Research on E-commerce Logistics Transportation Route Planning Method Based on Recurrent Neural Network

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Abstract. Aiming at the problem that the traditional transportation route planning method can adaptively allocate a small number of transportation points, which leads to the long time required for the final route planning, a recurrent neural network-based e-commerce logistics transportation route planning method is studied. Use recursive neural network to extract e-commerce logistics characteristics, calculate the adaptive probability parameters shown by individual transportation individuals, combine gene blocks to control adaptively processed transportation points, set transportation route neighborhood search mechanisms, and build transportation route cost constraint numerical relationships. Combining the congestion parameters generated when the vehicle is running, set the route planning plan, and finally complete the research on the transportation route planning method. After preparing the e-commerce logistics transportation data, simulate the planning of the e-commerce logistics transportation route, apply two traditional transportation route planning methods and the designed route planning method to experiment, and the results show: the planning time required for the designed route planning method The shortest.

Keywords: Recurrent neural network · E-commerce logistics transportation route · Planning method · Transportation point

1 Introduction

With the rapid development of cross-border e-commerce, cross-border e-commerce logistics has shown a relatively lagging situation. Data shows that 80% of the current international express delivery market is dominated by the "four major" international express companies, namely DHL, UPS, FEDEX and TNT. Some domestic express companies engaged in international express business still occupy a relatively small market share. In this context, domestic cross-border electronics suppliers generally cost high freight costs to deliver goods to overseas consumers [1]. In addition, the delivery cycle of these international express goods is generally too long, the overseas warehouses are seriously underweight, the return and exchange procedures are complicated and the cost

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is high. The lack of cooperation among cross-border e-commerce companies in our country, the loose body of supply chain logistics, and the unreasonable structure are another prominent problem.

Most cross-border e-commerce companies establish cooperation with cross-border logistics companies independently, without considering joint navigation to reduce the total cost of international express transportation. According to reports, since international express mails often need to meet a certain amount before they start shipping, if small items want to be shipped to customers quickly, they must pay a higher fee separately, which makes cross-border e-commerce companies "timeliness and cost" The contradiction between the two is in a dilemma. The other is the serious lack of after-sales service capabilities. According to relevant research released by the China E-commerce Research Center, returns are almost impossible to achieve in cross-border e-commerce. One is because the return of goods needs to go through various procedures and the process is very complicated, and the other is because of returns. The cost of logistics payment almost exceeds the price of goods, which leads to the phenomenon that many returned goods are directly destroyed in the bonded warehouse, and merchants send new products to customers [2]. Therefore, the lag of cross-border e-commerce logistics is not only reflected in the backward logistics infrastructure, but also in the lack of awareness of logistics cooperation and environmental constraints.

From the practice of the pilot, it can be seen that promoting the integration and coordinated development of logistics resources is an inevitable trend to promote the development of cross-border e-commerce. The strength of logistics capabilities determines the prosperity of cross-border e-commerce in a region. In the practice of promoting the development of collaborative logistics, the policies implemented by each pilot can be reflected in these aspects. First, establish industry common standards to promote win-win cooperation between logistics companies [3]. Because in the environment of lack of cooperation, logistics companies pay more attention to their competitive position among the peers, and pay more attention to competition rather than cooperation. A development model oriented to pure competition will cause logistics companies to only care about their own profits, and not to pay attention to the benefits that environmental improvements can bring to individual companies.

Aiming at the problem that the number of allocated transportation points is small and the time required for route planning is too long, this paper designs an e-commerce logistics transportation route planning method based on recurrent neural network. The specific research ideas are as follows:

Firstly, the recursive neural network is used to extract the characteristics of e-commerce logistics and calculate the adaptive probability parameters of individual transportation,

Secondly, by combining gene blocks to control the adaptive transportation points, the neighborhood search mechanism of transportation path is set, and the numerical relationship of transportation route cost constraint is constructed;

Then, combined with the congestion parameters generated by vehicles, set the route planning scheme, and finally complete the research on the transportation route planning method.

Finally, the effectiveness of this method is verified by experiments.

2 Research on E-commerce Logistics Transportation Route Planning Method Based on Recurrent Neural Network

2.1 Use Recurrent Neural Network to Extract E-commerce Logistics Features

When using the recurrent neural network to extract the characteristics of e-commerce logistics, the memristive numerical model in the network is called to sort the characteristics of e-commerce logistics into feature parameters [3], and the numerical relationship can be expressed as:

$$k = \frac{\left(R_o - R_f\right)^2}{D^2} \tag{1}$$

Among them, R_o represents the recursive cycle data set, R_f represents the e-commerce logistics characteristic function, and D represents the calibration parameter. Corresponding to the sorted characteristic parameters, a characteristic control process is formed, and the numerical relationship can be expressed as:

$$M(t) = \begin{cases} q(t) & t \le 1 \\ M(o) + k_i & 0 < k_i < c_1 \\ q(k) & k > 0 \end{cases} \tag{2}$$

