RESEARCH ON LOGISTICS DISTRIBUTION ROUTE OPTIMIZATION BASED ON DEEP LEARNING MODEL AND BLOCK CHAIN TECHNOLOGY

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ABSTRACT

The growing data age is reflected in all aspects of today's society. In the field of logistics, especially when the road conditions in urban areas are complex, how to select the optimal distribution path and reduce the distribution time is a problem worthy of attention. Aiming at the problems faced by traditional algorithms in solving the distribution of logistics vehicles in urban areas, however, the method based on regional chain technology can better solve the path optimization problem. A deep reinforcement learning algorithm based on attention mechanism and LSTM model is designed and applied to the distribution path planning of logistics vehicles. The distribution optimization path of logistics vehicles is obtained through sample training experiments, Thus, it provides a new idea for the optimization of logistics distribution path.

KEYWORDS

Regional chain technology; Logistics distribution route; Optimization; Attention mechanism; LSTM model

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1. PREFACE

With the rapid development of modern information technology and the arrival of the era of big data, a large amount of scientific and technological information has different values, which can promote the development of human science and technology to a certain extent [1-4]. With the in-depth development of cross-border e-commerce, people's demand for logistics efficiency has increased rapidly, and modern information technology has gradually entered the logistics field in this region. As one of the cutting-edge modern information technologies, blockchain technology is also trying to enter, but its applicability needs in-depth research. At the same time, economic cooperation has widened the gap between supply and demand of regional logistics services. In order to alleviate this contradiction, exploratory research is carried out on the applicability of blockchain technology in this field. From the component perspective, the regional logistics subject and the current situation of logistics demand make the blockchain technology applicable at the theoretical level. Based on the application scheme of each component, the applicability of blockchain technology at the practical level is further verified with the combination of simulation and analytic hierarchy process. This technology helps to improve the transparency of regional logistics services and build an efficient logistics mechanism [5-6].

At the same time, with the progress of science and technology society, people also put forward higher requirements for logistics distribution services, the most important of which is the punctuality of logistics distribution [7-8]. Therefore, for this requirement, it is required that the logistics distribution path should be optimized as much as possible. However, at present, specific urban areas such as communities and schools have complex characteristics such as dense customer nodes and fixed areas, so the optimization of distribution path is in an important research position. However, from the perspective of domestic research, there is little research on solving methods based on artificial intelligence. At present, domestic scholars mainly focus on heuristic algorithm, meta heuristic algorithm and its improved algorithm. Wei Xiaodi et al [9] used an improved algorithm of discrete flower pollination algorithm and discrete flower pollination algorithm, the flower pollination operator is redefined and combined with the improved genetic operator. Su Xinxin et al [10] relaxes the vehicle capacity and customer time window, adds the penalty to the objective function, uses the greedy algorithm to generate the initial solution, and then uses the tabu search algorithm to solve it. Four operators are used to search the solution of the neighborhood. In order to further expand the search range, they use the perturbation operator. At present, foreign research on VRP has successively emerged artificial intelligence methods such as pointer network and decoder network to optimize vehicle route. Mao et al [11] proposed a more practical mathematical model of vehicle routing problem with pick-up and delivery, and used the double termination criterion to generate a new solution by adding storage function and using intra line and inter line exchange.Cordeau et al [12] adopts a unified tabu search heuristic method: periodic and multi site vehicle routing problem with time window. The performance of the heuristic algorithm is evaluated by comparing it with the alternative method of benchmark instance with the characteristics of VRPTW problem.

We mainly elaborate the problem of logistics distribution path optimization, clarify that the main form of path optimization in logistics distribution is the problem of determining the starting and ending points, and introduce the method of deep learning in view of the shortcomings of the implementation process of traditional evolutionary algorithm in path optimization and the difficulties of logistics distribution path optimization in complex road conditions. The attention mechanism model based on deep reinforcement learning algorithm is improved, and the model is applied to the logistics distribution vehicle distribution path optimization problem. The strategy network model is built through model components such as delivery length memory neural network, decoder and attention mechanism module, and the logistics distribution path optimization problem is handled through numerical experimental training, verification, test and analysis, so as to promote the development of the logistics field.

2. ANALYSIS OF LOGISTICS DISTRIBUTION ROUTE OPTIMIZATION

2.1. LOGISTICS DISTRIBUTION PATH OPTIMIZATION

Logistics distribution path optimization is a complex problem, which is mainly to solve the problem of path selection in logistics distribution. Usually, the logistics distribution path optimization problem needs to consider the transportation capacity of vehicles, limited time, transportation cost and other conditions. In the actual logistics distribution activities, the proportion of these factors will change. Therefore, the research on the logistics distribution path optimization problem is also divided into many aspects, and the algorithms used are also various. When selecting the algorithm, we should combine the cost constraints such as distribution capacity and time, and fully consider the problems encountered in the actual distribution, so that the algorithm can get an excellent distribution route solution [13-14].

