution route planning. Through experimental analysis, the average distribution cost of method designed by this study was 9476 yuan, and the average carbon emission was 2871kg. Compared with the other three algorithms, the distribution cost was more than 15% lower, and the carbon emission was more than 12.5% lower. The planning method designed by the institute can achieve more reasonable, low-cost, and environmentally friendly logistics and distribution, and bring more satisfactory services to the lives of urban residents.**

Keywords*—Whale optimization algorithm; non-dominant ordering genetic algorithm; backpropagation network; logistics and distribution; path planning

I. INTRODUCTION

Logistics 4.0 is the embodiment of Industry 4.0 in the field of logistics, which refers to the digitalization of logistics. With the integration of information technology and the Internet, the logistics industry, e-commerce and other fields have been further specialized and cross-border cooperation [1]. As society and economy develop, consumer demand has become more and more abundant, and the demand for fresh food is increasing day by day [2]. Fresh products have a short shelf life, are perishable, and are easily damaged, so they consume more energy for a low temperature during distribution, which also leads to higher costs [3]. However, most of the current studies on the route planning of logistics vehicles for fresh products do not consider the actual road network complexity and time variation influence, and simply assume that the traffic situation between customer points is constant [4]. Logistics cost is directly related to travel time [5]. Existing studies have not taken into account the complexity of the actual road network and the time-variability of traffic conditions. Although many studies have focused on the importance of fresh food distribution route planning, most studies are still based on simplified assumptions, such as constant traffic conditions or fixed distribution costs, which are far from the reality. This assumption ignores the impact of various factors such as traffic congestion, road maintenance and weather changes on the distribution route in the actual road network, leading to the possibility that the planned route may not be optimal. Therefore, a logistics path planning model based on travel time is constructed by using non-dominated sorting Genetic Algorithm II (NSGA-II) algorithm and back propagation (BP) neural network. The innovation of the research is to integrate the road condition information of the fixed detection and the floating vehicle detection, and introduce the travel time prediction results into the trip planning to achieve a more reasonable and environmentally friendly logistics distribution. The contribution of this study is to provide a fresh food distribution route planning method that comprehensively considers the complexity of the actual road network and the time-varying traffic conditions, so as to improve the logistics efficiency and reduce the distribution cost. Compared with the traditional method, this method can more accurately reflect the actual road conditions and traffic conditions, so as to plan a more reasonable distribution route.

The study includes six sections. Section II analyzes the current research status. Section III is the method construction part, which describes the design of the logistics path planning method in detail. Performance analysis is given in Section IV. Results of the research is given in Section V. Finally Section VI summarizes the research methods and analysis results, and puts forward the prospects for future work.

II. RELATED WORKS

Since the issue of vehicle routing was raised, it has quickly received close attention in areas such as transportation planning, logistics, and portfolio optimization. Li et al. found that the entry point of the existing deep reinforcement learning-based solution method in solving the vehicle path problem was not applicable to the actual situation. In order to solve this problem, a new path planning algorithm was constructed by using the attention mechanism and decoder to minimize the vehicle travel time. Experimental analysis showed a superiority to most traditional heuristic methods [6]. Pan et al. considered the driving time, multiple trips of each vehicle, and the loading time at the depot at the same time. A hybrid meta-heuristic algorithm was constructed by using the adaptive large neighborhood search algorithm and the variable neighborhood descent algorithm. Experiments showed that the proposed algorithm had good robustness and effectiveness under different speed profiles and maximum travel time constraints [7]. Gmira et al. found that changes in travel practices within cities were ignored in existing approaches to routing of delivery vehicles. To solve this problem, a tabu search-based solution method for vehicle routing problem was proposed. By defining the driving rate on the road network, the route planning was adjusted in real time according to the time change [8]. Abdullahi et al. considered sustainable vehicle routing in the transport sector in three dimensions of economic, environmental and social dimensions. They proposed a weighted sum model that combined three dimensions and a constraint model. In addition, they proposed a partial random iterative greedy algorithm to solve the ensemble problem [9].

The NSGA-II algorithm has fast solution speed, good solution convergence and robustness. Li et al. established a multi-objective mathematical model for rail alignment optimization of high-speed railway by studying the multi-objective optimization problem of high-speed railway section with small radius curve. NSGA-II was used to find the optimal model solution. Experiments showed that this method effectively reduced rail wear and improved rail bending performance [10]. To solve the low resource utilization and low user service quality in workflow scheduling, Li et al. proposed a scoring and dynamic hierarchy-based NSGA-II. The algorithm aimed to minimize the maximum time to completion and cost of workflow execution. Experiments showed that this method effectively improved resource utilization [11]. In order to achieve effective management of water resources, Jalili A et al. proposed a water resource optimization strategy with the goal of maximizing the reliability of meeting demand. The strategy used the NSGA-II and the WEAP simulator model, and introduced the support vector machine into the model. Experiments showed that the average error rate of the rule obtained by this method was less than 2.5% [12]. BP neural networks have been widely used in many fields because of their strong flexibility, fault tolerance and adaptability. In order to more accurately predict the 28-day compressive strength of recycled insulated concrete, Tu et al. constructed a new prediction model using genetic algorithm and BP. The results showed that this combination achieved better stability and generalization of the model [13]. Lin et al. proposed a new speed prediction method to solve the problem that random driving cycle affected the control of fuel cell electric vehicles. In this method, BP predicted the velocity and incorporate it into the control strategy. Experimental results showed that compared with traditional rule-based strategies, the proposed method predicted vehicle speed with high accuracy [14]. Lyu et al. constructed a model of the relationship between tensile strength, wire drawing speed and formal velocity in the process of arc additive manufacturing using BPNN. Meanwhile, genetic algorithm and forward model were introduced for BPNN optimization. Results showed that the prediction error of the optimized model was less than 3% [15].