Among them, $q(t)$ represents a characteristic control function, $M(o)$ represents a continuous function, k_i represents an internal characteristic parameter, c_1 represents a memory parameter, and $q(k)$ represents a characteristic function. Under the control of the characteristic parameters, sort out the numerical changes of the characteristic function in the numerical interval. The numerical changes are shown in the following figure (Fig. 1):

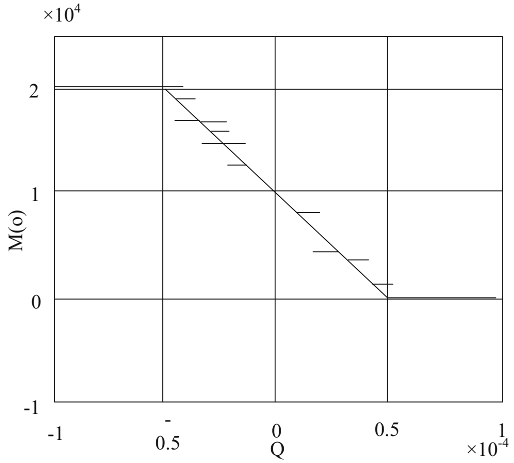


Fig. 1. Characteristic function changes

Under the change of the characteristic function shown in the figure above, combined with the characteristics of the numerical change, the intercept generated during the change is obtained. The numerical relationship can be expressed as:

$$b_0 = R - \sqrt{\frac{2\left(b - R_f\right)^2}{D}} \tag{3}$$

Among them, R represents the characteristic parameter, and b represents the calculated intercept parameter. Based on the above processing process, construct an intelligent value acquisition process, which can be expressed as:

$$u(e) = e\frac{\sum_{i=1}^{p} e(i)}{k-1} \tag{4}$$

Among them, $p_i = e^{\frac{t_1}{\sum f_i}}$ represents the control input parameter, $p_i = e^{\frac{t_1}{\sum f_i}}$ represents the numerical proportional function, and $p_i = e^{\frac{t_1}{\sum f_i}}$ represents the integral parameter of the e-commerce logistics movement path, and the meaning of the remaining parameters remains unchanged. Corresponding to the transportation paths of different control layers, combined with different types of e-commerce, the single neuron structure is set to a control process, which can be expressed as:

$$J = -k\frac{e}{q(i)} \tag{5}$$

Among them, $p_i = e^{\frac{t_1}{\sum f_i}}$ represents the neuron function in the control layer, and the meaning of the remaining parameters remains unchanged. Under the control of the above single neural structure, the transportation network is fixedly connected to the coordinate system, and the movement trajectory of the transportation logistics vehicle control point is processed into a homogeneous form, which can be expressed as:

$$\begin{cases} a = \left[a_x, a_y, a_z\right]^T \\ b = \left[b_x, b_y, b_z\right]^T \\ c = \left[c_x, c_y, c_z\right]^T \end{cases} \tag{6}$$

Among them, a, b, c represent the unit vector generated during the transportation process, and T represents the degree of freedom period. After sorting out the collected characteristic data, set up a neighborhood search mechanism for transportation routes.

2.2 Set Up a Nearby Search Mechanism for Transportation Routes

There are many configurable routes in the actual e-commerce transportation route. When setting the transportation route neighborhood search mechanism, adjust the neighborhood search probability according to its own fitness level, and obtain new ones through neighborhood search for individuals with low fitness. Individual, the adaptive probability shown by the transport individual can be expressed as:

$$p_i = e^{\frac{t_1}{\sum f_i}} \tag{7}$$

Among them, f_i represents the e-commerce transportation individual, t_1 represents the time required for the transportation process, and p_i represents the adaptive function probability. It can be seen from the above calculation formula that the adaptive probability depends on the fitness of the population and the fitness of the individual. If the population fitness remains unchanged, it will decrease as the individual fitness increases, that is, the smaller the individual fitness [4], the greater the probability of neighborhood search. On the contrary, the greater the fitness of the individual, the smaller the probability of neighborhood search, which is accomplished by gene inversion operations.

