Research on the Application of Smart City Super Brain in the Upgrading and Reconstruction of Expressway—Take Chengdu Old Chuan-Zang Road as an Example

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Abstract. This paper explores the smart city super brain traffic flow prediction method. Through monitoring and studying the traffic volume and average speed of related intersections in the morning and evening peak hour and one normal hour, a total of 7413 data are collected, of which 5930 are used as training sets and 1483 are used as test sets. Long short-term memory network (LSTM) method is used to predict the changes of traffic flow at important traffic nodes along old Chuan-Zang Road in Chengdu and the changes of vehicle speed at typical time of one day. The predicted results are highly coincident with the actual data, which proves the accuracy and effectiveness of the model. According to the predicted results, through the simulation analysis of the transformation scheme of important nodes, the traffic operation of the study section before and after the transformation is evaluated. The results show that the average delay of vehicles is reduced by 23.82% compared with that before the transformation, and the pollutant emission and fuel consumption are also significantly reduced. LSTM, with its unique advantages in processing sequence data and solving long-term nonlinear problems, provides algorithms and basis for urban road upgrading.

Keywords: Smart city brain, traffic flow prediction, LSTM, expressway enhancement and transformation.

1. Introduction

Old Chuan-Zang Road is the southwest main way in Chengdu's "3-ring and 16-radiation" expressway network system. The reconstruction project of Old Chuan-Zang Road (Third Ring Road-Main Toll Station Section) starts from the outer side of Changyi Road, 120m, and runs along Chengshuang Avenue to the main toll station. The red line of the road is 40m wide and the total length is about 42.7km. Based on the analysis of the traffic service level of Old Chuan-Zang Road section and intersection of Chengdu Expressway, this paper puts forward some suggestions on the expansion and reconstruction of this road, which has practical significance in engineering.

Through the analysis of the traffic service condition of important sections and intersections, this paper uses the idea of "gambling spot mining, congestion analysis, congestion control, effect evaluation", putting forward the upgrading and reconstruction scheme of sections and intersections. The traffic impact of the reformed scheme is analyzed, and suggestions for phased implementation are put forward.

In the field of intelligent transportation, SCB can analyze the travel characteristics of residents and predict the short and medium term traffic flow according to historical traffic data and relevant factors, providing an important basis for urban planning and road infrastructure reconstruction and expansion programs. How to predict traffic flow accurately and efficiently has become an urgent problem to be solved. Commonly used traffic flow prediction models are mainly divided into two categories: parametric model and non-parametric model [1]. The traffic flow in actual road network is very complex, and Kalman filter theory is difficult to accurately describe and the computational efficiency is low [2]. The seasonal autoregressive integrated moving average (SARIMA) model ignores the instability of time series [3]. Support vector machine (SVM) model, KNN model and neural network model have obvious advantages for nonlinear problems with high uncertainty [4]. With the continuous development of deep learning, more and more improved neural network algorithms have been applied to traffic flow prediction, and achieved better results than traditional traffic flow prediction models. Xia et al. introduced spatial attention mechanism and expansive causal convolutional neural network to propose a traffic flow prediction model based on spatiotemporal attention convolutional neural network, which fully tapped the complex spatiotemporal dynamic correlation of traffic flow to improve the accuracy of traffic flow prediction [5]. Zeng et al. proposed a directed graph convolution-short and long term memory neural network (DGC-LSTM) which can prevent the large-scale spread of congestion from the generation point and reduce the congestion degree of the entire road network [6]. Yuan et al. proposed extended-causal convolutional neural networks (DCFCN), which introduced extended convolution to increase the size of receptive field and obtain the long-term memory of sequences, thus improving the prediction accuracy and computational efficiency [7]. Ni et al. proposed a spatiotemporal graph neural network model based on information enhanced transmission, which integrates multiple modules to better fit the characteristics of spatiotemporal correlation, periodicity, linearity and nonlinearity of traffic flow dynamics [8].