(1)Concept of logistics distribution route optimization

The rapid economic development of our country also brings the leapfrog development of animal logistics industry, especially the rocket development of e-commerce, which has played a great role in promoting the development of logistics industry. The research on the optimization of logistics distribution has become increasingly important [15-16]. However, the current research mainly focuses on the small cars of trucks or express brothers. In the urban transportation network, the optimal route is solved according to the set algorithm model. The optimal route usually needs to consider five conditions [17-19]. The first is the means of transport, which needs to consider the types of means of transport and the cargo carrying capacity of the means of transport. The appropriate selection and allocation of means of transport is an important premise in the rationalization of transport. The second is the transportation link. At the beginning of transportation, goods need to be sorted and loaded. When the type and quantity of goods are large, this work will take up a lot of

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operation time and increase labor and packaging costs. Therefore, the distribution link shall be minimized in the distribution, so as to reduce the cost. The third is transportation time. In today's logistics, transportation time becomes more and more important. There are strict time requirements for the distribution of many items, such as perishable fresh food, items that must be delivered within a specified time limit, etc. Distribution time is not only the requirement of distribution, but also the intuitive embodiment of the distribution ability of logistics companies, which affects the satisfaction of customers. Reducing transportation time is very important to the development of logistics companies. How to reduce the delivery time is the focus of logistics distribution path optimization. The fourth is the transportation distance. Compared with the above factors, the transportation distance has less and less impact on the optimization of logistics distribution path in today's fast traffic environment. However, the increase of transportation distance will also lead to the increase of uncontrollable factors. Now the high incidence of traffic accidents and the increase of road obstacles make the risk cost greatly increase when the transportation distance becomes longer. Therefore, in the optimization of logistics distribution path, we should also try to shorten the transportation distance. The fifth is the transportation cost, which is the key of logistics distribution. After all, logistics distribution is a business activity that pursues the maximization of benefits. The transportation cost mainly includes human cost and loss cost. Now the human cost is getting higher and higher. This problem can be effectively solved by improving the work efficiency of logistics personnel [20-24].

According to different constraints, distribution problems can be roughly divided into the following categories: traveling salesman problem (TSP), collection and forwarding problem, time limited path optimization, multi vehicle path optimization, path optimization with loading capacity constraints, path optimization with compatibility constraints, etc [25-29]. Some literatures are divided into static path optimization problem SVRP and dynamic path optimization problem DVRP according to the treatment methods of the changes of influencing factors in logistics distribution. In today's logistics distribution links, most of the logistics distribution path optimization problems can be regarded as the traveling salesman problem and the problem of determining the starting and ending points. The continuous and rapid growth of traffic flow leads to complex and changeable traffic conditions. Therefore, in the logistics distribution path optimization problem, the research on the logistics distribution path optimization problem based on dynamic road conditions has very important research significance and application value.

(2)Logistics distribution path optimization

In modern logistics distribution, goods are often sent directly to customers from distribution centers or stores. At this time, the form of logistics distribution path optimization is: knowing the departure and arrival places, selecting the best transportation route in the urban transportation network, delivering goods in the shortest time and improving distribution efficiency. The specific form is shown in Figure 1.

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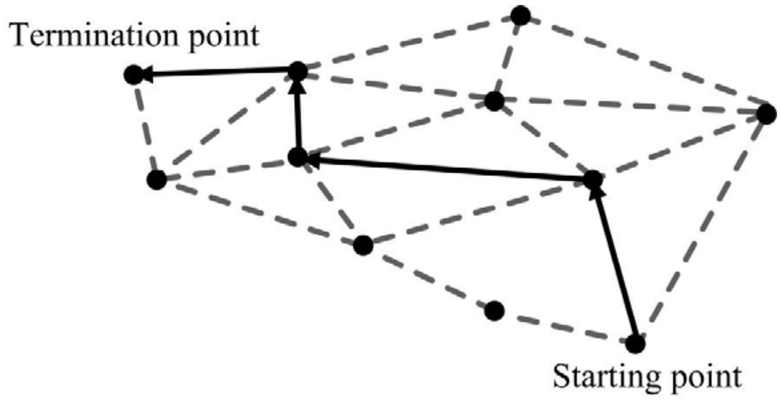

Figure 1 Schematic diagram of starting and ending points of distribution

As can be seen from Figure 1, distribution vehicles start from the starting point, each line represents a road section, and nodes represent intersections. The optimization process is to select the route with the lowest weight value in the urban transportation network to reach the distribution terminal.

