Traffic Problems of Linjiao's Turning Passage in Lhasa City from the Perspective of Traffic Sociology

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Objectives: The transportation problem of Linjiao transit passage in Lhasa City from the perspective of traffic sociology is studied.Methods: Firstly, the research history and current situation of experts in the field of traffic congestion prediction are studied. The common parameters and models of congestion prediction are analyzed. Results:Combined with the complexity of road traffic structure and the possession of a large number of high-dimensional traffic data records, the use of a prediction model is finally determined based on RNN-RBM deep learning network. Through the research and analysis of all-day road traffic flow data, accurate judgment and prediction of traffic congestion status are made. Conclusion: In this paper, the role of the RNN model on the time axis and the state judgment of the RBM network are used to predict the traffic congestion based on the characterization of the congestion sequence.

Keywords:Transportation sociology; Lhasa city; Linjiao transit passage; Traffic
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The transfer is in the Tibetan Buddhist society and is still popular among the general public [1]. On the snowy plateau known as the "third pole", the formation and development of the turn of the war and the local social tradition of Tibet's "political and religious unity" have a profound historical origin. In the Lhasa city, the profile of the forest is found. With the passage, the increase of people flow and traffic flow is currently facing a series of traffic problems. Traffic congestion is the main traffic problem that will be faced in the development of the region. In addition to the real-time traffic obstacles caused by itself, it will also cause safety, delay, lost time, pollution and energy consumption and other issues [2]. Based on this, the traffic problem of the Linjiao transit passage in Lhasa from the perspective of traffic sociology is studied.

The driving speed refers to the ratio of the mileage of the road section of the vehicle to the travel time consumed by the section. Vehicle traffic refers to the number of vehicles passing through a section of the road section per unit time [3]. At present, parameters such as driving speed, traffic flow, road surface occupancy, and vehicle density are still the main parameters for determining traffic congestion. According to the survey, driving speed and traffic volume are the most predictive congestion prediction parameters [4]. The traffic state is studied more extensively with the driving speed as a parameter. The research on traffic flow as a parameter is very popular in domestic and foreign markets in recent years [5]. Based on this, these theoretical methods are used to study the traffic problem of the Linjiao transit passage in Lhasa.

In this paper, a prediction model based on RNN-RBM deep learning network is used to obtain accurate judgment and prediction of traffic congestion state through research and analysis of all-day road traffic flow data. By using the improved RNN cyclic neural network algorithm, the existing data is learned to determine the data sequence of the congested road segment, and the hidden layer parameters which can characterize the deep features of the data are obtained. Using the role of the RNN model on the time axis and the state judgment of the RBM network, the traffic congestion situation is predicted based on the characterization of the congestion sequence.

In the existing traffic congestion prediction problem, many research results of domestic and foreign researchers are mainly focused on the processing and analysis of traffic sensor data, public transportation floating car data, map app user data, etc., thus establishing correlation. The object relationship model predictive traffic congestion is achieved [6].

The collection of traffic data is mainly from taxi or bus floating car data, and the vehicle GPS records data attributes such as vehicle position, direction and speed information [7]. This type of data is the most widely used data source due to its real-time record, large amount of data, complete information, strong regularity and wide range. Through various models and algorithms, the researchers have made these floating car data and urban roads have strong correlations in time and space. They can calculate and predict various types of traffic parameter information, and finally achieve the purpose of accurately predicting traffic congestion status. [8]. There are also some frequently mentioned ways to accurately detect vehicle information data, such as radar detection, video monitoring, ultrasonic detection, ground-sensing coil detection, infrared detection, etc. These devices can be used to obtain a variety of traffic information parameters, such as: Road occupancy, traffic flow, speed. With the development of science and technology, road information is more widely available, such as mining from GPS-enabled mobile devices, Bluetooth devices, mobile maps, and user data of navigation products, as well as traffic from social media such as Sina Weibo. There are many events for data mining. After obtaining the basic data through these technical means, the researchers have done a lot of processing and mining, and made traffic congestion prediction according to the design model under different conditions. Some scholars use the loop detector and floating car data to perform regression analysis by extending the Kalman filter method to estimate the traffic state of the whole network. Some scholars use vehicle sensors to measure traffic conditions and propose a beacon-based traffic congestion algorithm, ABEONA, which predicts recent road conditions by capturing current and recent traffic trends. The following is a brief introduction to the research status of traffic congestion prediction based on different information parameters.