The above logistics distribution cost model is designed based on the problem of vehicle route planning. How to design a fast and effective intelligent optimization algorithm is the key to solving this problem. The basic Drosophila optimization algorithm is a fast optimization algorithm with high efficiency and few adjustable parameters, but its main disadvantages are that it is easy to fall into local search and cannot solve optimization problems with discrete variables. Here, under its basic framework, the idea of simulated annealing algorithm and genetic algorithm is introduced, and an optimization algorithm suitable for the above model is discussed. The algorithm flow chart is shown in the figure below (Fig. 2):

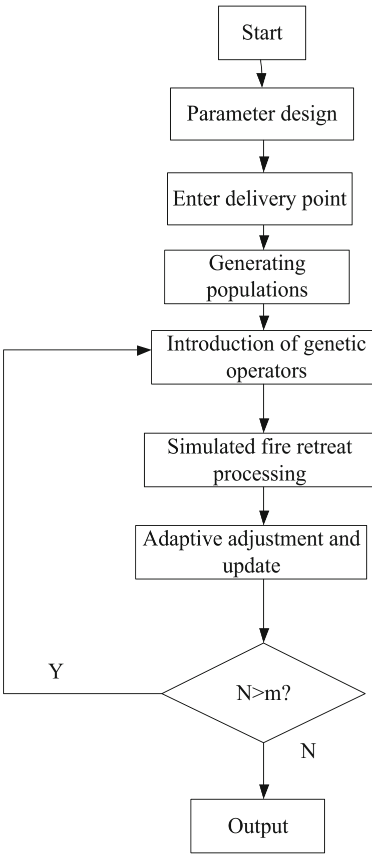


Fig. 2. Constructed neighborhood search algorithm

Under the neighborhood search algorithm shown in the figure above, the number of delivery vehicles and the number of vehicles are deployed, and the delivery task of each truck is abstracted into a set of gene blocks. The delivery plan is expressed as a combination of different gene blocks, and the delivery combination processing process can be expressed for:

$$m = \frac{l + r}{h} \tag{8}$$

Among them, l represents the length of the delivery route, r represents the radius of the similar path, and h represents the length in the gene block. Continuously adjust the distribution process corresponding to the node, adjust the distribution process, the adaptive processing process can be expressed as:

$$f(u) = \frac{\gamma \sum_{k=1}^{K} u_k}{v} \tag{9}$$

Among them, γ represents the delivery parameters, u_k represents the path planning function, and v represents the delivery speed. Under the corresponding distribution speed control, the trend of route planning changes, as shown in the following figure (Fig. 3):

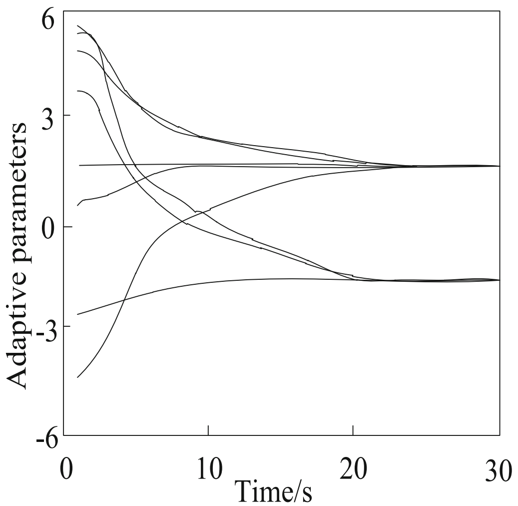


Fig. 3. Route planning trends

Under the route planning trend control shown in the figure above, the pheromone generated during the initial delivery trajectory correction process is used to select the planning direction, and the execution heuristic parameters of the lower layer can be expressed as

$$\rho(t) = \frac{\alpha}{\sum_{k} (\tau(t)\eta_k)} \tag{10}$$

Among them, α represents the number of pheromone produced, $\tau(t)$ represents the visibility function, η_k represents the transfer parameter, and k represents the number of paths. In the process of continuous execution, in order to enhance the accuracy of executing adaptive parameters and control the adjustment amount of pheromone, the processing process can be expressed as:

$$\Delta\tau = \frac{p^k}{d} \tag{11}$$

Among them, $\Delta\tau$ represents the adjustment amount, p^k represents the pheromone parameter, and d represents the calibration path length. After controlling the distance of processing pheromone, introduce a random direction, execute the above-mentioned structural formula, set the random probability constant, and fix the pheromone within a logistics adaptation range [5], and build an adaptive pheromone update process. Expressed as:

$$L\tau = \frac{1}{n}\sum_{i=1}^{n}|B_i|^2 \tag{12}$$

Among them, n is the number of environmental intervals in the logistics matching interval, and B_i represents the logistics structure function. Taking the search mechanism set above as the restriction condition, construct the numerical relationship of the transportation route cost constraint.