2.2. COMPLEXITY OF LOGISTICS DISTRIBUTION ROUTE OPTIMIZATION

In recent years, great changes have taken place in the way, environment and requirements of logistics distribution in China, such as the intelligent management of modern logistics, the changes of logistics transportation tools, customers' higher requirements for logistics distribution standards and increasingly complex traffic conditions. It also puts forward new requirements for the algorithm of logistics distribution path optimization. The traditional algorithm mainly exists in today's logistics distribution path optimization: the solution mode is single, the research on the change of path in path optimization is not accurate enough, and the distribution route cannot be changed flexibly when the traffic conditions change [30].

(1) Complexity of road condition changes

Road conditions many accidents will have a serious impact on road traffic. For example, accidents, road construction, infrastructure construction, abnormal weather, holidays and other events will reduce the road capacity or make it impassable. The traditional algorithm does not consider or deal with these influencing factors. The method is simple and rough, and the calculation accuracy of the influence value on the road condition is very low. In the route optimization, congestion and section gradient are taken into account, and the equivalent consumption is transformed into a flat road with a certain length, which is optimized by the traditional algorithm [31-33]. There is also a logistics distribution route optimization algorithm based on travel time prediction by using the historical average method to predict the road travel time [34-35]. The processing of these algorithms is relatively simple, and the complexity of road conditions is not fully considered.

(2) Complexity of logistics distribution

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In the actual logistics distribution link, the driver in the distribution process, the route selection mainly depends on past experience or colleagues' suggestions, which can deliver the goods quickly and effectively [36]. Or in large logistics companies, provide traffic flow guidance services to drivers through intelligent logistics software. These methods have achieved good results in practical application, but there are also some problems. In a new distribution area, drivers need to spend a lot of time getting familiar with the road, which seriously affects the efficiency of distribution. And listening to the experience of others can not guarantee the correct and timely choice in the complex road. In addition, it is difficult for the distribution personnel to understand and analyze the huge and updated information such as the surge of logistics business volume and the expansion of service area, the large-scale construction of cities and the new planning of road construction. The huge logistics distribution network has difficulty in memorizing information.

3. RESEARCH ON OPTIMIZATION OF LSTM LOGISTICS DISTRIBUTION PATH BASED ON BLOCKCHAIN

3.1. INTRODUCTION TO REGIONAL CHAIN TECHNOLOGY

Blockchain technology is a decentralized distributed database. A continuous record storage structure is formed on the block with time stamps. The block contains various recording applications, such as clearing, smart contract, etc. the data recording node calculates the hash through a specific algorithm, and the current hash, previous block hash, data record, etc. are recorded in the block. Such a data system is credible, so blockchain is a tool for manufacturing credit, and the irreversibility and irreversibility of blockchain technology are all highlighted.

However, regional chain technology has many advantages. Blockchain adopts distributed accounting and storage, and there is no centralized hardware or management organization. Therefore, the rights and obligations of any node are equal. Moreover, the blockchain system is open in nature. In addition to the private information of the trading parties being encrypted, the data of the blockchain is open to all. In the blockchain, any human intervention will not work, changing the trust in "people" to the trust in machines [37]. It enables all nodes in the whole system to exchange data freely and safely in the untrusted environment. In addition, once the information is verified and added to the block in the blockchain, it will be permanently stored and cannot be modified, which improves the corresponding security. In addition, there are regular changes in the changes of urban traffic conditions in a certain period of time. There must be the characteristics of road condition information in this large amount of traffic data. Compared with the traditional neural network, the regional chain technology has a stronger ability to extract the characteristics of traffic data through the setting of multi hidden layer parameters. After the self coding learning and training of road information features, the internal correlation of road information features is closer, so that the prediction of future road conditions is more accurate. Provide accurate road condition parameters for logistics distribution path

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optimization. Compared with traditional algorithms, the optimization results in actual distribution are more accurate.

3.2. INTRODUCTION TO LSTM MODEL

LSTM is an improved version of sample RNN. RNN will be affected by short-term memory, but LSTM can remember longer sequences. During back propagation, RNN will disappear gradient. If the gradient value becomes very small, it will not continue to learn. LSTM can solve this series of problems. Figure 2 shows a unit structure of LSTM model σ And tanh represent the feedforward network layer, where σ The activation function in is sigmoid.

