Logistics Distribution for Path Optimization Using Artificial Neural Network and Decision Support System

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Logistics distribution for path optimization using artificial neural network and decision support system

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Abstract: Deep learning techniques are developing rapidly and are promising solutions for various problems. The rapidity of society has led to a common problem faced by companies in the logistics market: real-time logistics and distribution path optimization. This paper establishes a model for the logistics distribution path optimization problem, which aims to improve the traditional algorithm's optimization capability under complex urban road conditions. A detailed introduction is made to each part of the model, introducing weight updates to the ant algorithm for optimization, solving the unreasonable problem of the ant algorithm's setting of road parameters, and proposing the DBNTFPO algorithm. Relevant applications of deep learning technology are analysed to explore the relationship between deep learning technology and the real-time distribution of vehicle paths as an optimization problem. Finally, the challenges issued by the real-time logistics distribution path optimization problem to deep learning are drawn out using a decision support system. Finally, the effectiveness and feasibility of this paper's algorithm in practical logistics distribution are demonstrated through example analysis.

Keywords: real-time logistics; decision support system; deep learning; path optimization; relationships; challenges

1 Introduction

The cost of logistics and distribution accounts for the largest proportion of the whole process. The reasonable arrangement of distribution routes has a great impact on the speed, cost and efficiency of distribution, especially in today's road traffic congestion and vehicle increase, scientific planning of logistics distribution can improve logistics efficiency and enhance economic development[2].

In practice, the key to logistics and distribution activities is the optimisation of logistics and distribution routes, which is also closely related to the development of e-commerce[3]. Route optimisation of freight vehicles can improve economic efficiency and achieve rational and efficient logistics. The study of logistics and distribution route optimisation is the basis for the development of intelligent logistics, modern e-commerce and intelligent regulation of transport[4]. At the same time, route optimisation provides reasonable traffic guidance for cities and thus improves the urban traffic environment. Therefore, research on distribution path optimisation is of great scientific significance and application value[5].

Deep learning technology is developing rapidly and the application prospects are expanding. However, the information society has prompted companies in the logistics

market to face a common problem - real-time logistics and distribution path optimisation[6]. All industries today contain varying degrees of logistics and distribution, and thus companies must pay attention to the real-time logistics and distribution chain. The use of information technology to find better and more scientific and reasonable dynamic logistics and distribution flexible paths can enhance the core competitiveness of logistics enterprises. The rational development of real-time logistics distribution paths can reduce logistics costs and improve operational efficiency to a certain extent[7].

Deep learning is currently used in a wide range of fields. Deep learning is extremely powerful and can learn any reasonable behaviour, and thus has an extremely wide range of applications. For example, [8] proposed a novel approach to bankruptcy prediction based on deep learning, which uses extreme gradient augmentation to learn the synthesis of decision trees. In conclusion, in the current society where information technology is increasingly flourishing, deep learning can be combined with data from various situations for learning and training. Industries need to capture all kinds of information from big data and need to optimise their own production and operational arrangements in a more scientific and rational way if they are to seize the opportunities of the market. There are two main types of logistics and distribution: mid-tier logistics and end-to-end logistics and distribution. Mid-tier logistics distribution is usually higher than end-tier logistics distribution, and generally refers to the distribution of a steady volume of demand to a fixed customer, which is usually a retail shop type of customer[9]. Terminal logistics distribution is at the end of the whole logistics distribution process, such as express delivery, takeaway delivery and so on. Nowadays, China's logistics market is developing at a high speed, customer orders are highly variable and traffic pressure remains high, so enterprises must consider the impact of road traffic conditions on logistics and distribution route selection when setting distribution routes.