2.3 Constructing Numerical Relations of Cost Constraints for Transportation Routes

Under the control of the above-mentioned transportation path neighborhood search mechanism, whether it is to establish a new distribution center or transform the original equipment base into a logistics product distribution center, the enterprise needs to pay related on-site purchase fees, construction fees, construction facility rental fees, and building materials Expenses, etc., are construction costs. After the construction of the distribution center is completed, it will enter the operation stage [6]. In order to ensure the seamless connection between the upstream and downstream of the supply chain, the products can be efficiently transferred in the distribution center, and certain labor costs need to be paid, which is the operating cost of the distribution center. Due to the small difference in daily transaction volume, equipment purchase fees, water and electricity fees, and therefore operating costs have relatively small changes. Assuming that the construction and operating costs of each candidate center are fixed and known conditions, the construction and operating costs of the e-commerce transportation transfer station can be expressed as:

$$\begin{cases} C_r = \frac{\sum\limits_{r\in G} Z_r}{F} \\ C_a = \frac{\sum\limits_{r\in G} A_r}{F} \end{cases} \tag{13}$$

Among them, C_r represents the construction cost, C_a represents the operating cost, Z_r represents the project construction function, F represents the construction period, A_r represents the maintenance cost function, and G represents the distance parameter of the transit center. The transportation cost specifically refers to the vehicle cost incurred by fuel and vehicle maintenance during the delivery of the product to the customer. Transportation costs are closely related to distance traveled, vehicle speed and time. The influencing factors are the vehicle model, the unit distance cost of the vehicle, the driving speed, the distance from the supplier to the distribution center, the distance from the distribution center to each retailer [7], the distance between the retailer and the retailer, and the distance of the vehicle Travel time, etc. The transportation cost of fresh food cold chain logistics mainly includes two parts. One part is the transportation cost from the supplier to the distribution center, and the other part is the transportation cost from the distribution center to the retailer:

$$C_i = \frac{C_p + d_r}{Z_r} \tag{14}$$

Among them, C_p represents the cost incurred during driving, d_r represents the distribution function, and the meaning of the remaining parameters remains unchanged. In order to control the redundant time generated in the distribution process, using the hybrid time window to control the time generated during the distribution process and control the loss, the numerical relationship can be expressed as:

$$C_p = \frac{t \sum_{r \in G} Z_r}{E_k} \tag{15}$$

Among them, E_k represents the redundant function generated by the e-commerce distribution process, and the meaning of the remaining parameters remains unchanged. The control cost constraint is divided into five processing levels, and the cost constraint level changes are shown in the following figure (Fig. 4):

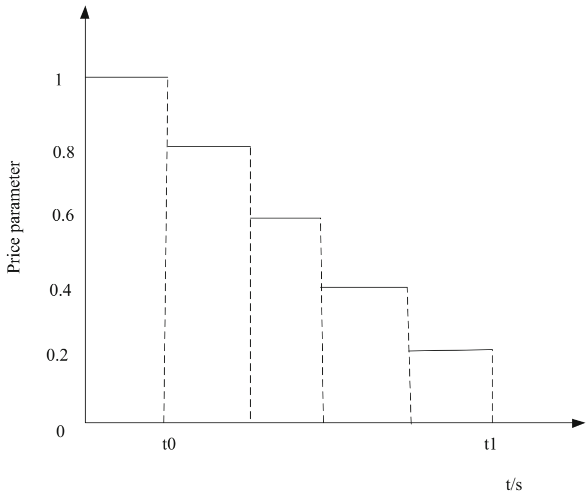


Fig. 4. Cost constraint level

Under the cost level control shown in the above figure, the two-level planning model is used to control costs, and both the upper and lower levels have unique target decision-making powers. It adheres to the principle of implementing planning and decision-making under the condition of maximizing the interests of all people, and discovering the best decision among the upper and lower goal decisions, so that its decision-making strategy achieves a systematic and complete effect [8]. In this way, the control power is in the hands of different levels of managers, so that the overall planning can be carried out more fully and comprehensively, and the value standards of all parties have been considered. Therefore, this method is closer to the reality. Under the control of the set value agreement value relationship, corresponding to the value size of different parameters, set the transportation route planning plan.

2.4 Realize Transportation Route Planning

Under the above-mentioned e-commerce transportation cost constraint numerical relationship, combined with the impact of urban road network traffic conditions, the distribution process is treated as a time-sensitive process [9], and the driving speed is time-varying. It is difficult to directly calculate the travel time of the vehicle on the distribution section, and it needs to span a time period to complete a certain section. Therefore, when constructing the transportation route plan, calculate the vehicle travel time under the time-varying road network condition to control the congestion speed of the vehicle. At this time, the vehicle is congested The duration can be expressed as:

$$t_h = \begin{cases} \frac{d_i}{v_c}, v_c \leq a \\ \frac{v_i - v_c}{v_f}, 0 < v_c \leq u \\ \frac{d_i}{v_f}, t_a \geq a + 1 \end{cases} \tag{16}$$