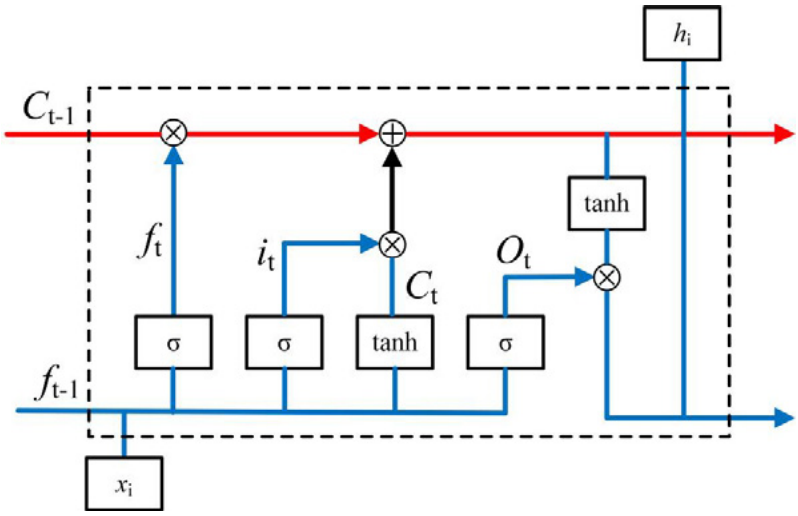

Figure 2 Structure diagram of LSTM model unit

The LSTM model has the characteristics of "long-term and short-term memory", which can be analyzed in this way. It can be seen from Figure 2 that the part shown by the red line is long-term memory. There is only a small amount of linear interaction on this line, which can realize the passage of information from the whole cell structure without change. The part shown by the blue line is short-term memory, which has three parts. The first part is the forgetting gate, It will use ht-1 and Xt to determine which information in the previous unit state Ct-1 is removed. The function formula used is (1):

$$f_t = sigmoid(W_{fx}X_t + W_{fh}h_{t-1} + b_f), \quad (1)$$

The second part is the input gate, which determines which information is put into the unit state, mainly including two steps. The first is that the tanh layer generates the candidate value $C_t^{'}$ that can be added to the state, where $C_t^{'}$ is shown in formula (2). The second is that the sigmoid layer generates the activation value it of the input gate based on ht-1 and Xt, where it is shown in formula (3):

$$C_t^{'} = \tanh(W_{cx}X_t + W_{ch}h_{t-1} + b_c), \quad (2)$$

$$i_t = sigmoid(W_{ix}X_t + W_{ih}h_{t-1} + b_i), \quad (3)$$

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The results of the first and second parts jointly determine the new cell state Ct, where Ct is shown in formula (4):

$$C_t = f_t \odot C_{t-1} + i_t \odot C_t^{'} , \qquad (4)$$

The third part is the output gate, which determines which information in the unit state is used for production output. The function used is shown in formula (5) (6):

$$o_t = sigmoid(W_{Gx} X_t + W_{Gh} h_{t-1} + b_G) , \qquad (5)$$

$$h_t = o_t \odot \tanh(C_t) . \qquad (6)$$

3.3. LOGISTICS DISTRIBUTION VEHICLE ROUTING PLANNING MODEL

All learning algorithms are learned through data. By analyzing the data characteristics of customer requirements, customer location information and demand information, we quantify the location information and demand information of customer nodes, and use the deep reinforcement learning method to design an end-to-end framework to solve the logistics vehicle routing problem [38]. In this method, the training strategy network and value network model only observe the reward signal and follow the feasibility rules to find the near optimal solution for the problem samples sampled from the given distribution. It can be simply explained as a parameterized probability estimation model based on attention mechanism or actor strategy network [39]. The structure of strategy network model is shown in Figure 3.