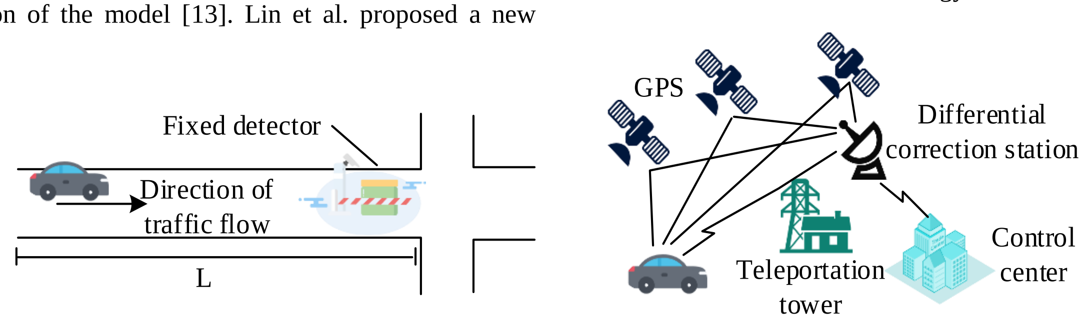
In summary, most studies on vehicle routing problems do not consider the complexity of the actual road network and the time variation of traffic conditions. Therefore, based on the travel time prediction, the NSGA-II algorithm and BP neural network were used to construct a logistics vehicle transportation path planning model. It aims to achieve the lowest total cost and the lowest carbon footprint of logistics vehicle path planning.

III. Design of Logistics Vehicle Path Planning Model using NSGA-II and BPNN

In the era of Industry 4.0, the logistics transmission system is inseparable from the support of intelligent logistics technology and equipment, to further realize the logistics intelligence, the research takes the prediction of path travel time as the starting point to build a logistics vehicle path planning model.

A. Path Travel Time Prediction using Improved BPNN

As an important comprehensive indicator, the travel time of road sections can directly reflect the information of road traffic conditions, and then provide data support for travelers to plan travel routes [16-18]. In the actual traffic data collection process, fixed detector technology and floating vehicle technology are usually used to collect data such as traffic flow and road parameters. Traffic parameters such as vehicle speed, road traffic flow, and occupancy can be obtained through fixed detectors [19-21]. The floating vehicle technology generally uploads its own instantaneous speed, latitude and longitude and other information to the information center according to the vehicle of the wireless positioning equipment through GPS positioning technology. The working principle of the fixed detector as well as GPS technology is shown in Fig. 1.



(a) Fixed detector detection (b) GPS

Fig. 1. The working principle of the fixed detector and the GPS technology.

The road travel time obtained by the fixed detector is divided into two parts: the normal passage time and the delay time caused by the traffic light. The calculation method for the normal passage time of the vehicle is shown in Eq. (1).

$$t_d = \frac{L}{\bar{v}} \tag{1}$$

In Eq. (1), L is the total length of the road section, $\bar{v}$ is the average vehicle speed under the fixed detector, and t_d is the normal time of the vehicle. In this study, the Webster timing method is used to calculate the signal light delay time, and the calculation method is shown in Eq. (2).

$$t_l = 0.9 * \mu * \left[\frac{c(1-\lambda)^2}{2(1-\lambda x)^2} + \frac{x^2}{2q(1-x)} \right] \tag{2}$$

In Eq. (2), c is the traffic light period, λ is the proportion of effective green light time, q is the traffic flow data, μ is the probability of delay due to the traffic light, C is the saturation capacity of the entrance road, x is the lane saturation, and t_l is the time of delay due to the signal light. The probability of delay due to traffic lights and the calculation of lane saturation are shown in Eq. (3).

$$\begin{cases} x = q / (\lambda C) \\ \mu = \dfrac{(c-g)q - L2}{(c-g)q}, (c-g)q \geq b \\ \mu = 0, (c-g)q < b \end{cases} \tag{3}$$

Although the fixed detector can obtain the traffic parameters of the road to a certain extent, the traffic information it collects is not complete, and it is difficult to comprehensively and accurately describe the traffic conditions of the entire road network. The study divides the vehicles in the road network into four categories: vehicles that need to be stopped at any time during the journey, vehicles such as ambulances, vehicles that do not obey normal traffic rules due to special circumstances, sightseeing vehicles, and vehicles traveling on normal roads. The road travel time calculated by the floating car technology is shown in Eq. (4).

$$t_2 = \frac{4 v_1 v_2 v_3 v_4 L}{v_2 v_3 v_4 + v_1 v_3 v_4 + v_1 v_2 v_4 + v_1 v_2 v_3} \tag{4}$$

In Eq. (4), L is the distance length predicted by the floating vehicle technology, t_2 is the travel time based on the road section L, and v_1, v_2, v_3, and v_4 are the average speeds of the four types of vehicles, respectively. However, due to the scattered spatial and temporal distribution of floating vehicles in the road network, it is difficult for the floating vehicle data to accurately reflect the road section situation. To this end, the study considers merging the two data. Before data fusion, it is necessary to perform spatiotemporal matching of multi-source data, and the traffic flow data collected in the same period is screened out to prepare for the subsequent prediction model. In this study, BPNN is selected to construct a travel time prediction model, but there are limitations in BPNN, such as long learning time and slow convergence speed. Therefore, the whale optimization algorithm (WOA) is used to improve it to avoid the BP neural network falling into the local optimal solution. Fig. 2 shows the principle of the WOA.

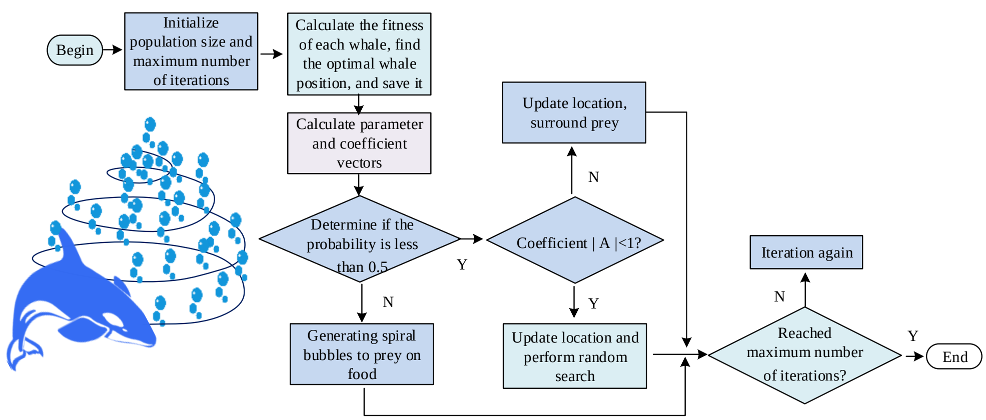


Fig. 2. Principles of the whale optimization algorithm.