Most of the existing improved neural network algorithms consider the spatio-temporal characteristics of traffic flow, but there are still a various of shortcomings existing, such as the complexity of model design and parameter selection, Overfitting and underfitting problems, defects in interpretability and fairness and other stuffs.

In the study of expressway reconstruction, a common approach is to improve road traffic capacity by adjusting the lane layout and lane width. For example, Zhang used the traditional "four-stage" method to predict the traffic demand of the expressway and determined the scale of the expressway reconstruction and construction based on the analysis of traffic demand and capacity-the number of expressway lanes set [9]. Luan used VISSIM simulation software found that increasing the lane width can improve traffic capacity [10]. Ge took urban expressway ramps as the research object, combined with Intelligent Network Technology, and proposed the control strategy of expressway ramp in the intelligent network environment, and the simulation results show that the proposed control strategy can improve the efficiency of the road network [11]. Yi found that the optimization effect of adding variable ramps in the required area is better than adding any traditional fixed ramp, but the proposed model is not simulated and analyzed [12]. Wang proposed to accelerate the coordinated construction of the skeleton road network, and optimizing the entrance and exit settings of units along the line are important paths for improving the traffic efficiency of the expressway network [13]. He found the possible structural problems of urban road network in the planning scheme according to the evaluation results of fractal method, proposed corresponding structural optimization measures and obtained the improved planning adjustment test case [14].

This paper provides a sample for the traffic flow prediction expressway intersections by improving the neural network calculation method. Compared with the traditional field investigation, this method greatly reduces the labor cost and makes up for the defects of the commonly used traffic flow prediction model. Through the simulation analysis of the intersection transformation scheme, the quantitative analysis of the congestion mitigation effect with a series of indicators provides a method and path for the optimal selection of the intersection transformation scheme, which can provide a basis for the decision-making of the government and relevant Functional departments.

2. Method

2.1. Data Source

The data in this paper is provided by Chengdu Transaction Investment Information Port, the traffic volume and speed data of six research sections are selected from May 22 to 28, 2023 in the direction of the north section of Chengshuang Avenue, Jialing Road(out of the city direction),Jialing Road(into the city direction), Inner Side Section 1 of the west 3rd Ring Road, Section 5 of the South 3rd Ring Road(outside), Section 5 of the South 3rd Ring Road(inside), a total of 8-9 o'clock in the morning peak, 10-11 o'clock, and 17:30-18:30 in the evening peak for systematic training and prediction, and the data includes a total of seven attributes such as covering lanes and road lanes. Among them, the flow and speed can best reflect the overall situation of traffic operation, and the flow rate and speed are selected as input attributes, and the data set is shown in Table 1.

Table 1. Sample Dataset

Location	Direction	Flow	Speed	Driveway covered	Road lanes
Chengshuang Avenue	out of the city	16	25.38	2	3
Jialing Road	out of the city	15	10.4	2	4
Jialing Road	into the city	32	33.59	3	4
West 3rd Ring Road	inside	30	8.63	\	\
South 3rd Ring Road	inside	47	72.72	\	\
South 3rd Ring Road	outside	79	26.03	\	\

2.2. PIndicator Selection and Data Preprocessing

Traffic volume and average speed collection in 60s time intervals, the dataset is divided by road segment and collection time, some road sections are collected for less than seven days, 80% of the data in the data set is divided into training sets, the remaining 20% is divided into test sets, Python is used for predictive model programming analysis, the computer processor is 1.4 GHz quad-core Intel Core i5, the graphics card is Intel Iris Plus Graphics 645, and the memory is 8 GB 2133 MHz LPDDR3.Due to complex conditions such as the environment, the collected data may have noise or outliers, resulting in incomplete or inaccurate data sets, and the preprocessed data is normalized:

$$\mathrm{y} = \frac{y - y_{min}}{y_{max} - y_{min}} \tag{1}$$

In formula, the maximum and minimum values for the data are $\mathrm{y_{max}}$ and $\mathrm{y_{min}}$ respectively.