Among them, v_i represents the travel speed of the logistics vehicle when the traffic is not congested, v_f represents the average speed during half-way congestion, u represents the congestion coefficient, t_a represents the travel time, and v_c represents the travel speed when the entire journey is congested. Construct an adaptive motion process controlled by a single neuron, which can be expressed as:

$$\frac{\overline{M}}{V}\kappa = \overline{B}\tau \tag{17}$$

Among them, $\overline{M}$ represents the angular velocity of the moving vehicle, $\overline{B}$ represents the attitude function generated by the moving vehicle, and κ represents the formation parameter, and the meaning of the remaining parameters remains unchanged. Under different paths of logistics transportation, the corresponding formation parameter values are different. After the formation parameters are fuzzy processed, a set of output parameters are output, which can be expressed as:

$$\begin{cases} \tau_1 = \dfrac{\sum\limits_{k=1}^{n} \mu_{k-1}}{\kappa} \\ \tau_2 = \dfrac{\sum\limits_{k=1}^{n} \mu_{k+1}}{\kappa} \end{cases} \tag{18}$$

Among them, τ_1 and τ_2 represent the output parameters, μ_k represents the fuzzy output function, and the meaning of the remaining parameters remains unchanged. Processing the above output processing parameters are integrated into a data set, in order to arrange all output parameters into a reasonable output sequence of path nodes, and control the convergence of the movement speed function relationship of logistics vehicles, and control the movement speed to satisfy the following numerical relationship:

$$\lim_{t \to t+1} \left\| \frac{U_F}{U_t} \right\| = 0 \tag{19}$$

Among them, U_F represents the ideal driving process of the logistics vehicle, and U_t represents the actual convergence function produced by the logistics transportation vehicle in the time period. In order to control the logistics transportation vehicle as the best operating point, the driving path is treated as a controllable space, as shown in the following figure (Fig. 5):

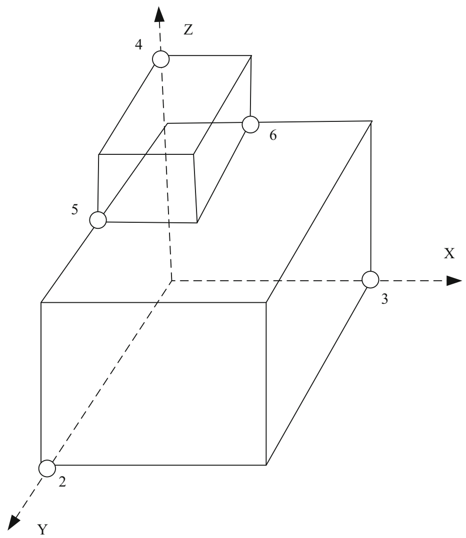


Fig. 5. Regulation of operating space

In the operating space shown in the figure above, when the transport vehicle travels to a point in the space, use MATLAB to compile a calculation example program to optimize the model and design algorithm for the established three-dimensional loading constraint of the fresh product recycling path Perform calculations to solve. In the process of calculation, the vehicle loading inspection algorithm is called for each pick-up route generated by the genetic taboo algorithm, and the loading inspection algorithm is used to check whether the fresh packaging of each route can be loaded successfully [10] to ensure that each cycle All the pickup routes can be loaded successfully. Within the calibrated value points, the circular transportation route formed is as shown in the figure below (Fig. 6):

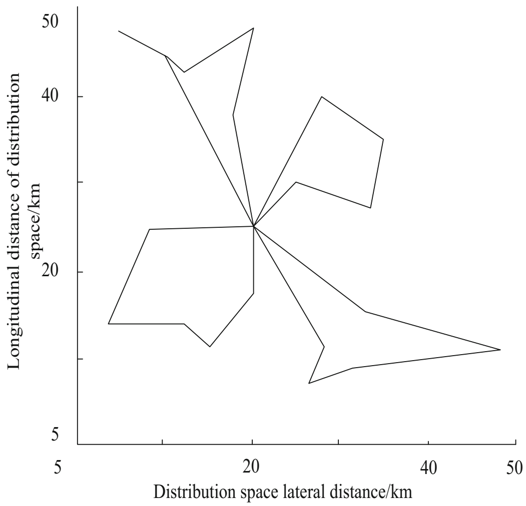


Fig. 6. Formed transportation route plan

Under the transportation route plan shown in the above figure, the existing operation center is used as the processing point, and after the traffic congestion route is reasonably avoided, the planning of the logistics transportation route is finally realized.

3 Simulation

3.1 Experiment Preparation

Since there is currently no standard case database for multi-logistics center joint delivery, and considering that there are many situations in the customer orders of e-commerce companies, the calculation examples 8201, 8202, 8203, 8204, 8205, Solomon's VRP standard test problem database are used. 8206, 8207, 8208, 8209, 8210, 8211, 8212, RC201, RC202, RC203, RC204, RC205, RC206, RC207 and RC208, use the customer coordinates, time window, demand, service time and other data of the above examples as experiments Basic data of the test case. The number of customers in each example is 100, divided into two different customer coordinate distributions. The customer coordinates of the R type example are random distribution, and the customer coordinates of the RC type example are mixed distribution. Each calibration example has 2 logistics centers, the coordinates are (33, 30), (67, 61).