Firstly, the BPNN topology is determined, and the travel data of two road sections are input into the model, and the predicted road travel time is fused and output. This is shown in Eq. (5).

$$t = \omega_1 t_1 + \omega_2 t_2 \tag{5}$$

In Eq. (5), t_1 is the travel time of the road section detected by the fixed detector, ω_1 and ω_2 are the weights of the data collected by the fixed detector and the floating vehicle, respectively. The S-type tangent function is used as the transfer function of cryptolayer neurons, as shown in Eq. (6).

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \tag{6}$$

In Eq. (6), $f(\cdot)$ is the transfer function of the output layer, and the S-type logarithmic function is the neuron transfer function of the output layer. Hidden layer's neurons are twice the output layer's neurons plus 1. The error between the network output and the expected output is shown in Eq. (7).

$$E=\frac{1}{2}\sum_{k=1}^{K}(y_k-o_{k'})^2=\frac{1}{2}\sum_{k'=1}^{K'}\left[y_{k'}-g\left[\sum_{j=1}^{J}\omega_{jk'}f\left(\sum_{i=1}^{m}\omega_{ij}t_i+b_j\right)\right]\right]^2 \quad (7)$$

In Eq. (7), E is the error value, K', J, and m are neurons' number in the output, hidden, and input layer, b_j is the threshold value of the neurons in the hidden layer, $\omega_{jk'}$ is the neurons' weight between the hidden and output layer, ω_{ij} is the neurons' weight between the input and hidden layer, $y_{k'}$ is the expected output value, and $o_{k'}$ is the output result of the final output layer. The learning rate of the BP network was determined to be 0.01 by experimental analysis. After initializing the BPNN weights and thresholds, WOA is used to find and solve the optimal weights and thresholds. The training set's mean square error is taken as a fitness function of WOA. After the continuous iteration of the algorithm, the smaller the fitness value, the greater the error, and the more accurate the prediction result. According to the actual demand of the problem, the number of neurons in input layer, hidden layer and output layer of BP neural network is initially determined. Then the weights and thresholds of the network model are randomly initialized, WOA algorithm is used to optimize the parameter combination, and the fitness value of the population is updated through continuous iteration. At the end of the iteration, the optimal parameter combination is obtained. Fig. 3 shows the flow of the WOA-BP algorithm.

B. *Logistics path planning Based on NSGA-II algorithm and BP neural network*

The research question is that in a fresh product distribution center, there are z delivery vehicles responsible for delivering goods to N individual customer points, and the maximum vehicle load, the demand of the customer point and the soft time window are the same. Each vehicle returns to the distribution center when task is done. The distribution process is divided into two phases, namely initial distribution and forecast planning, and the stages and assumptions are shown in Fig. 4.

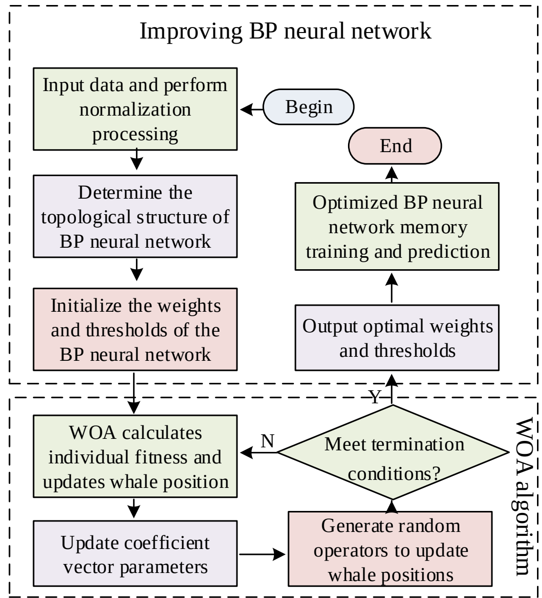


Fig. 3. Flow of the WOA-BP algorithm.

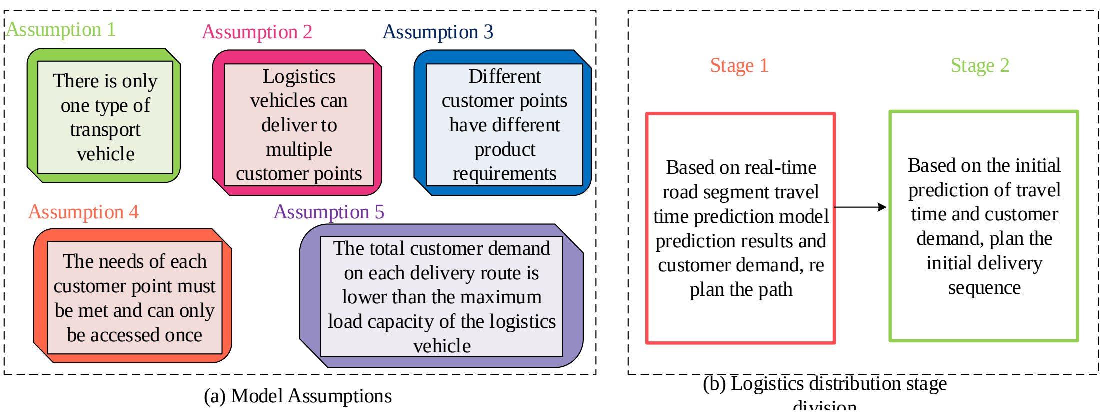


Fig. 4. Study hypothesis and distribution stage division.