In traditional logistics delivery route setting, it is usually largely left to the driver to choose his own route based on experience or advice from colleagues. If a new delivery customer is added, then the driver needs to spend some time to choose the driving path. Moreover, traditional delivery vehicle routes are set up largely without theoretical consideration of real-time traffic flow[10]. When the theoretical path is put into practice, it is difficult to fit the theoretical path perfectly with the actual situation due to the dynamic changes in traffic conditions and the increase or decrease in customer volume. In this paper, deep learning is applied to the problem of formulating real-time logistics distribution path optimisation from a theoretical perspective, providing a reference for logistics enterprises' distribution path arrangement, which is of great practical importance[11].

2 Related work

2.1 Optimal solution

The real-time vehicle routing problem is an extension of the simple vehicle routing problem (VPR), which requires consideration of both the spatio-temporal nature of the delivery vehicle and the real-time requirements of the customer unit[12]. The spatio-temporal nature of the delivery vehicle encompasses the actual conditions of the

delivery vehicle in space as well as in time. The real-time vehicle routing problem is strongly related to dynamic traffic conditions. Currently, scholars at home and abroad have conducted extensive research on this class of problems. In [13], clustering algorithms are combined with genetic algorithms to further analyse the conditions that delivery vehicles need to meet in time and space, so that VRPTW can be optimised. [14] Combined with the Lagrangian relaxation method of forward dynamic programming, this appears to be an exact solution.[15] incorporated the selection operation in genetic operators into an ant colony algorithm and constructed a hybrid algorithm to obtain a more optimal solution to the problem. Foreign scholars extended the simple vehicle path problem in many aspects and multiple dimensions. [16] effectively solved the vehicle path problem with capacity-constrained delivery vehicles and customer point-in-time window requirements by improving the selection and variation operations in the genetic algorithm; [17] obtained a more optimal solution of VRPPD by using the forbidden search algorithm as the main body and also the domain operation and clustering algorithm. [18] used two different hybrid genetic algorithms to find a more optimal solution for simple VPR.

2.2 Deep learning and logistics distribution combined

Many scholars have applied deep learning to the optimization of logistics distribution paths based on road conditions, and have achieved significant results. [9] efficiently found the optimal path through a neural combinatorial optimisation strategy based on deep reinforcement learning. [19] provides a comprehensive survey focusing on the use of deep learning models to improve the intelligence of transport systems, and then shows how various deep learning models can be applied to a variety of transport applications. [20] demonstrates that path planning obtained using robotic training methods in deep learning is more rational and that the algorithms are faster at finding the best. With dynamically changing customer demand and traffic road conditions, the training-based exploration of time-varying environments by means of deep learning is a better solution direction for logistics and distribution path optimization. [21] built a logistics distribution path optimization algorithm based on a model of self-coding network based on deep learning.[22] also used deep learning to make short-term predictions of traffic flow conditions.

3 DBNTF model □ □

The DBNTF model begins with the construction of a DBN model, which uses unsupervised learning of the traffic data. The DBN model is then followed by a surtax classifier, which is trained supervised by the set traffic class value Y with labels, to complete the prediction function of the model[23].

3.1 DBN model construction □ □

The DBN model is set to five, and the structure diagram is shown in figure 1: □

Figure 1 Five-layer DBN structure □ □

The five-layer DBN structure is already well suited to the needs of traffic data for learning[24].□

3.2 DBNTF model analysis □

The DBNTF model is trained by layer-by-layer RBM pre-training and BP algorithm tuning, and the training process is shown in Figure 2:

Figure 2 Training of the DBNTF model □

The number of layers is denoted by m and the position in the current layer is denoted by n . Then node j is denoted by a_{32} , node k is denoted by 4, and the initialized weight W is the smaller value, which leads to the node calculation formula as follows:

$$a_n^m = \sigma \left(\sum_k w_{nk}^m a_k^{m-1} + b_n^m \right) \quad (1)$$

□ In the above equation, w_{nk}^m represents the connection value (weight) between

the kth nodal neuron in layer m-1 and the nth nodal neuron in layer m. b_n^m represents the bias unit and the activation function Sigmoid is represented by σ . □

$$\sigma = \frac{1}{1 + e^{-z}} \quad (2)$$

The addition of the activation function serves to vary the model non-linearly for the purpose of greater learning ability, and the summation unit is given by:

$$z_n^m = \sum_k w_{nk}^m a_k^{m-1} + b_n^m \quad (3)$$

The above equation can be reduced to the following form by transformation:

$$z^m = w^m a^{m-1} \quad (4)$$

At this point the output of the m-layer is defined by the non-linear transformation of the S-shaped function: □ □

$$a^m = \sigma(z^m) = \sigma(w^m a^{m-1}) = [\sigma(z_1^m), \sigma(z_2^m), \dots, \sigma(z_n^m)] \quad (5)$$

Using the theory of regularization to make the necessary modifications to the loss function, the new function equation is: □ □

$$C = \frac{1}{2M} \sum \|y - a^m\|^2 + \frac{\gamma}{2M} \|W\|^2 \quad (6)$$

To address the phenomenon of overfitting of the model, the upper part of the equation denotes the mean squared error, enhancing the representation of the coefficient matrix W in the regularisation. k is a set positive number and M is denoted as the number of data in the sample. The resulting expression for the minimum of the coefficients W and the loss function is as follows: □

$$\begin{cases} w = [w^2, w^3, \dots, w^m] \\ \min \frac{1}{2M} \sum \|y - a^m\|^2 + \frac{\gamma}{2M} \|W\|^2 \end{cases} \quad (7)$$

In the classification stage it is necessary to manually set the learning sample data with labels to provide to the classifier for learning, and the classifier learns to classify the reconstructed feature volume set based on the set of labeled data, and can perform classification operations on the feature volume set once the learning capability is obtained [25]. The training set is first constructed, and the vector V of traffic information features and traffic influencing factors is learned by the DNN model to obtain a new vector X. The prediction model is to output 10 traffic class values (0-9), with class 0 indicating impassable and class 9 indicating a traffic section with very few vehicles and unobstructed traffic. The class labels $y^{(i)} \in \{0, 1, 2, \dots, 9\}$ are set for each vector based on the manually set class values to represent the ten class values to be predicted by the classifier, which gives the expression for the set of labelled vectors as: □

$$L = \{(x^1, y^1), (x^2, y^2), \dots, (x^m, y^m)\} \quad (8)$$

The softmax model is a generalized variation of the logistic regression model in multiclassification research. For the set training set input with labeled vector set L, the more used method can be chosen to estimate the probability value $p = (y = j | x)$ for each class j by setting the hypothesis function, so that the hypothesis function h^x can be expressed as: □

$$h_{\theta}^{(x^{(i)})} = \begin{bmatrix} p^{(y^{(i)}=0 | x^{(i)}; \theta)} \\ p^{(y^{(i)}=1 | x^{(i)}; \theta)} \\ \vdots \\ p^{(y^{(i)}=9 | x^{(i)}; \theta)} \end{bmatrix} = \frac{1}{\sum_{j=1}^{10} e^{\theta_j^T x^{(i)}}} \begin{bmatrix} e^{\theta_1^T x^{(i)}} \\ e^{\theta_2^T x^{(i)}} \\ \vdots \\ e^{\theta_k^T x^{(i)}} \end{bmatrix} \quad (9) \quad \square$$

□

$$j(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m \sum_{j=1}^k 1\{y^i = j\} \log \frac{e^{\theta_j^T x^{(i)}}}{\sum_{i=1}^k e^{\theta_j^T x^{(i)}}} \right] \quad (10)$$

$y^{(i)}$ is the output traffic level value is a 10-dimensional feature vector, the kth non-zero is 1 for the traffic level value K-1, the traffic level value Y for the capacity, Y value is the label data of the DBNTF model during supervised training, Y value is solved by the following formula: □

$$Y = \frac{v_t}{v_{\max}} \left(1 - \frac{cn}{Cn_{\max}} \right) \times 9 \varphi \quad (11)$$