METHODS

Vehicle Routing Problem

Vehicle Routing Problem (VRP) is often used in the research of path planning problems, which is the most important component of vehicle intelligence. Optimizing vehicle routing problem can effectively improve driving efficiency, reduce time and energy loss. It can also effectively improve the driving quality. Since the optimal vehicle path selection in the path congestion state occupies the most important position in the field of vehicle intelligence, many scholars have proposed a series of intelligent algorithms to optimize the vehicle path problem. At the current stage, the optimal path congestion state is optimal. The vehicle path mining method includes a vehicle path optimization method based on an ant colony algorithm, a vehicle path optimization method based on a neural network algorithm, and a vehicle path optimization method based on an improved Dijkstra algorithm. The three methods have their own advantages and disadvantages, as shown in Table 1.

Table1
Comparison of three path optimization algorithms

	Ant colony algorithm	Neural network algorithm	Dijkstra algorithm
Ad vant age	The ability to search for better solutions is easy to implement.	High precision	Simple and easy to understand
sh ortco min g	It takes longer time, slower convergence speed and easy to fall into local optimum.	Hidden layer parameters are complex and time-consuming.	Path repeated calculation; path weight can not be negative.

The ant colony algorithm has the ability to search for better solutions. A slight modification can be combined with a variety of algorithms, which is easy to implement. However, when the parameters are not set properly, the solution speed is very slow and the accuracy of the solution is poor, and it is required to find the optimal. The solution needs to guarantee a certain number of cycles, the calculation amount is large, the solution takes a long time, and the convergence speed is slow and it is easy to fall into the local optimum. The neural network algorithm has high precision, but the hidden layer parameters are computationally complex and take a long time. The Dijkstra algorithm can find the optimal path, but the number of traversal times is high, the efficiency is very low, and the path weight cannot be negative, which is not suitable for the assignment of congested road segments.

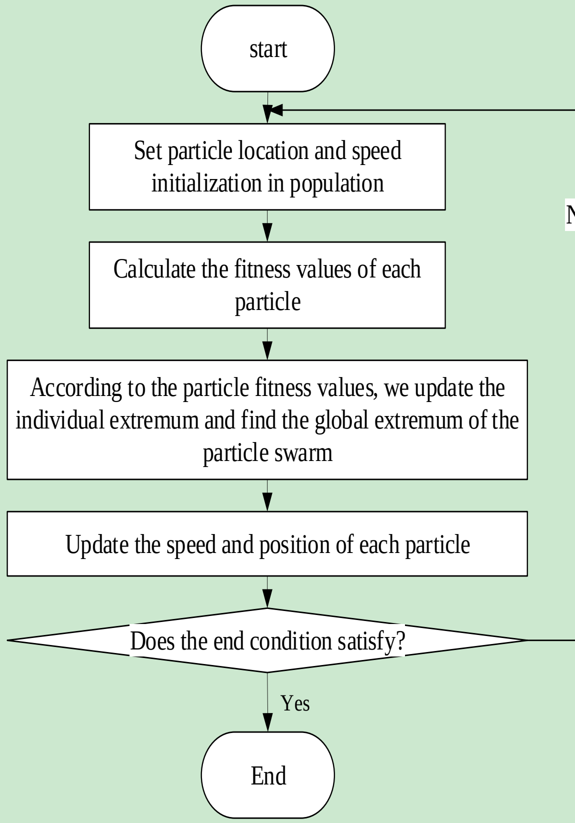
All the above three methods have certain limitations. From the existing research comparisons, it is found that the particle swarm optimization algorithm has certain advantages in research and utilization. The particle swarm optimization algorithm utilizes the sharing of information by individuals in the group, so that the motion of the whole group produces an evolution process from disorder to order in the problem solving space, so as to obtain the optimal solution of the problem. As a bionic intelligent algorithm, the particle swarm optimization algorithm is widely used in path planning to find the optimal solution because of its fast search speed and easy implementation. This chapter will also use the improved particle swarm optimization algorithm to solve the vehicle path problem and solve the road segment. The problem of path selection is during the congestion period.

Particle Swarm Optimization Algorithm and Optimization

Particle Swarm Optimization (PSO) is a kind of group intelligence algorithm. By simulating the predation behavior of birds, the birds communicate with each other to find the optimal solution and pass it to the whole bird group to achieve convergence. Particle swarm optimization has a fairly fast approximation of the optimal solution and can effectively optimize the parameters of the system. The essence of particle swarm optimization is to use its own experience and group experience to adjust its state, which is the key to the excellent characteristics of particle swarm optimization. Therefore, the particle swarm optimization algorithm is used to solve the advantages of multi-dimensional group optimization to solve the problems that need to be solved in the paper.