At the initial moment of delivery, according to the prediction results of the road section travel time proposed above, the actual road network is transformed into a travel time network between customer points. On this basis, considering the economic cost and environmental cost and taking the vehicle load and time window as constraints, the fresh food logistics path planning model is constructed. Before building the model, the costs incurred in distribution activities are analyzed. The calculation method of vehicle operating costs is as follows in Eq. (8).

$$C_o=\sum_{z=1}^{Z}P_1a_z \quad (8)$$

In Eq. (8), a_z is a variable with a value of 0 or 1, and 1 indicates that the logistics vehicle z is put into use, P_1 is the fixed cost such as vehicle maintenance, and C_o is the operating cost of the logistics vehicle. The method for the vehicle cooling cost is shown in Eq. (9).

$$\begin{cases} C_f = C_{f1} + C_{f2} \\ C_{f1} = \sum_{z=1}^{Z}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N} t_{ij}^{k} y_{ij}^{k,z} C_r \\ C_{f2} = \sum_{z=1}^{Z}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N} t_{i,s}^{z} y_{ij}^{k,z} C_d \end{cases} \tag{9}$$

In Eq. (9), C_f, C_{f1}, and C_{f2} are the total refrigeration cost, transportation refrigeration cost and unloading refrigeration cost, respectively, $y_{ij}^{k,z}$ is a value of 0 or 1, and 1 represents the k path of z through the customer points i and j, $t_{i,s}^{z}$ is z's service time at i. The goods distributed by fresh food logistics are susceptible to deterioration and decay due to the influence of ambient temperature and oxygen, resulting in losses. The cost calculation method for the loss of goods during transportation is shown in Eq. (10).

$$C_l = \sum_{z=1}^{Z}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N} P_2 q_i \left[1 - e^{-\gamma_1^z \left(t_i^z - t_0^z\right)}\right] + \sum_{z=1}^{Z}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N} P_2 Q_{ij}^{k,z} \left(1 - e^{-\gamma_2 t_{i,s}^z}\right) \tag{10}$$

In Eq. (10), C_l is the cost of damage to the vehicle, P_2 is the unit price of the goods, q_i is the demand for the customer point i, γ_1 and γ_2 are the freshness decline rates in the process of transportation and unloading of the goods, respectively, t_0^z is the moment when the logistics vehicle z leaves the distribution center, t_i^z is the moment of the logistics vehicle z arrival at the customer point i. Customers have strict requirements for perishable fresh products' reception time, usually with a time frame. To do this, the study describes the time frame requested by the customer as a soft time window. If it is delivered outside the time window, there will be a penalty cost. The calculation of the penalty cost is shown in Eq. (11).

$$C_p = c_{ew}\sum_{z=1}^{Z}\sum_{i=1}^{N}\max\left(T_1 - t_i^z, 0\right) + c_{lw}\sum_{z=1}^{Z}\sum_{i=1}^{N}\max\left(t_i^z - T_2, 0\right) \tag{11}$$

In Eq. (11), c_{lw} is the penalty cost per unit time for the vehicle's late arrival, C_p is the penalty cost, $[T_1, T_2]$ is the delivery time range required by the customer and c_{ew} is the penalty cost per unit time for the vehicle's early arrival. The transportation cost of the vehicle is shown in Eq. (12).

$$C_t = \sum_{z=1}^{Z}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{ij}^{k,z} P_3 \left[t_{ij}^{k} \times W\left(Q_{ij}^{k,z}\right)\right] \tag{12}$$

In Eq. (12), K is the number of transportation paths, $W\left(Q_{ij}^{k,z}\right)$ is the fuel consumption of the load Q of z on the k path between the customer point i and j, and t_{ij}^{k} is the predicted travel time of the logistics vehicle from the customer point i to the customer point j in the k path. P_3 is the unit price of fuel. Carbon emissions are calculated as shown in Eq. (13).

$$C_c = c_0\sum_{z=1}^{Z}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} t_{ij}^{k} e_{co2} \cdot W\left(Q_{ij}^{k,z}\right) + c_0\sum_{z=1}^{Z}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} \omega t_{ij}^{k} Q_{ij}^{k,z} \tag{13}$$

In Eq. (13), e_{co2} is the CO2 emission factor, c_0 is the carbon emission penalty cost per vehicle. Based on the above contents, the planning model is constructed, as shown in Eq. (14).

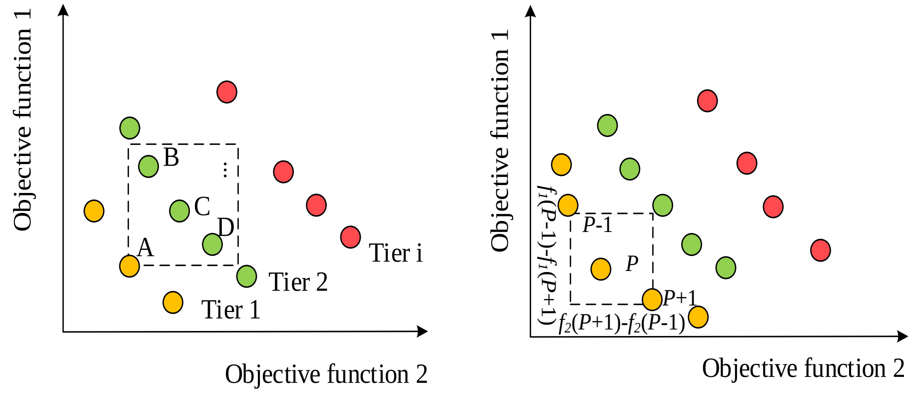
$$\begin{cases} MinC = C_o + C_f + C_l + C_p + C_t \\ MinC_c \end{cases} \tag{14}$$

The constraints of the model are that the customer points to be delivered are N. The total demand of customer points on each delivery route must not exceed the maximum load capacity of the logistics vehicle. Each customer point is served by only one logistics vehicle. There are Z vehicles at the distribution center. The loading capacity of the vehicle when it departs from a customer point is the demand sum of the next customer point and the loading capacity when departing from that next point. The distribution process for each logistics vehicle is continuous. After constructing the mathematical model of the problem, NSGA-II optimizes the multi-objective. On the basis of the traditional NSGA, NSGA-II quickly sorts the individuals in the population by defining the non-dominant set and the dominant set, which reduces the computational complexity, and introduces a management strategy to eliminate the inferior individuals in the population. The crowding and crowding comparison operators were used to ensure the population diversity. The calculation principle of non-dominant layer ranking and individual crowding distance is shown in Fig. 5.