3.3 Training of the DBNTF model □ □

The training of the DBNTF model for road condition prediction based on deep belief networks is also the process of solving for the internal weight coefficients W of the model. The magnitude of the traffic data samples is relatively small, so batch gradient descent is used, and there is equation (11) to obtain the parameter matrix W. The equation for updating the parameter matrix is: □ □

$$w_{nk}^m := w_{nk}^m - \mu \frac{\partial C}{\partial w_{nk}^m} \quad (12)$$

The symbols in the middle of this equation are assignment operators and M denotes the learning rate. Thus each iteration in batch gradient descent requires solving for the partial derivative of the weight parameter W for each unit node of the deep learning model. The operator matrix is: □ □

$$\nabla C = \begin{bmatrix} \frac{\partial C}{\partial w_{10}^m} & \frac{\partial C}{\partial w_{11}^m} & L & \frac{\partial C}{\partial w_{1k}^m} \\ \frac{\partial C}{\partial w_{20}^m} & \frac{\partial C}{\partial 2} & L & \frac{\partial C}{\partial w_{2k}^m} \\ L & L & L & L \\ \frac{\partial C}{\partial w_{n0}^m} & \partial c_{n0}^m & L & \frac{\partial C}{\partial w_{nk}^m} \end{bmatrix} \quad (13)$$

The DBNTF (Deep belief network traffic forecast) algorithm is combined with logistics and distribution route optimization, and a DBNTF-based logistics and distribution route optimization algorithm is proposed. The DBNTF model and algorithm are used to solve the time-sharing traffic level value of the road section, and the time-sharing traffic level value P is introduced into the traffic network to build a time-sharing traffic network with weight. The effectiveness and feasibility of this paper's algorithm in practical logistics distribution[27].

4 DBNTF-based logistics distribution path optimization model □ □

In order to facilitate the solution of the DBNTF-based logistics and distribution path optimisation algorithm, a DBNTF-based logistics and distribution path optimisation model is constructed. The model is based on the traffic level values solved by the DBNTF model, the construction of a time-sharing traffic network with weights and an improved ant algorithm, and finally the optimal path based on logistics and distribution information. □ □

4.1 Path optimisation ideas □ □

Logistics distribution belongs to the branch and end transport in logistics transport, with the characteristics of short distribution distance, small scale and high frequency, and high requirements for time, so it is necessary to choose the distribution route dynamically according to the change of road condition information[28].

In Chapter 3, the prediction of road conditions parameters was completed. Path optimisation also requires knowledge of the traffic network in the distribution area, distribution information (departure time and distribution point), and the distribution route after the solution of the path optimisation algorithm. The steps of route optimisation are shown below.

(1) Based on the traffic class values with time tags obtained in Chapter 3, the corresponding road section weights are calculated by transformation.

(2) Obtain the traffic network of the distribution area and combine it with the weights to construct a time-shared traffic network map with weights.

(3) Use path optimisation algorithms to solve the distribution routes in the time-sharing weighted traffic network based on the distribution information.

4.2 Construction of the path optimization model □ □

Based on the idea of path optimization, the logistics distribution path optimization process is summarized and summarized, so as to build a logistics distribution path optimization model based on DBNTF. As shown in Figure 3: □ □

Figure 3 DBNTF-based logistics distribution path optimization model □

From Figure 3 it can be seen that the logistics distribution path optimisation model focuses on the two aspects of the construction of the time-sharing traffic network with weights and the solution of the improved ant algorithm. Firstly, each module of the model is described: road data: the road data contains traffic data and factors influencing road conditions (weather, weekends, etc.), which need to be pre-processed and setting labels (required for model training).

Logistics and distribution information: Logistics and distribution information are the input information for the path optimisation model, including distribution departure time and distribution location.