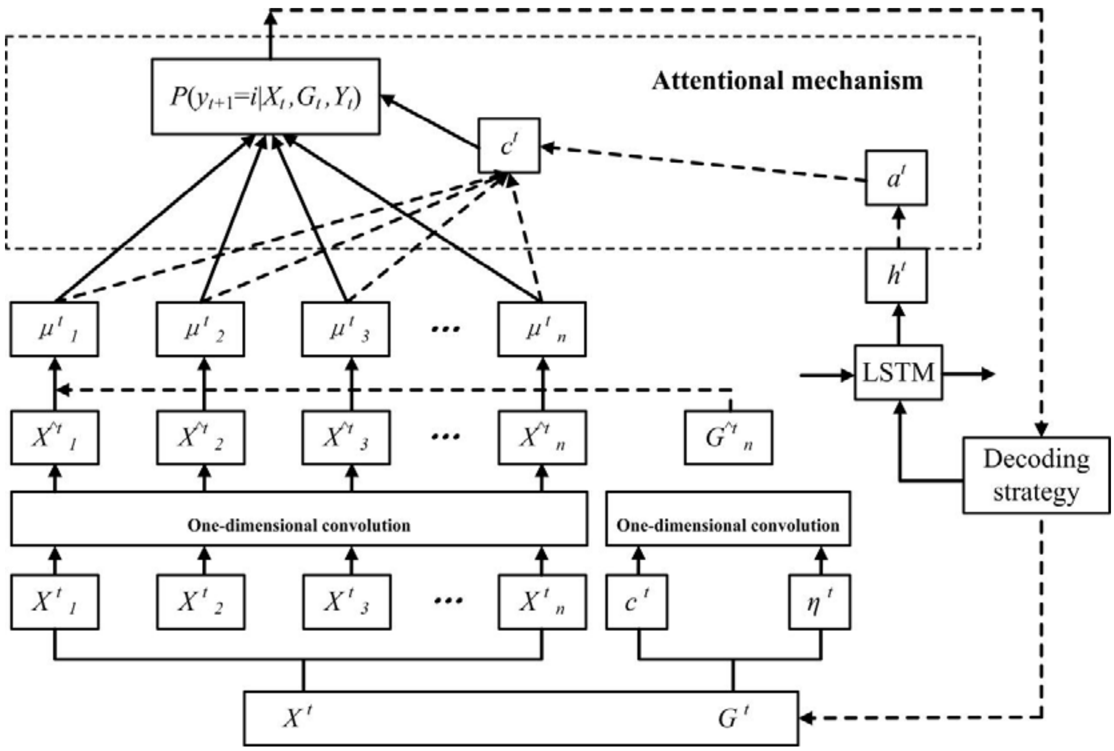

Figure 3 Attention mechanism model based on deep learning reinforcement learning algorithm

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This model includes three parts: customer state information fusion module, attention mechanism module and LSTM module. The customer state information fusion module can transform the structured local and global data information into high-dimensional vectors and fuse the information. The attention mechanism module can estimate the probability of each node I. The LSTM module can remember a longer sequence of customer nodes and improve the solution quality of the model to deal with the customer scale of unmanned fleet and distribution path.

(1)The first part of the model is to map the local and global state information of reinforcement learning into a high-dimensional vector space through one-dimensional convolution operation. In this process, the abstract features of customer location time interval, customer goods demand and unmanned vehicle loading are extracted through deep neural network, as shown in Figure 4.