In this study, the initial population is established by the coding method of natural integers. In the algorithm process, it is necessary to evaluate the chromosomes through the fitness function, and the higher the adaptation value of chromosomes, the higher the probability of entering the next generation. The fitness function is set as the total cost reciprocal of distribution target and the carbon emission objective function in Eq. (15).

$$\begin{cases} F_1 = \dfrac{1}{object1} \\ F_1 = \dfrac{1}{object2} \end{cases} \tag{15}$$

In Eq. (15), $object1$ and $object2$ are the two objective functions, F_1 and F_2 are the fitness functions of the total distribution cost and the carbon emission target, respectively. Fig. 6 shows the NSGA-II specific flow.



(a) Non dominated hierarchical sorting chart

(b) Individual crowding calculation

Fig. 5. Principle of non-dominant layer ordering and individual crowding distance calculation.

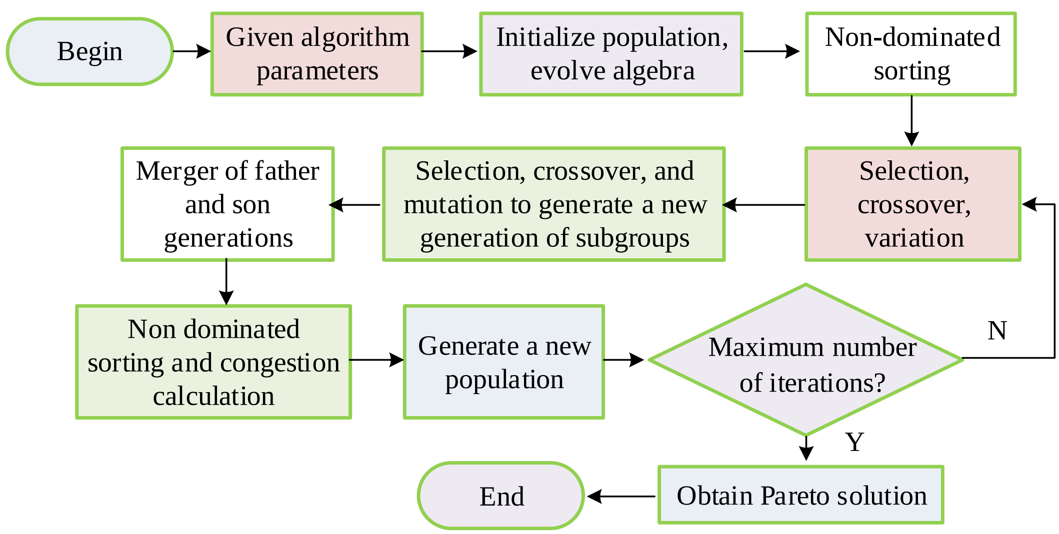
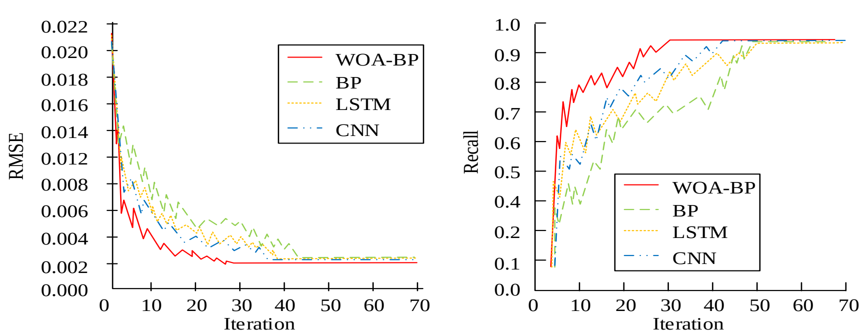


Fig. 6. Specific flow of the NSGA-II algorithm.

IV. Performance Analysis Experiment of Logistics Vehicle Path Planning Model

In order to test the training of the road segment travel prediction model designed in this study, WOA-BP was trained with a single BP network and common neural networks, including convolutional neural network (CNN) and long short-term memory network (LSTM), in the same simulation environment. The training of the four models was recorded for comparison, as shown in Fig. 7.



(a) RMSE (b) Recall

Fig. 7. The training comparison of the four models.

In Fig. 7, WOA-BP's convergence is significantly improved compared with the single BP network model. It is also better than the other two models. As shown in Fig. 7(a), the Root Mean Square Error (RMSE) value is reached after 28 iterations of WOA-BP, while the BP network begins to converge after 41 iterations, and the CNN training reaches 43 times, which is 21 iterations more than WOP-BP and 37 times for LSTM training. As shown in Fig. 7(b), WOP is trained only 30 times to reach the target recall value and begins to converge, which is 15 times less than that of a single BPNN, while both LSTM and CNN are trained more than 40 times.

To further verify the designed trip prediction model stability by this study, road sections data with different distance lengths were used for prediction. At the same time, in order to ensure the comprehensiveness and advancement of the experiment, the current popular prediction model was compared with the constructed prediction model (model 1). The comparison models include the road section travel time prediction model using the improved genetic Kalman algorithm (model 2), the travel time prediction model using the optimization limit learning machine (model 3), the path travel time prediction model using the spatiotemporal feature depth learning model (model 4), and the travel time prediction model using particle swarm optimization wavelet neural network (model 5). Fig. 8 shows the specific results.