The flow of the particle swarm algorithm is shown in Figure 1:

Figure 1
Particle Swarm Optimization Algorithm Flow



In the process of using the particle swarm optimization algorithm to solve the optimal path, if a particle finds the current optimal position, other particles will move closer to it. If the point happens to be a local optimal condition, the particle iteration in this region will be closed. By the limit, the particle swarm will stop at this point and it is impossible to continue the iterative search for other regions. Because of the faster iteration and the premature convergence, the premature phenomenon that the particle termination condition jumps out of the loop belongs to the local optimum and cannot obtain the optimal solution. The experiment cannot detect the optimal path when encountering the congestion of the road segment, so the particle swarm is needed. The algorithm is improved.

In this paper, an improved particle swarm optimization algorithm with adaptive dynamic adjustment of inertia weight is introduced to solve the model to avoid premature convergence. That is, as the number of iterations increases, the inertia weight changes from the largest to the smallest, as shown in equation (1):

$$w = w_{\max} - \frac{t*(w_{\max} - w_{\min})}{t_{\max}} \quad (1)$$

The larger the w value is, the stronger the global optimization ability is, and the convergence is slower. It is suitable to use $w_{\max}$ in the initial stage of iteration. On the contrary, the smaller the w value, the stronger the local optimization ability and the faster convergence.

Problem Description and Mathematical Model

This chapter studies the optimal path problem of vehicles in congested sections. Let $G=<N,E>$ be an undirected graph, where set

$N=\{n_1,n_2,\dots n_n\}$ represents a set of vertices, and $E=\{(n_i,n_j)\,|\,n_i,n_j\in N, i\neq j\}$ is an arc set. Then, $N=\{n_0,n_1,\dots n_j\}$ in the set N is the intersection location set, and $E=\{(n_i,n_j)\,|\,n_i,n_j\in N, i\neq j\}$ is the link between the two traffic lights.At the time of (n_i,n_j), the remaining traffic capacity of the road section is k_{ij}, $k_{ij}=M_{ij}-o_{ij}$, of which M_{ij} is the maximum allowable traffic volume of the road section, o_{ij} is the existing capacity of the road section at time t, and $o_{ij}<0$ if the traffic is congested.

In order to simplify the model and verify the optimization ability of the particle swarm optimization algorithm under ideal conditions, the following hypothesis is proposed: the length of each road segment is the same, except for the different congestion conditions, the road facilities are identical; the vehicle performance is unchanged, the driving speed is the same, which has a positive linear relationship with the remaining road capacity of the road, and there are no other factors affecting the speed of the vehicle.

Then, for a given n_i, n_j, the existing flow o_{ij} and the maximum allowable traffic M_{ij} are known on all paths from n_i to n_j. When $k_{ij}=M_{ij}-o_{ij}>0$, it means that the road has traffic capacity. The vehicle can select the road segment. According to the model, the larger the traffic volume can be, the higher the vehicle speed is. The road length is the same as L, which means that the road can accommodate the traffic volume. The road section is faster.

When using particle swarm optimization to optimize the optimal path of urban traffic roads, treat each car as a particle and assign an initial value to each particle. Test the roads in the urban road network where the experiment is conducted. According to the previous chapter, the traffic flow prediction is weighted. The group consisting of n particles in the road network runs at a certain speed within the right undirected vector graph. In the process of iterative processing, each particle changes its position based on its historical optimal position and the historical optimal position of other particles in the group, which is infinitely close to the optimal route.

The nearest interpolation method is used to form the initial solution, and then the CFPSO is used to optimize the initial solution to obtain the optimal solution. The most recent interpolation method starts from the starting position. In all the paths from i to j, if point a is the signal point closest to the starting point, the path is prioritized, and then the next signal point b is searched. The b customer point must satisfy the following points. Condition: The path has not been previously discharged, and the total cost between the intermediate signal points a, b is the smallest. If the current route reaches the target location j, the intermediate point in the route is removed and a new path is started. And so on, until all paths have been routed, all paths from i to j are traversed.

The solution is represented by an initial signal point and an intermediate signal point corresponding to the allowable traffic flow. The arrangement of a solution is 0-5(7)-6(5)-2(4)-1(2)-4(1);0(0)-3(8)-7(-4)-8 (-4)- 4(3), indicating that there are two controllable driving paths, which are a sub-path consisting of 0, 5, 6, 2, 1, 4 and another sub-path consisting of 0, 3, 7, 8, and 4, where 0 represents the starting signal point 0, and other numbers represent the signal points of the path. The road between the number in parentheses and the previous signal point can instantly accommodate traffic flow.