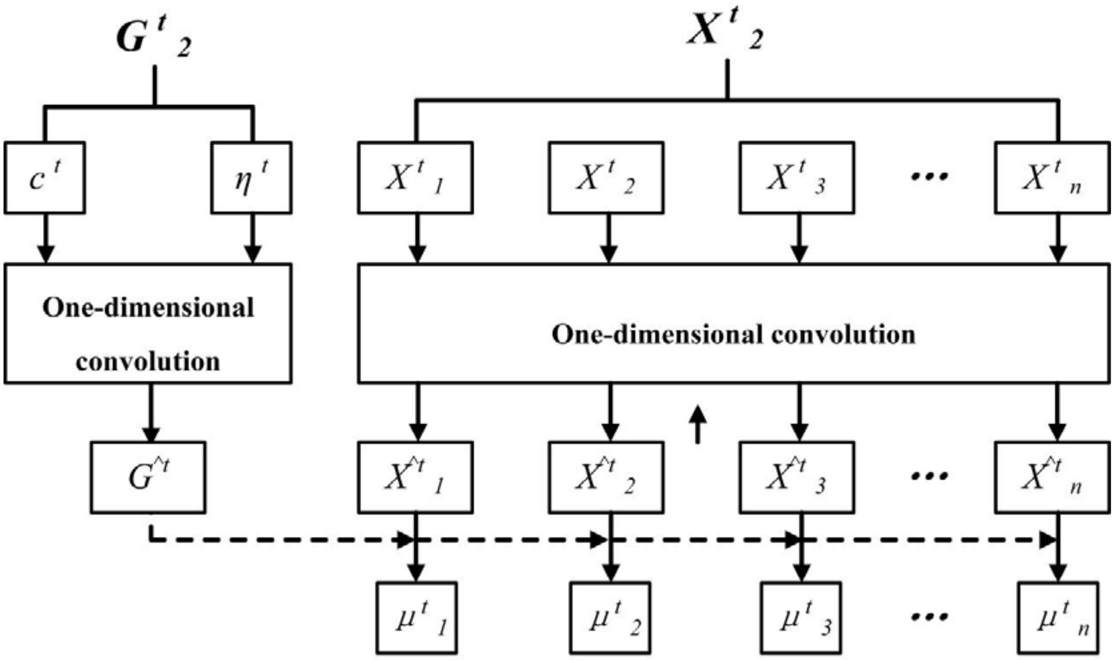

Figure 4 Reinforcement learning state input information fusion module

For customer i, its local information can be expressed by formula (7) and mapped into $\hat{X}_i^t$ vector with ξ dimension through one-dimensional convolution. In order to reduce the amount of parameters, all customers share the weight of one-dimensional convolution. Another one-dimensional convolution layer is used to map the global variable to the $\hat{G}^t$ vector space of dimension ξ, where the global variable is shown in equation (8).The dynamic and static elements contained in local information and global information learn their characteristics in two different convolution layers, and finally fuse them, just like multi-layer information fusion in supervised learning resnet50, and $\hat{G}^t$ and $\hat{X}_i^t$ are combined in a weighted linear way through the ReLU activation function, and finally the fusion information μ_i^t of customer node i is obtained. As shown in equation (9), it contains both global information and local information.

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$$X_i^t = (x_i, y_i, e_i, l_i, d_i^t)\ . \quad (7)$$

$$G^t = \{\eta^t, c^t\}\ . \quad (8)$$

$$\mu_i^t = \mathrm{Re}\,LU(\theta_1 \hat{X}_i^t + \theta_2 \hat{G}^t)\ . \quad (9)$$

The attention mechanism can effectively deal with the expansion of the scale of customer nodes. When decoding customer node i, we pay more attention to the part of customers entering the customer node. The processing ability of the attention mechanism in the face of the expansion of the scale of customer nodes is used to calculate the access probability of each node i. Firstly, the attention weight is calculated. Firstly, the similarity between the hidden state ht of the recurrent neural network and the fusion information μ_i^t of each node I is calculated to obtain v_i^t. Then, after obtaining the similarity between each customer node i and the hidden state, the attention weight a_i^t is obtained by softmax normalization transformation, and the obtained attention weight is used to calculate the weighted sum of the input information μ_i^t to obtain ct, and then the probability distribution of each customer node I is obtained [40]. The calculation diagram of attention mechanism for solving the route planning of unmanned logistics distribution fleet is shown in Figure 5, and the calculation process is shown in formulas (10) - (16).

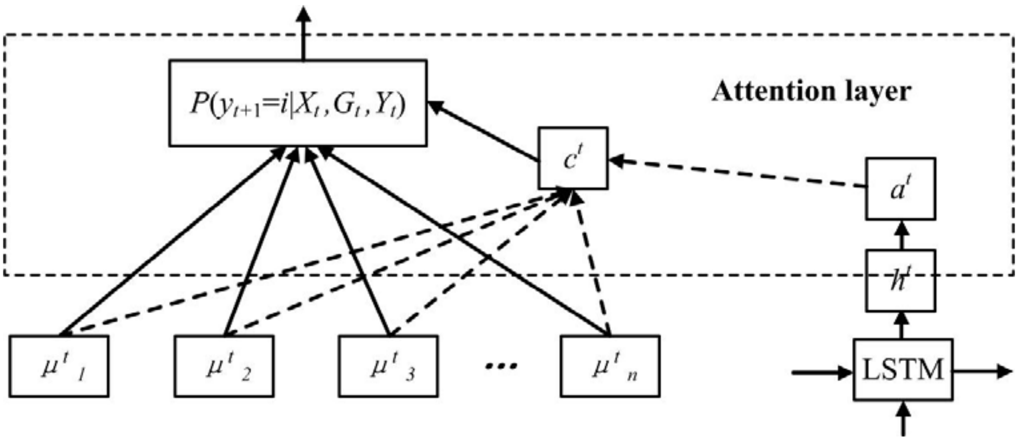

Figure 5 Calculation diagram of attention mechanism for solving logistics distribution path planning

$$v_i^t = \theta_v yanh(\theta_u[\mu_i^t, h^t])\ , \quad (10)$$

$$a_i^t = Soft\max(v^t)\ , \quad (11)$$

$$c^t = \sum_{i=0}^{|V_c|+1} a_i^t \mu_i^t\ , \quad (12)$$

here ht is the hidden state output of recurrent neural network LSTM, v_i^t is the i-th term of vector v^t , tanh is a nonlinear activation function, θ_v, θ_u are a trainable variable, $|V_c|$ is the number of customer nodes, among them are:

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$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}, \quad (13)$$

$$Soft\max(x_i) = \frac{e^{xi}}{\sum_k e^{xk}}, \quad (14)$$

Then calculate the probability estimate of each customer, where g_i^t is the i-th element of g^t, θ_g, θ_c are trainable variables:

$$g_i^t = \theta_g \tanh(\theta_c[\mu_i^t, c_t]), \quad (15)$$

$$p_i^t = Soft\max(g^t). \quad (16)$$

(3) In Section 3.1, the long-term and short-term memory neural network is introduced. Its input has three parts. In the specific application here, the hidden state output ht-1 at the previous time, the cell state ct-1 at the previous time. The input of LSTM is $\hat{X}_{y^t}^t$ representing the information of customer node yt and the hidden state ht-1 of the previous time. The output hidden state ht is used as the input of attention mechanism to calculate attention weight.