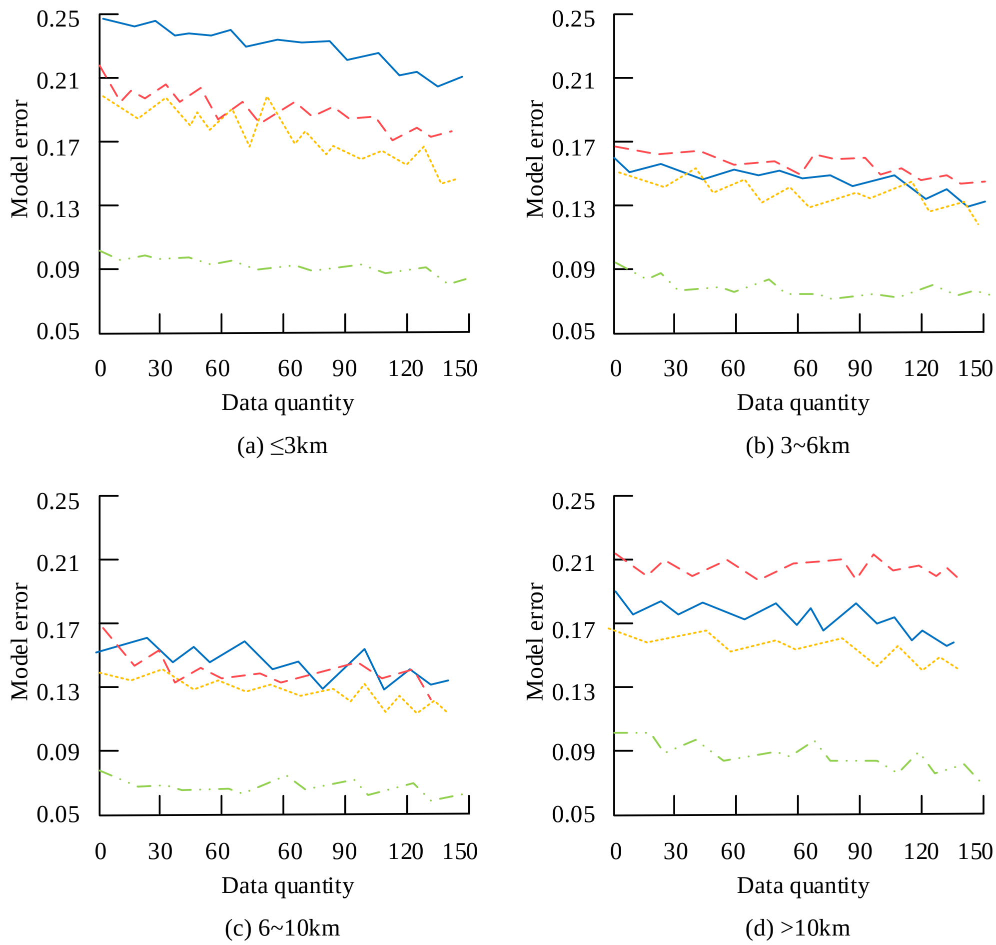
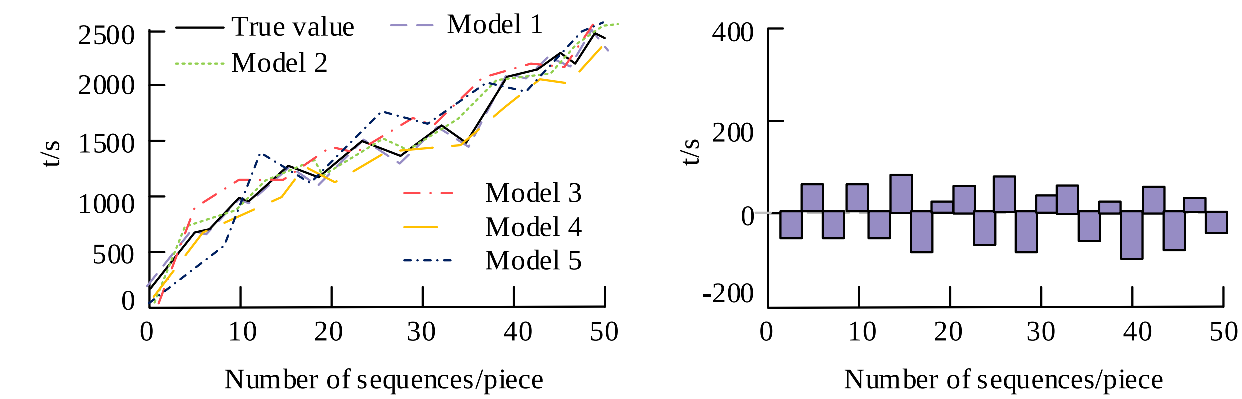


Fig. 8. Model prediction error for the five models at different distances.

As shown in Fig. 8(a), the prediction error of less than 3 km is generally high, which is due to the fact that the short-distance trajectory data is more seriously affected by traffic conditions. As shown in Fig. 8(b), the prediction error is further reduced in the prediction of the 3~6km road section, and the error of model 1 is reduced by 0.2, significantly higher than that of the other four. In Fig. 8(c), the error of all five models is less than 0.15. In Fig. 8(d), the error values of both models 2 and 4 have increased significantly, while model 1 remains stable below 0.10. From the contents of Fig. 8, as the predicted distance data increases, the five models' prediction error increases, and the increase of model 1 is the smallest, which indicates that model 1 has good stability. Moreover, the average error of model 1 is less than 0.10, which can achieve more accurate travel time prediction. To fully prove model 1's effectiveness, the error between the true value and the predicted value of 50 trajectory data was randomly extracted from the test set, and the error was arranged according to the driving time from long to short. The prediction accuracy of the five models is known through calculation. Fig. 9 shows the details.