The evaluation of the solution is mainly to see if the total travel time of the vehicle is the shortest, and whether the route can be optimized. According to the theorem of the particle swarm optimization algorithm, if there is a feasible solution and the distance relationship between points and points conforms to the triangle inequality, there will be at most one common intermediate signal point in any two paths of the problem optimization solution. If there are more than one common intermediate signal point in any two paths, the intermediate signal points need to be combined to reduce the common intermediate signal points, so that the total travel time of the vehicle is reduced, and the vehicle path problem is optimized. In addition, according to the model hypothesis, the length of the road segment is assumed to be L, and the speed increases with the increase of the traffic capacity, thereby quantitatively indicating the time consumption of the road segment and comparing them to verify the validity of the model. According to the model hypothesis, the comparison value is not absolute, but the relative contrast is the shortest optimal path.

RESULTS

Experimental Environment and Data

Road network data set: road network information (road network, road system composed of roads of the same level or the same level, which are connected to each other in a network); road segment (link, directional road section defined by two end points)).

Traffic flow data set: A certain period of time is used to study the traffic flow data of traffic sections in Nanming District of Guiyang City. The data used is the data traffic data of 155 road sections from 6 am to 8 pm. A total of 30 days of raw data is recorded, and the sampling interval is 30 s. Among them, there are 58 end point traffic lights, and the adjacent signal lights are connected into a path. The data can well reflect the road conditions in the whole area, and reflect the traffic flow on the road between 58 signal lights in the area in real time. Each piece of data contains attributes such as the signal device number, vehicle driving direction, real-time traffic volume, time, and its attributes are shown in Table 2.

Table2
Attribute List of Traffic Flow Data

Current node	Target node	traffic flow
t14	t11	[10,8,5,0,0,23,13 , … , 23]
T10	t111	[0,0,0,1,0,0,0 , … , 1]
t122	t129	[0,…,23,27,26,18,14 , … , 5]

According to the mean point change theory, the raw data is processed in batches, and the traffic flow in 5 minutes is taken as a traffic flow sequence to find the sequence of change points, such as x=(7,7,8,16,13,5,6,10,13, 4), which is calculated according to the existing data. When $\bar{x}$ =11, s^2 =38, it is calculated with a 95% confidence level, and then the traffic flow interval is calculated when the congestion occurs [7, +∞].

The original data includes no-vehicle flow sections, all-day traffic flow less road sections, few congested road sections, and other non-changing road sections, which are excluded from prediction. Meaningless data is rejected. Data that, not have predictive meaning during the experiment, needs to be cleaned during the data cleaning phase, to prevent it from interfering with the experiment. The cleaned data is rearranged. After finishing, there are 42 road traffic data remaining. The raw traffic data is preprocessed, and the noise data of the interference experiments such as erroneous data and redundant data are removed to provide reliable data for analysis. Table 3 shows the raw data cleaning process.