Traffic network topology: The topology of the traffic network is mainly based on the official traffic network map for processing and transformation.

Time-sharing traffic network with weight: The time-sharing traffic network with weight changes with time, and the weight of the traffic network also changes, based on time-sharing traffic level values and the topology of the traffic network.

Improved ant algorithm: The ant algorithm with weight update is a simple solution to the traditional and algorithm for the road condition parameters, and introduces a time-dependent weight parameter based on the time-dependent traffic class values.

Optimal route: The optimal distribution route is found by the improved ant algorithm.

4 . 3 Improving the ant algorithm □

The ant algorithm is proposed based on the path optimization problem, which has good solving ability for the path optimization problem, and the algorithm is executed in parallel. In response to the unreasonable setting of road parameters by the traditional ant algorithm, the weight update is introduced into the ant algorithm, which makes the improved ant algorithm have better optimisation finding ability for logistics

distribution in complex road conditions[29].

Pheromone which is actually an abstract quantity, the amount of information changes is inversely proportional to the total length of the path, so it is a quantity that reflects the total length of the path and transmits it cumulatively. In logistics and distribution can be understood as the route with good road conditions, the more willing the distributor is to take, this paper takes Q/Z as the amount of change in pheromone, where Q is a constant. Expectation is a reflection of the length of a single path, which is inversely proportional to the length of the path as well as the pheromone. Expectation represents the cost of a single path and is commonly used by the ant algorithm to represent $1/d_{ij}$.□

$$\eta_{ij} = \frac{1}{d_{ij} \cdot w_l} \quad (14)$$

In the logistics distribution problem, each time an ant returns to the distribution centre, a distribution route is completed, and then the ant starts again from the distribution centre to search for the next route. The ant does not reach its destination until it has traversed all the distribution points.□ □

From the above description of the ant algorithm logistics distribution the path equation can be derived as: □ □

$$d_{ij} = s \times w_l \quad (15)$$

Bringing the weight update into the equation gives: □ □

$$d_{ij}^t = s \times w_l^t \quad (16)$$

w_l^t can be derived from Equation 16, where the ant updates the weight parameter based on the current moment once for each distribution point it moves.□ □ □

5 Examples and experimental verification □ □

Neither the theoretical model nor the algorithm alone can demonstrate well whether the model and algorithm proposed in this paper have practical utility. The best way to validate the algorithm is from both example and simulation verification. Therefore, this paper uses the central traffic network of Nanning as the background of the case, and solves the distribution problem of multiple distribution points using the DBNTFPO algorithm proposed in this paper.□

5.1 Example presentation □

Take the example of a city logistics delivery company that delivers a certain kind of goods to 30 delivery points at 7am and 7pm, the location of these 30 points is shown in the figure below:

Figure 4 Distribution point locations □

There are three vehicles going out for delivery at a time and three vehicles delivering this type of goods followed by other goods, so the shorter the delivery time the better, short delivery times are efficient and bring economic benefits to the driver and the logistics company. Drivers usually rely on experience and historical habits to choose their delivery routes, but with the high traffic flow in the city centre, frequent congestion and complex road conditions, personal experience often does not work. The traffic network data of Nanning City was transformed through a pairwise network to obtain 4,152 intersection nodes in Nanning City. Finding the optimal solution for 30 delivery points out of 4152 intersection nodes is a very complex process.