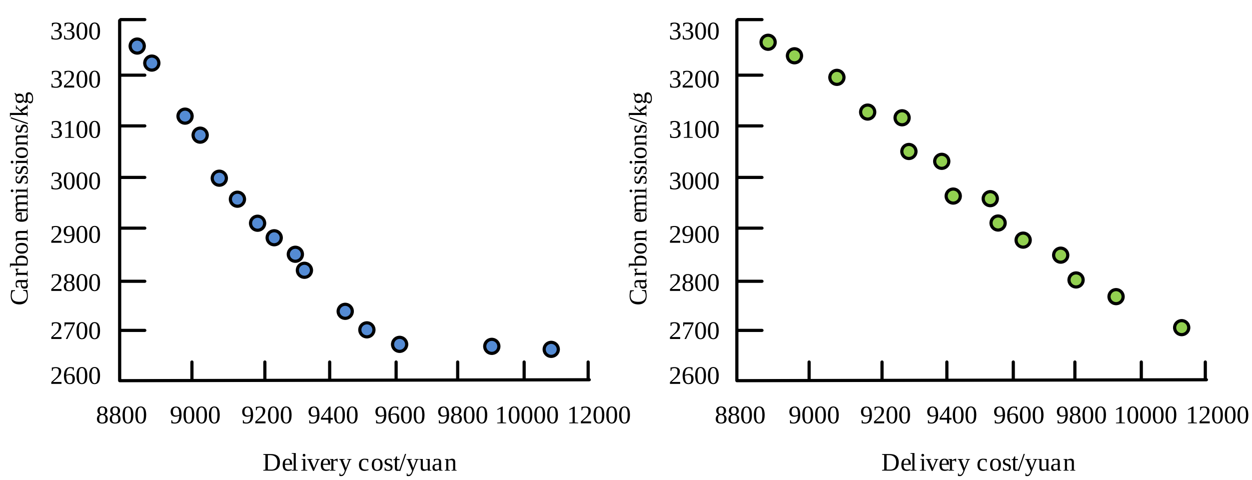


(a) Fit to the true value (b) Error of Model 1

Fig. 9. Comparison of travel time prediction accuracy for different models.

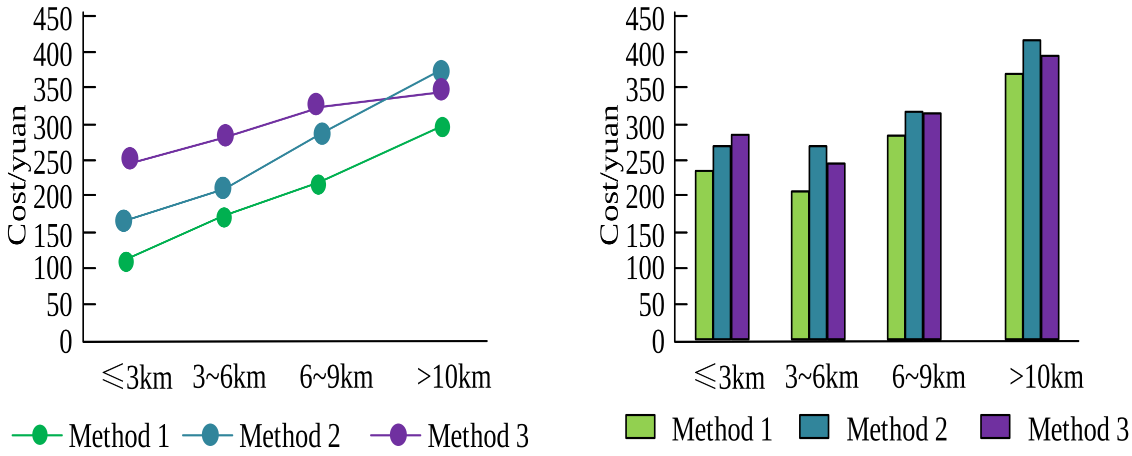
In Fig. 9(a), the prediction accuracy of model 1 for trajectories can reach more than 90%, which fully proves the effectiveness of the model. Moreover, the change curve of model 1 is basically consistent with the real value, and the accuracy of model 1 is higher than that of the other four models. It is found from Fig. 9(b) that the error results of some trajectories have large prediction errors, which is due to the excessive traffic lights in this road section, which leads to the increase of prediction error. However, the error of model 1 is less than 300s, which can meet the needs of logistics and transportation. In the logistics planning, the complexity of the road network and the time variability of traffic conditions are considered in the model. In order to test the study's rationality, the experimental model was compared with the model's operation without those considerations. The comparison results are shown in Fig. 10.

In Fig. 10(a), the model without traffic has lower distribution costs and carbon emissions overall, while Fig. 10(b) shows that the model with traffic is higher than the model without traffic at both target solutions. This is due to the fact that models that do not take into account traffic conditions do not accurately plan the delivery scenario, which will not lead to the closest to the real delivery cost. To further verify the planning method's performance (method 1) designed by the study, the multi-dimensional time-varying data was combined with the set unit time cost of a single fresh food logistics vehicle, and the results of the agricultural product logistics distribution planning method using genetic algorithm (method 2) and the logistics planning method using particle swarm optimization (method 3) were compared. The study was carried out in the distribution network data of two different distribution studies. The results are shown in Fig. 11.



(a) A model that does not consider the timely variability of traffic conditions (b) A model that considers the timely variability of traffic conditions

Fig. 10. Research model and model operation without considering road network complexity and traffic conditions.



(a) Area A (b) Area B

Fig. 11. Comparison of planning effects of different methods in two different distribution examples.

As can be seen from Fig. 11(a), the fixed costs of the three methods are basically the same in Area A, but the transportation costs, loss costs and penalty costs are quite different. The total cost obtained by method 1 is 350 yuan, while the cost of method 2 reaches 410 yuan and the cost of method 3 is 394 yuan. In Fig. 11(b), the total cost of distribution in Area B has increased significantly compared with Area A, which is due to the complex road conditions in Area B, the large number of residents, the need for longer planning routes, and the longer delivery time. The total cost of method 1 is still lower than that of the other two methods.

To further test the planning effect of method 1, three methods were used to carry out path planning under representative examples. The results of the delivery vehicles, route planning time, total distance of route delivery, total cost of delivery and carbon emissions were also listed. Table I shows the details.

TABLE I. COMPARISON OF THE DISTRIBUTION SITUATION OF THE THREE METHODS

Project		Distribution vehicle / vehicle	Pway planning time / minutes	Total path distribution distance / km	Total cost of delivery / yuan	Carbon emission /kg
Method 1	Example 1	13	245	4285.5	8829.1	3255.1
	Example 2	12	217	4183.2	9512.3	2698.4
	Example 3	14	228	4378.4	1055.55	2675.3
Method 2	Example 1	21	359	6158.7	1545.6	3815.8
	Example 2	23	361	6184.4	1523.8	3424.7
	Example 3	22	366	6842.5	1545.7	3482.6
Method 3	Example 1	18	335	5841.4	1242.12	3546.4
	Example 2	17	328	5748.1	1351.54	3415.8
	Example 3	16	330	5694.8	1228.45	3451.5

In Table I, the average distribution cost of method 1 is 9476 yuan, and the average carbon emission is 2871 kg. Compared with the other three methods, the cost of distribution is more than 15% lower, and the carbon emission is more than 12.5% lower. As for the transportation distance, the transportation distance of method 1 is 4282km, which is significantly less than that of the other three methods. Based on the above, it can be seen that the design method of the research institute can achieve logistics path planning with lower cost and carbon emissions and ensure that the delivery is completed within the time required by customers.