2.3. Method Introduction

Long Short-Term Memory (LSTM) neural networks are a special type of recurrent neural network (RNN) that processes and predicts time series data. Compared with traditional RNNs, LSTM networks are more effective in modeling long-term dependencies, which can solve the problems of gradient vanishing and gradient explosion faced by traditional RNNs. In terms of traffic flow forecasting, LSTM can capture long-term dependencies, extract multiple patterns and features from data, effectively process multivariate inputs, and adapt to traffic flow data at various time scales, with excellent performance in forecasting at different time steps.

The LSTM neural network prediction model established in this paper has a number of iterations of 50, dimension 2, a learning rate of 0.001, and a batch size of 42, in addition, Adam optimizer is used to optimize the model.

3. Results and Discussion

3.1. Descriptive Analysis

3.1.1 Traffic flow forecasting

In order to better display the effect of model prediction, and at the same time, it is convenient to visually display the traffic flow change law of different study sections, and predict traffic flow separately for different road sections. From the visualization results, it can be seen that the prediction results of the model highly coincide with the actual values, which accurately reflects the trend of traffic flow, and the relevant features are helpful for analyzing and predicting traffic congestion and other traffic phenomena. The prediction results of traffic flow are shown in Figures 1- 6:

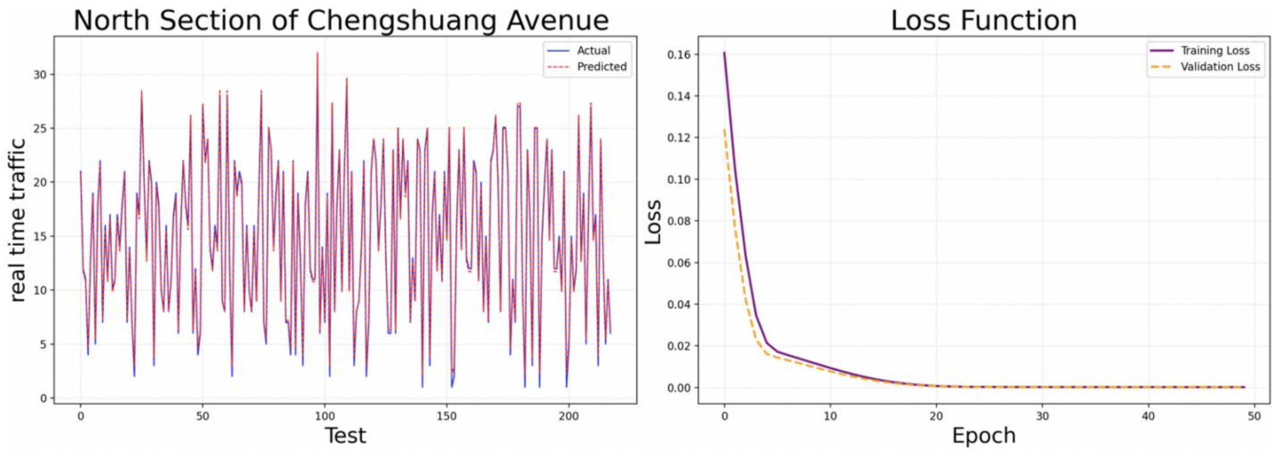

Fig. 1 Forecast Result of North Section of Chengshuang Avenue

As Figure 1 shows, from 10 to 11 a.m. on Chengshuang Avenue, the traffic volume is mainly concentrated at about 15veh/min, about 18veh/min during the evening rush hour, and the maximum traffic volume is 33veh/min, and the overall traffic operation is better than other study sections, because of the large number of samples in this section, the accuracy of model prediction is higher.