The optimal route is composed of several connected road sections, and an optimal route may contain hundreds of road sections. For reasons of space, this paper compares different algorithms in terms of the number of route solutions, the average number of road sections contained in the solution and the distribution time, to verify the effectiveness of this paper's algorithm in logistics distribution [29]. □ □

5.2 Case results and analysis □

In order to verify the effectiveness of the algorithm in this paper, three vehicles delivering a certain kind of goods were used to select routes by different methods, which are: an algorithm, driver experience method and DBNTFPO algorithm. In consideration of the realistic situation and the need for algorithm evaluation, the validation time was set to a certain week in March. The average values of the number of delivery routes and the number of sections included in the delivery routes in a week for the three methods are shown in Table 1: □

Table 1 Number of solutions by method during the week

Algorithm	Number of Solutions	Average number of sections
Ant algorithm	1	789
Driver experience method	25	172
Dbntfpo algorithm	59	175

The traditional ant algorithm has a fixed path length, which is not updated after one solution, and the driver relies on driving experience to choose the route. The DBNTFPO algorithm relies on the advantage of rich traffic data to produce a large number of route solutions. The average number of road sections for these three algorithms does not differ much, as road conditions vary greatly from section to section and routes contain many sections, not necessarily in short time. How good these route solutions are also needs to be evaluated by distribution time.

Figure 5 distribution diagram of three methods within one week □

The delivery time data is obtained from the records of the delivery drivers. From Figure 5, we can see that the time advantage of this paper's algorithm is relatively obvious, and the delivery time is relatively stable. The traditional ant algorithm has a single route, with large fluctuations in time changes and poor risk resistance. The driver's experience method is also unstable, and the driver mainly selects the route based on his personal experience, and the delivery is relatively stable, but the route is not optimal.

5.3 Simulation validation and analysis □

The biggest advantage of simulation validation is that it can be simulated many

times with sufficient amount of data. The tool for simulation validation is MATLAB2012R, which randomly selects the traffic level data between 5 am and 22 pm of a certain day, constructs a time-sharing traffic network, and uses three algorithms, namely genetic algorithm, traditional ant algorithm and DBNTFPO algorithm, for comparison test, every 1 hour (12 time slots) departure in the form of determined start and end points. The comparison results are shown in Figure 6: □

Figure 6 Delivery time comparison chart □

The above figure shows the change of delivery time in consecutive time periods within a day, which can be seen that the delivery time changes at any time with obvious ups and downs. In this paper, the ant algorithm based on weight update is shorter than both traditional ant algorithm and genetic algorithm in terms of delivery time within a day, and the advantage is more obvious during the peak commuting hours, and the change of delivery time also reflects the change of road conditions to a certain extent. □

Figure 7 Effect of route optimisation in different cities

As shown in Figure 7, the algorithm of this paper combines the deep learning model to learn the road condition information and solve the distribution route based on the road condition prediction, which solves the problem of non-adaptation of the traditional algorithm in today's complex road condition and provides a new method for logistics distribution route optimization, which works well in actual logistics distribution and has practical guidance significance for the drivers' distribution route planning.

Due to realistic conditions and difficulties in data collection, the case validation data are relatively small, but sufficient to reflect the advantages of the algorithm in this paper. Although not enough for smaller distribution scales to show the great benefits of load forecasting for logistics and distribution route optimisation, the analysis of traffic data by using deep learning methods shows great potential for guiding urban logistics activities.□

6 Conclusions

In response to the explosive growth of big data in the information age, the links between information technology and industrial production and various economic activities are becoming closer and closer. The contemporary logistics market is developing rapidly, and the optimal arrangement of its distribution paths is a key point in the logistics activities of the entire enterprise in the distribution business of each enterprise. This paper establishes a model for the logistics distribution path optimisation problem, which aims to improve the traditional algorithm's optimisation-seeking ability under complex urban road conditions. Each part of the model is

described in detail, the weight update is introduced into the ant algorithm to solve the unreasonable problem of the ant algorithm's setting of road parameters, and the DBNTFPO algorithm is proposed. Finally, through example analysis, the effectiveness and feasibility of this paper's algorithm in practical logistics of distribution are proved.□

Data Availability for this work

The dataset used to support the experimental results are included within the paper.

Conflicts of Interest

I declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

I don't receive any funding.

Consent

I have full consent for the publication of this paper.

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