In order to verify the effectiveness and rationality of the proposed model, the research applies the solution obtained by the designed method to the actual case, and analyzes the distribution route, vehicle use, and wastage of the proposed solution. First of all, study the selection of takeout delivery scene, fresh house distribution, e-commerce warehousing. And through the simulation analysis, the transportation situation between the solution and the traditional logistics distribution is obtained. In addition, the study invited industry experts and representatives of logistics companies to evaluate the applicability of the proposed solutions and models. Evaluation scores range from 0 to 10, with higher scores indicating higher applicability of the proposed solution. The specific results are shown in Table II.

TABLE II. TEST THE RESULTS OF THE EFFECTIVENESS OF THE SOLUTIONS AND MODELS PROPOSED BY THE STUDY

Distribution scenario		Delivery distance (km)	Vehicle use (vehicle)	Attrition rate (%)	Usability
Delivery scene	Before the application	3.54	4	13.47	6.45
	Post applicationem	2.84	2	5.05	8.95
	P	<0.05	<0.05	<0.05	<0.05
Fresh house with	Before the application	13.85	6	12.84	6.48
	Post applicationem	10.58	3	6.47	9.01
	P	<0.05	<0.05	<0.05	<0.05
E-commerce warehousing	Before the application	352.47	15	18.44	7.02
	Post applicationem	287.46	12	9.74	9.34
	P	<0.05	<0.05	<0.05	<0.05

It can be seen from Table II that after applying the solution proposed by the research Institute, the distribution distance, vehicle use and loss rate of each distribution scenario have been significantly optimized. For the takeout delivery scenario, the delivery distance was reduced from 3.54km to 2.84km, a reduction of nearly 20%. The number of vehicles in use was reduced from 4 to 2, a reduction of 50%; the attrition rate decreased from 13.47% to 5.05%, a reduction of more than 60%. Fresh house distribution and e-commerce warehousing scenes also showed a similar optimization trend. These results show that the proposed solutions can significantly reduce distribution costs, improve logistics efficiency, and reduce resource waste and environmental pollution.

V. RESULTS OF THE RESEARCH

Based on the above experimental and analytical results, the following conclusions can be clearly drawn. By comparing the distribution situation of three different route planning methods, it is found that method 1 has excellent performance in terms of distribution cost, carbon emission and transportation distance. Compared to other methods, the average delivery cost of Method 1 is reduced by more than 15%, carbon emissions are reduced by more than 12.5%, and shipping distances are significantly less. This fully proves the effectiveness of the method designed by the research institute in achieving lower cost and carbon emission logistics path planning. When the designed solution is applied to the actual case scenario, it is found that the distribution distance, vehicle use and loss rate of each distribution scenario are significantly optimized. For the takeout delivery scenario, for example, the delivery distance was reduced by nearly 20%, the number of vehicles used was reduced by 50%, and the attrition rate was reduced by more than 60%. Fresh house distribution and e-commerce warehousing scenes also show a similar optimization trend. These results show that the proposed solution has not only theoretical value, but also high practical application value, which can effectively improve logistics efficiency, reduce resource waste and environmental pollution. Finally, through the evaluation of industry experts and representatives of logistics enterprises, the applicability and effectiveness of the proposed solution are further verified. The evaluation results show that the proposed solutions have generally high applicability scores, indicating that they have great potential in practical applications.

VI. CONCLUSION

As economy and society continuously develop, fresh products is increasingly needed. However, due to the need for refrigeration and preservation of fresh products, the cost has increased significantly. In order to improve distribution efficiency, reduce distribution costs, and reduce carbon emissions, this study considers the road network complexity and the actual traffic conditions variability on the basis of previous studies. A new logistics path planning model was constructed by using the NSGA-II and BPNN. Through experimental analysis, compared with the single BPNN, the convergence of WOA-BP was significantly improved. It took only 28 iterations to achieve the best convergence accuracy. With the increase of the data of the predicted distance, the prediction error of the five models increased, and the increase of model 1 was the smallest, which indicated that model 1 had good stability. Moreover, the average error of model 1 was less than 0.10, which achieved more accurate travel time prediction. The average distribution cost of method 1 was 9,476 yuan, and the average carbon emission was 2,871kg. Compared with the other three methods, the cost of distribution was more than 15% lower, and the carbon emission was more than 12.5% lower. Based on the experimental content, the path planning method designed by the research can reduce the distribution cost and carbon emissions, and bring more satisfactory delivery services to customers. Only one type of delivery vehicle was considered in the study, but in practice, multiple types of delivery vehicles may occur. Therefore, it can be further discussed in the future research process to solve the problem of multi-type vehicle distribution.

Through in-depth analysis and innovative methods, the study has made significant contributions to the knowledge system in the field of logistics path planning. Through the combination of NSGA-II algorithm and BP neural network, a new logistics path planning model is successfully constructed. This model not only considers the complexity of the road network, but also fully considers the variability of actual traffic conditions, thus improving the accuracy and practicability of route planning. This innovative method provides a new way of thinking and methodology for the follow-up research.

As can be seen from the above experimental results, the designed route planning method has excellent performance in terms of distribution cost and carbon emission. In the analysis of practical application cases, the applicability and practicability of the proposed solution are verified.

The logistics path planning model constructed in this study can be used as the basic framework for future research. On this basis, the subsequent research can further explore how to optimize the model parameters, improve the prediction accuracy and expand the application range of the model. Secondly, the proposed solutions and experimental results can provide a strong reference for future research.

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