According to the actual situation of urban distribution, the total service time of the logistics center is set to 960 min, and the earliest time for the vehicle to depart from the logistics center is 7:00, set to 0 time, corresponding to the READY TIME of the logistics center in the calculation example, and return to the logistics center The latest time is 23:00. Every 15 min is regarded as a time period, divided into 64 time periods, that is, 7:00 to 7:15 is the first time period, and so on. According to the urban traffic law, set 8:00 to 9:00 and 18:00 to 19:00 as the traffic jam time period, and the other time periods as the normal driving time period. The average vehicle speed is set to 60 km/h, and the vehicle speed during the traffic jam time period is set to 30 km/h. After the basic parameters are set, use Matlab R2016a to program and run on a computer with a 2.30 GHz processor and 4G memory. In order to verify the effectiveness of the multi-logistics center joint distribution model, a comparison experiment was conducted between the multi-logistics center joint distribution mode and the multi-logistics center independent distribution mode. Within the area, plan the distribution path of e-commerce logistics, and the planned distribution path structure is shown in the following figure (Fig. 7):

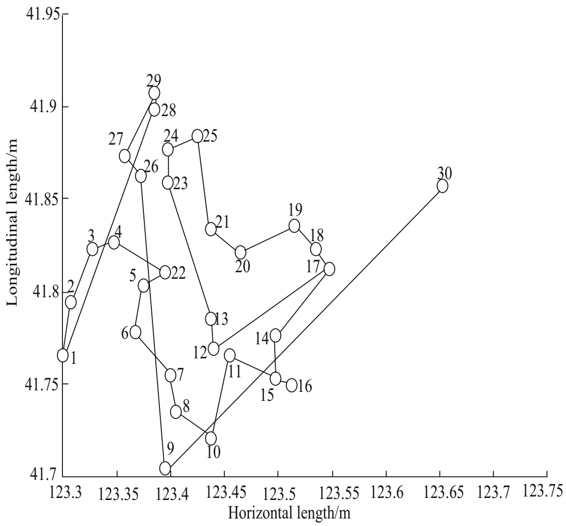


Fig. 7. Set delivery route

Under the distribution route set in the above figure, a distribution center finally determined in 10 alternative logistics centers is No. 37, the location is (123.45, 41.8), 4 distribution vehicles are used, and two traditional route planning methods are used. The designed route planning method is tested to compare the performance of the three route planning methods.

3.2 Results and Analysis

Based on the above experimental preparations, 20 examples in the test question library were randomly selected, and the e-commerce logistics timeliness was defined according to the parameters of the examples. The numerical relationship of the timeliness parameters can be expressed as:

$$PX = \frac{\left(\sum \theta(t_i)d_i\right)}{\sum d_i} \tag{20}$$

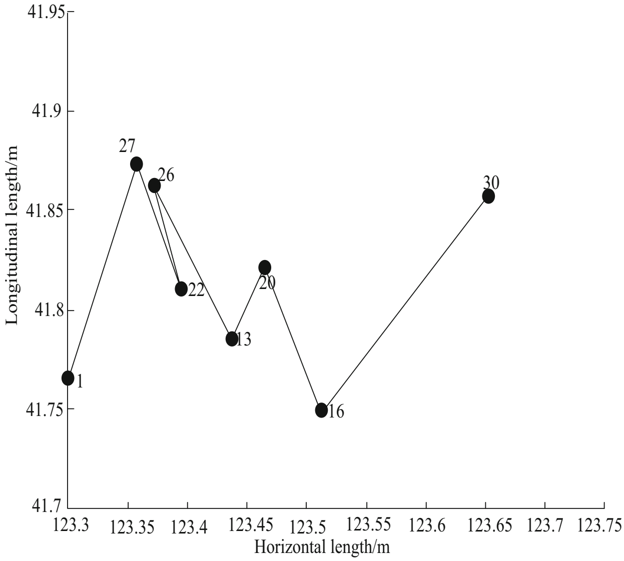
Among them, $\theta(t_i)$ represents the time cost consumed, and d_i represents the actual time of the vehicle's arrival. Under the control of the above-mentioned numerical relationship, the final time-dependent parameter results of the three route planning methods are shown in the following Table 1:

Table 1. Results of the time-dependent parameters of the three route planning methods