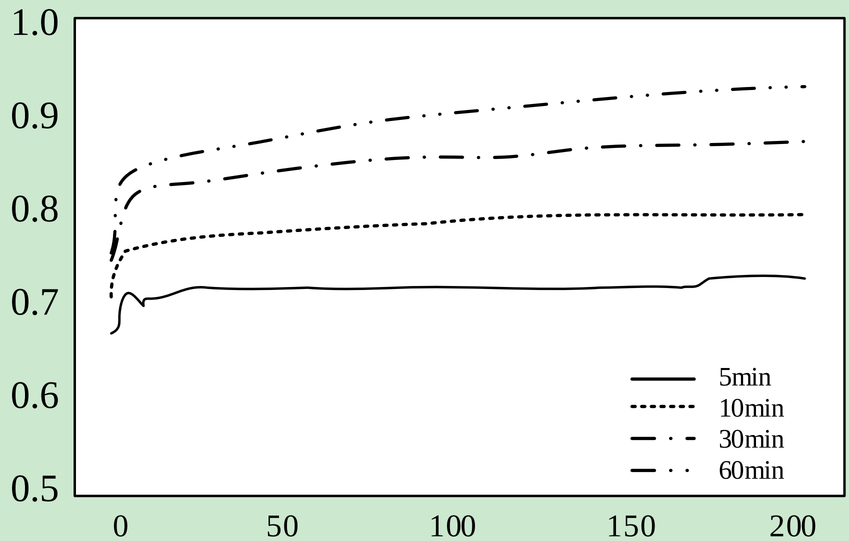
Table3
Raw Data Cleaning Process

Data cleaning	Sample vehicle flow	Method
Remove no traffic flow section	[0,0,0,0,0,0,0 , … , 0]	Filter out the section of $x_1 = x_2 = \ldots = x_{n1680} = 0$
Remove fewer traffic flow	[0,0,0,1,0,0,0 , … , 1]	Filter out the section of $x_1 = x_2 = \ldots = x_{n1680} < 7$
Few congested roads	[0,0,0,1,2,1,1 , … , 1]	There is only one change point in a few days.
High capacity road section	[21,18,18,16,17,19,18 , … , 5]	Filter out $x_i > 7$, but there is no variable value section.

Experimental Results and Analysis

Calculating the RBM part output result value 0,1, the training set accuracy rate is 72.2%, and the test set accuracy rate is 68.9%. In order to carry out the effect discussion, the time interval of judging the congestion sequence is set to 5 min, 10 min, 30 min, 60 min, and the parameter selection experiment is performed. The experimental results are shown in Figure 2.

Figure 2
Comparison of Accuracy Rates at Different Time Intervals

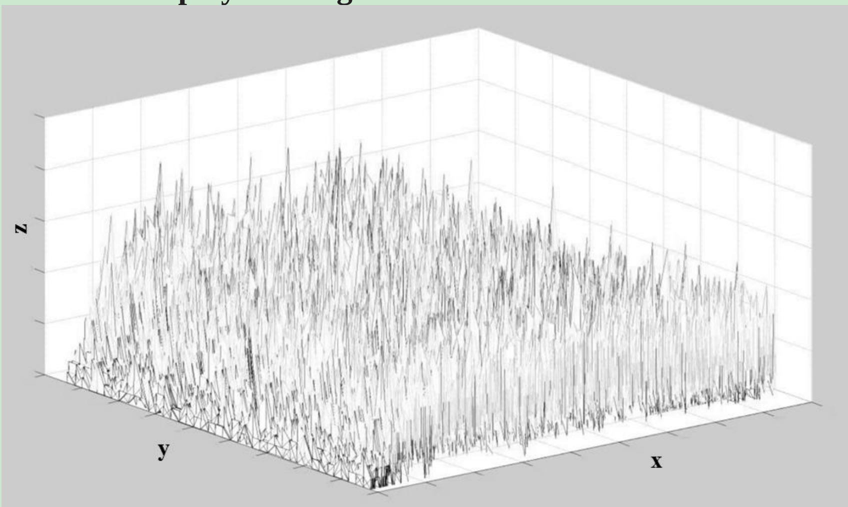


The analysis results show that with the extension of the time interval of the congestion sequence, the prediction accuracy of the model is positively correlated with the growth of the time interval. When the time interval is changed from 5 minutes to 1h, the training set accuracy can be increased to 95%, which means that the aggregation level of the traffic flow sequence has an influence on the prediction result. The reason for the analysis is that the time interval becomes longer, the data aggregation degree becomes higher, the traffic condition does not change significantly over a long period of time, and the training accuracy becomes high. However, because the time interval becomes longer, the traffic state is not reflected enough in the time period, and the specificity and sensitivity are poor. Therefore, it is necessary to be cautious when selecting the time interval.

At the same time, it can be found that the accuracy rate increases slowly with the increase of the number of iterations in the experimental range. The larger the time interval and the degree of data aggregation are, the more accurate the increase rate with the number of iterations is. In most cases, the iteration can be converged about 200 times, and the training accuracy remains almost unchanged.

In order to intuitively experience the improved RNN model training, the experimental results of the improved RNN network will be introduced. The output of the experimental set is shown in Figure 3:

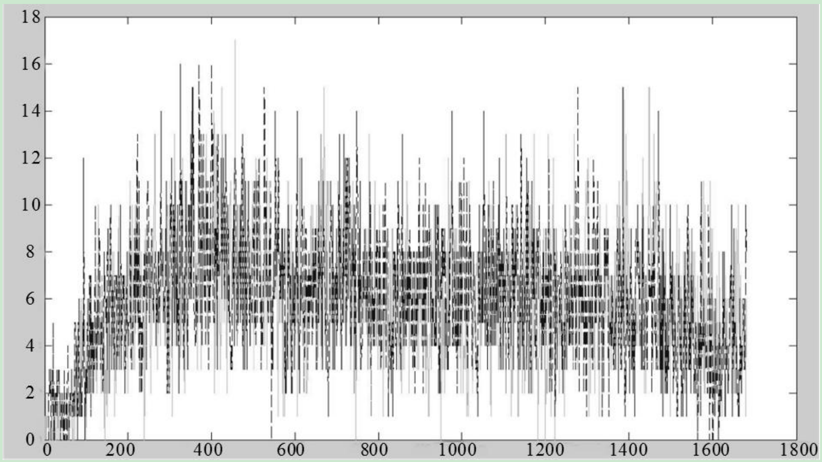
Figure 3
Display of Congestion Prediction Results



Among them, the x-axis is the all-day time period, the y-axis is 42 different roads, and the z-axis is the predicted traffic flow. The red part is a congested section.

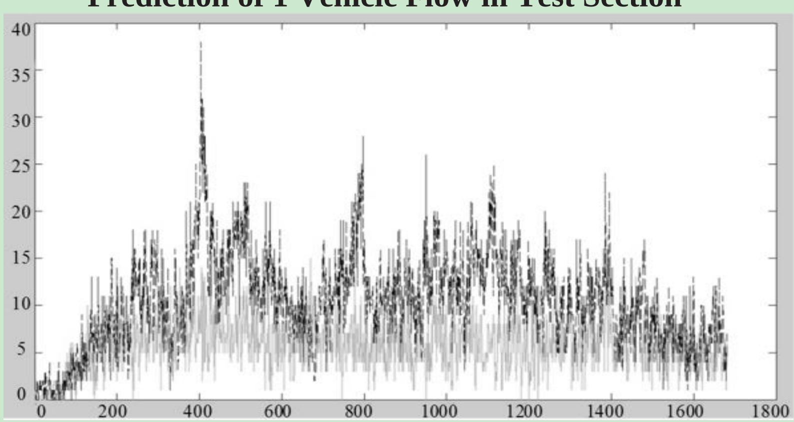
In order to visualize the improved model training effect, the predicted traffic value of the test section 1 before and after the improved RNN is compared with the real value. Looking at the improved traffic test results of the test section 1 day, as shown in Figure 4, the mean square error mse = 0.57, the accuracy is higher.

Figure 4
Prediction of 1 Vehicle Flow in Test Section



The RNN is not improved on the test section 1 one-day traffic flow prediction result, as shown in Figure 5, the mean square error mse = 2.25, the accuracy is low.

Figure 5
Prediction of 1 Vehicle Flow in Test Section



In large-scale urban transportation networks, as the time interval becomes longer, the model training data sequence grows geometrically. During the training process, RNN gradually loses the ability to learn far-reaching information because of the gradient decrement. Later, the nodes in the urban traffic congestion dynamic prediction model study the node perception of the previous time decreases. Therefore, it is necessary to adjust to get the appropriate parameters, but this parameter may not be suitable for individual road data. The improved RNN network can accurately obtain the characteristic congestion sequence, the parameter selection and the data aggregation degree are more suitable for the prediction model, the training accuracy becomes higher, the specificity and sensitivity are better. Finally, the optimal path selection experiment is carried out, and the optimal path selection is compared with the improved particle swarm optimization algorithm.

It is relatively less time-consuming to reach the same destination segment after the improvement, indicating that the improved path is a better solution, which fully reflects the improved superiority.

DISCUSSION

In this paper, a prediction model based on RNN-RBM deep learning network is used to obtain accurate judgment and prediction of traffic congestion state through research and analysis of all-day road traffic flow data. The improved RNN network maintains the original self-learning, self-adaptation, and good ability to process data sequences in the RNN network, and improves its defects in large-scale urban transportation networks that cannot be perceived by distant data points in large urban traffic networks. The RBM model can accurately output the traffic status to 0 and 1, which is convenient for the identification of traffic congestion. Through the simulation experiment, the improved traffic congestion prediction model has better incremental learning characteristics compared with the improved RNN-RBM network, and the prediction accuracy of the test set traffic congestion is increased by about 20%. In the planning experiment of the optimal route, some conditions are assumed under ideal conditions, and an experimental model under ideal conditions is established. The results show that the improved RNN-RBM model has higher prediction accuracy, and the improved particle swarm optimization algorithm has better effect in iterative optimization of optimal path, which can provide more accurate prediction information for traffic congestion prediction, traffic travel and traffic control. .

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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