3.4. REINFORCEMENT LEARNING ALGORITHM

Deep reinforcement learning algorithm based on round trajectory reward is used to train strategy network and value network model [41-43], the main algorithms are as follows: first initialize the network weight parameters θ,j, generate N VEPTW training instances and iterate circularly epoch→∞, regenerate into a batch of training samples (M training samples from N) $X_{[1]}, X_{[2]}, \ldots, X_{[M]}$, loop n=1,2,...M, select $y_{[n]}^{i_{n+1}}$ according to the model probability distribution $P_\theta(y_{[n]}^{i_{n+1}} | X_{[n]}^{i_n}, | G_{[n]}^{i_n}, | Y_{[n]}^{i_n})$, until all node requirements are 0, then calculate track reward R [44-45]. The training results are obtained according to equations (17) - (18):

$$d\theta = \frac{1}{M}\sum_{i=1}^{M}[R(Y_{[i]}) - v_\varphi(X_{[i]})]\nabla \log P_\theta(Y_{[i]} | X_{[i]}), \quad (17)$$

$$d\varphi = \frac{1}{M}\sum_{i=1}^{M}\nabla_\varphi \left[R(Y_{[i]}) - v_\varphi(X_{[i]})\right]. \quad (18)$$

4. EXPERIMENTAL RESULTS AND ANALYSIS

This experiment considers the practical problems of urban logistics distribution, such as the loading capacity of logistics vehicles. For different sizes of distribution tasks, use distribution vehicles with different loading sizes to carry out numerical simulation experiments on the distribution tasks with customer sizes of 5, 15 and 25 in the end area of the city, and select the distribution vehicle models with unmanned

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vehicle loading capacity of 15, 25 and 35 respectively. The experimental results will give the optimized distribution path.

Using the training set to verify the test set data, 18000 instances are generated as the training set, 180 instances are the verification set and 180 instances are the test set. Each instance is a logistics vehicle distribution task problem with fixed customer size and distribution center. The customer node data of verification set and test set are generated in the same way as the data of training set. The information of customer i is expressed by equation (19):

$$X_i^t = (x_i, y_i, e_i, l_i, d_i^t), \tag{19}$$

The customer demand is randomly selected from the discrete number {1,2,3,4,5,6} and the location x_i, y_i of the customer and the distribution center is randomly generated in the surface space of $[0,1]\times[0,1]$. This study uses this to simulate the urban area. For the three customer scale distribution tasks, logistics distribution vehicles with loading capacity of 15, 25 and 35 are selected respectively.

Table 1 Vehicle information of different customer sizes

Task	Loading capacity C	Vehicle speed V
VRPTW-5	15	v
VRPTW-15	25	v
VRPTW-25	35	v

The training set generates 18000 instances. Each iteration batch selects 180 vrptw-5 from 18000 instances as a training batch. Each training batch makes a gradient update to the strategy network and evaluation network. After completing all the instance data, it is used as an iterative epoch. After each epoch is completed, the model is tested with the verification set. The verification set of this study is composed of 180 instances. The running time of the verification set is collected, Average fleet, total distribution mileage, average reward and other information to evaluate the model. Set 25 epochs for iterations, and each iteration completes one epoch to verify the verification set. When 25 iterations are completed, the model training is completed, and the test model stage is entered. 180 instances are randomly generated from the data of the test set and the verification set in the same way, and finally the optimal logistics distribution path is obtained.

The global and local information studied are mapped into 128 dimensional vectors through two different one-dimensional convolutions, and the hidden state output of LSTM is 128 dimensions. All trainable variables begin to officially enter the training stage after a period of pre training. In order to make the model have generalization ability, let the agent contact more environmental conditions and diversify the situations that the model may encounter, In training, this study adopts the strategy of random sampling. When testing, it adopts random decoding and greedy decoding, and compares the advantages of the two decoding strategies. Experiments are carried out on three VRPTW problems. The scale of customer service nodes are 5, 15 and 25 respectively. For the problem of each customer scale, 180 examples are tested and solved.