Study name	Aging parameter		
	Traditional route planning method 1	Traditional route planning method 2	Route planning method
8201	0.31	0.67	0.87
8202	0.33	0.57	0.85
8203	0.34	0.51	0.92
8204	0.36	0.69	0.86
8205	0.39	0.51	0.91
8206	0.37	0.61	0.88
8207	0.36	0.53	0.86
8208	0.33	0.55	0.88
8209	0.32	0.62	0.88
8210	0.33	0.67	0.88
8211	0.34	0.53	0.89
8212	0.38	0.52	0.91
RC201	0.38	0.64	0.91
RC202	0.33	0.54	0.92
RC203	0.32	0.58	0.89
RC204	0.35	0.56	0.89
RC205	0.32	0.59	0.85
RC206	0.39	0.52	0.93
RC207	0.39	0.66	0.88
RC208	0.34	0.58	0.94

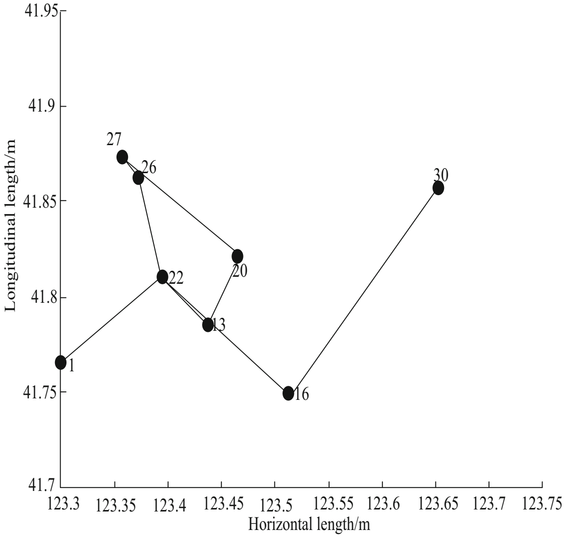
According to the defined numerical relationship of timeliness, it can be seen that under the control of three route planning methods, the planned routes show timeliness of different numerical magnitudes. From the parameter results in the above table, it can be seen that the timeliness parameter of the traditional route planning method 1 is around 0.34, and the route planning by this route planning method has the worst timeliness. The traditional route planning method 2 has an average time-efficiency parameter of about 0.6, and this route planning method has better time-efficiency for planning routes. The time-efficiency parameter of the designed route planning method is about 0.89. Compared with the two traditional path planning methods, the time-efficiency parameter of the designed route planning method is the largest, and the time-efficiency of the planned transportation route is the strongest.

In the above experimental environment, point 1 is calibrated as the starting point of logistics transportation, and the three route planning methods are controlled. The planning points are 8, 16, 20, 13, 22, 27, 26, and point 30. In actual delivery, compare the three The route result of transportation route planning, the route result of route planning is shown in the figure below (Fig. 8):

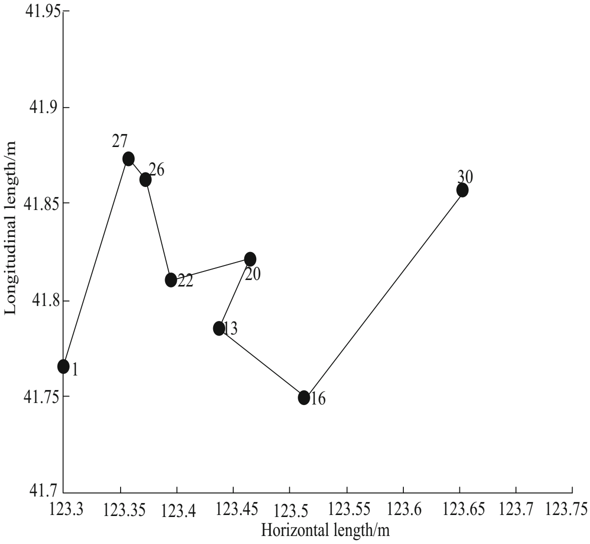


(a) Traditional route planning method 1 Route planning results

Fig. 8. Three route planning methods planning route results



(b) Traditional route planning method 2 Route planning results



(c) Designed route planning method route planning results

Fig. 8. continued

Under the control of three kinds of route planning, the points in the route of the experimental preparation distribution plan are selected. According to the actual planning results, it can be known that the traditional route planning method 1 can obtain the longest route and the actual transportation cost is relatively large. The traditional route planning method 2 The obtained route is longer, and the actual cost is lower. The designed transportation route planning method can obtain the shortest route. Compared with the two traditional route planning methods, the designed route planning method has the shortest route planning.

Keeping the above experimental environment unchanged, corresponding to the experimental data sets prepared for the experiment, apply three route planning methods to process the e-commerce transportation data in the calculation example, take the host computer to start planning and processing the e-commerce logistics transportation route as the time statistics starting point, and display the final route structure as the time statistics cut-off point, and finally the planning time results required by the three route planning methods, The mean planning time of the three route planning methods under 50 iterative experiments is obtained, as shown in Table 2.