After the model training, the test set data is used to test the model. The test decoding strategy adopts random decoding and greedy decoding. Figure 6 shows different distribution route schemes to achieve the optimal logistics distribution route. Due to the different tasks to be performed by different distribution vehicles and the different capacity of distribution vehicles, the optimal route will also be different. Three recommended routes are generated from each different logistics distribution starting point to the destination. Due to the complexity of the road and the problems of selection, it can be seen that figure 6 (a) shows three logistics vehicle distribution routes under vrptw-5: blue line {1,2,3,4}, red line {5,6,7,8}, green line {9,10,11}, and blue line is the optimal logistics vehicle distribution route; Figure 6 (b) shows three logistics vehicle distribution paths under vrptw-15: blue line {1,2,3,4}, red line {5,6,7,8}, green line {9,10,11,12,13}. Red line is the optimal logistics vehicle distribution path; Figure 6 (c) shows three logistics vehicle distribution paths under vrptw-25: red line {1,2,3,4,5}, blue line {6,7,8,9}, green line {10,11,12,13}. Blue line is the optimal logistics vehice distribution path.

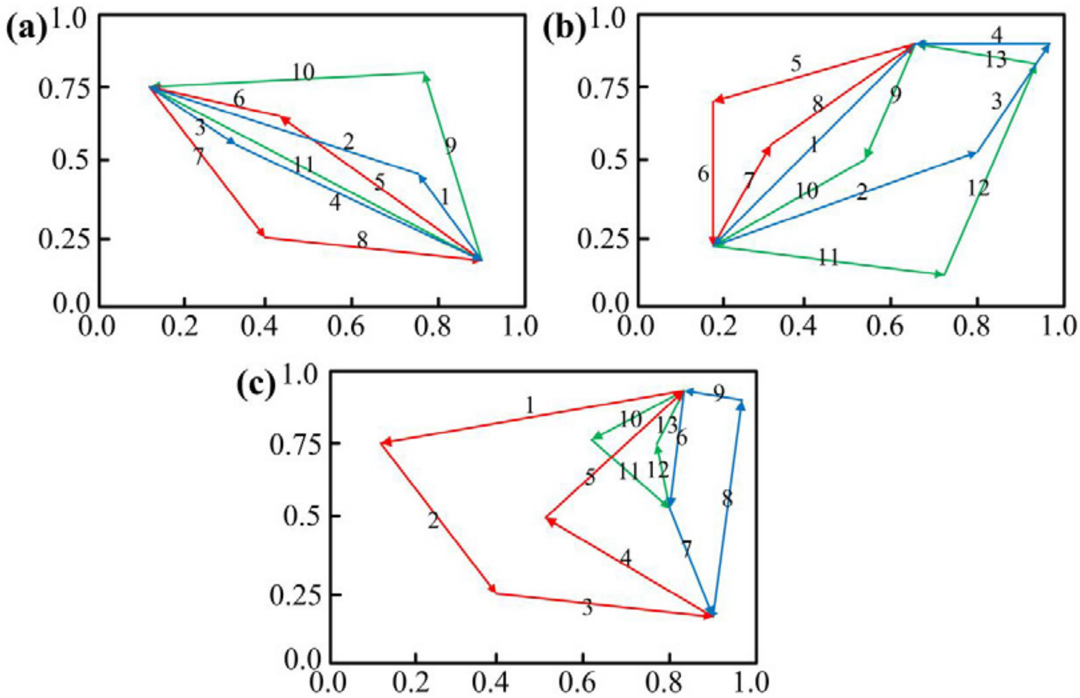

Figure 6 Logistics distribution optimization path with (a)VRPTW-5; (b)VRPTW-15; (c)VRPTW-25

5. IN CONCLUSION

With the rapid development of modern society and entering the Internet era, online shopping has become people's daily life, which makes the logistics industry more and more prosperous. At the same time, it will also put forward higher requirements for logistics distribution, especially in path planning, the logistics distribution method of

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applying science and technology has played a more and more important role. The research results of in-depth learning and reinforcement learning have gradually appeared in the research of artificial intelligence method in vehicle routing problem. Compared with the traditional problem-solving algorithm, the method based on regional chain technology to solve the path optimization problem is more attractive. Therefore, a deep reinforcement learning algorithm based on attention mechanism and LSTM model is designed and applied to the distribution path planning problem of logistics vehicles. The training set is designed for sample test training. 18000 examples are generated from the training set. Experiments are carried out on three VRPTW problems, and then iterative calculation is carried out. Each of them obtains three recommended paths of logistics distribution vehicles, Finally, the shortest optimized logistics distribution path is obtained, which promotes the logistics distribution technology in the information age.

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