Table 2. Planning time required for the three route planning methods

Study name	Planning time/s		
	Traditional route planning method 1	Traditional route planning method 2	Route planning method
8201	9.1	6.4	4.6
8202	13.7	6.7	4.5
8203	10.8	6.8	4.3
8204	12.9	6.4	4.3
8205	12.3	7.1	4.4
8206	9.4	6.4	4.4
8207	11.2	6.6	4.5
8208	13.1	6.7	4.5
8209	12.7	6.7	4.5
8210	12.9	6.8	4.6
8211	11.5	6.9	4.7
8212	11.4	7.7	4.7
RC201	12.4	6.6	4.4
RC202	10.8	7.2	4.1
RC203	12.9	6.1	4.7

(*continued*)

Table 2. (*continued*)

Study name	Planning time/s		
	Traditional route planning method 1	Traditional route planning method 2	Route planning method
RC204	12.9	6.9	4.3
RC205	10.9	7.1	4.1
RC206	12.5	6.9	4.1
RC207	11.1	7.2	4.5
RC208	12.3	6.2	4.8

Under the time statistical period defined above, according to the planning time results obtained from the statistics in the above table, the average planning time of the traditional route planning method 1 is about 11.8 s, and the actual planning time required is the longest. The average planning time required by the traditional route planning method 2 is about 6.7 s, and the actual planning time required for the transportation route is relatively short. The average planning time required by the designed route planning method is about 4.4 s. Compared with the two traditional route planning methods, the designed route planning method requires the shortest planning time.

4 Concluding Remarks

The advantage of cross-border e-commerce is that it has stronger information aggregating and processing capabilities than traditional trade. The reduction of information asymmetry increases the mutual understanding of the two trades and reduces unnecessary doubts. At the same time, the cost and efficiency of information interaction are also Greatly increase. Use information advantages to reduce its costs and increase its transaction volume. Second is the effectiveness of information. Comprehensive information helps both parties to the transaction establish intuitive trust. However, after all, the differences in the field, product, and characteristics of the transaction cause huge differences in information. The buyer needs to be able to find it for his own field or product. Comprehensive and true information, and this information has a strong reference value. The availability of logistics data is a characteristic embodiment of the improvement of logistics service quality. For route planning, data is an intuitive tool for observing its past credit, experience, and achievements. Its value lies in reflecting the development of e-commerce logistics and transportation.

This paper will study how to obtain lower e-commerce logistics transportation cost in the future.

References

1. Wang, L., Wang, B.-q., Liu, J.-g., et al.: Study on malicious program detection based on recurrent neural network. Comput. Sci. **46**(07), 86–90 (2019)
2. Chen, H., Chen, J.: Recurrent neural networks based wireless network intrusion detection and classification model construction and optimization. J. Electron. Inf. Technol. **41**(06), 1427–1433 (2019)
3. Tan, F., Li, C., Xiao, H., et al.: A thermal error prediction method for CNC machine tool based on LSTM recurrent neural network. Chin. J. Sci. Instrum. **41**(09), 79–87 (2020)
4. Li, F., Xiang, W., Chen, Y., et al.: State degradation trend prediction based on double hidden layer quantum circuit recurrent unit neural network. J. Mech. Eng. **55**(06), 83–92 (2019)
5. Li, S., Wang, S.: Recurrent convolutional neural networks-based mobile robot localization algorithm. Comput. Eng. Appl. **55**(10), 240–243+249 (2019)
6. Liu, S., Liu, X., Wang, S., Muhammad, K.: Fuzzy-aided solution for out-of-view challenge in visual tracking under IoT-assisted complex environment. Neural Comput. Appl. **33**(4), 1055–1065 (2020). https://doi.org/10.1007/s00521-020-05021-3
7. Liao, L., Zhang, X.: Multi-depot low-carbon logistics vehicle routing considering customer satisfaction. Inf. Control **49**(04), 420–428 (2020)
8. Liu, S., Li, Z., Zhang, Y., Cheng, X.: Introduction of key problems in long-distance learning and training. Mobile Netw. Appl. **24**(1), 1–4 (2018). https://doi.org/10.1007/s11036-018-1136-6
9. Juntao, L.I., Mengmeng, L.U., Doulin, L.I., et al.: Research on the logistics path planning of fuzzy time window multi-objective cold chain. J. China Agric. Univ. **24**(12), 128–135 (2019)
10. Lu, S., Hu, Y., Qu, S.: Joint optimization of tow-trains dispatch and conflict-free route planning in mixed-model assembly lines. Procedia CIRP **97**(13), 253–259 (2021)