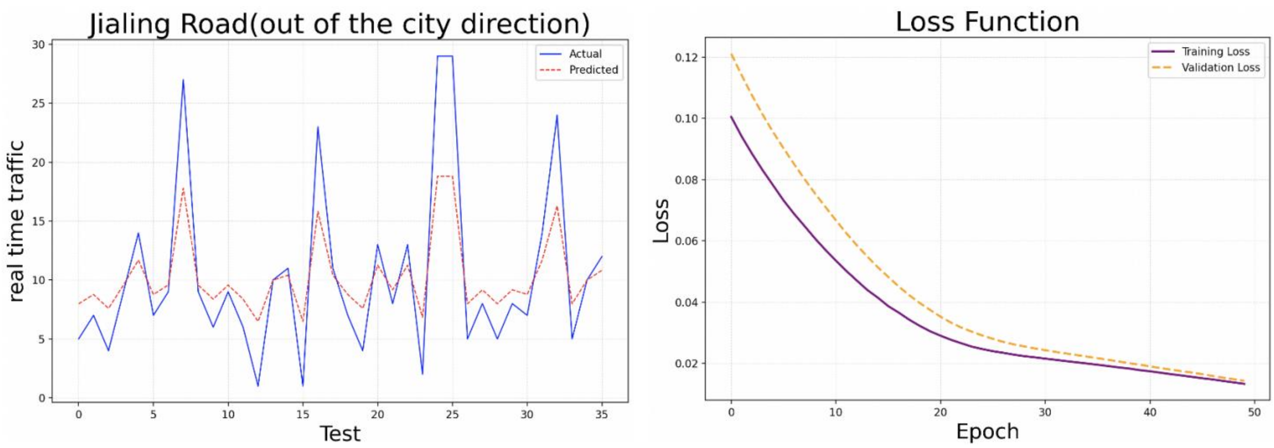

Fig. 2 Forecast Result of Jialing Road (out of the city direction)

As Figure 2 shows, during the evening rush hour, the impact of the first traffic control, the traffic volume of Jialing Road out of the city changes greatly, and the actual results are more obvious than the predicted results, and the traffic flow in the direction of the city reaches up to 29veh/min, because the sample size of this section is relatively small, the error is large, and the convergence speed is slow.

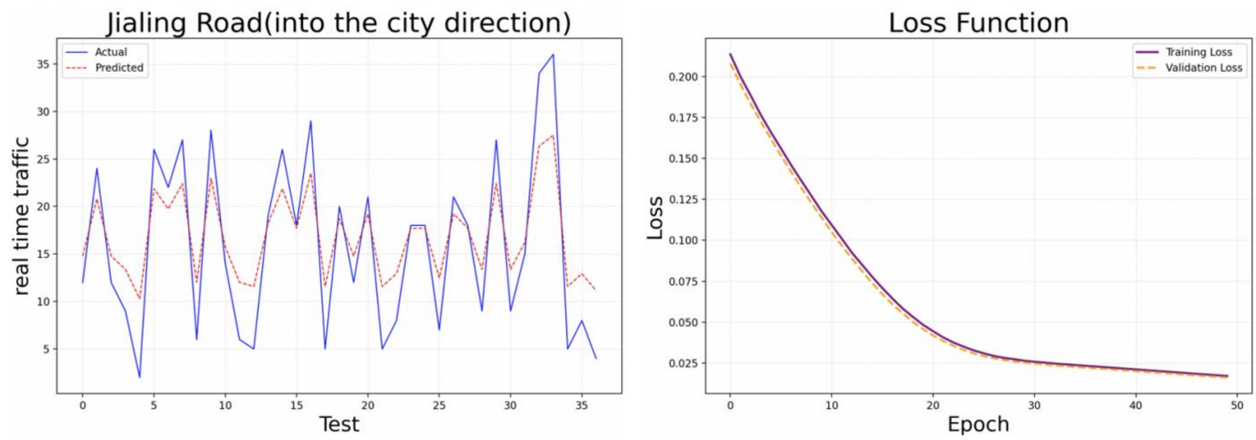

Fig. 3 Forecast Result of Jialing Road (into the city direction)

As Figure 3 shows, compared with the direction of leaving the city, the traffic volume of Jialing Road is large, and many staff members outside the city return to the city, the actual traffic volume changes more than the predicted results, and the average traffic volume during the evening rush hour is about 18veh/min, the sample size is small so the convergence speed is slower.

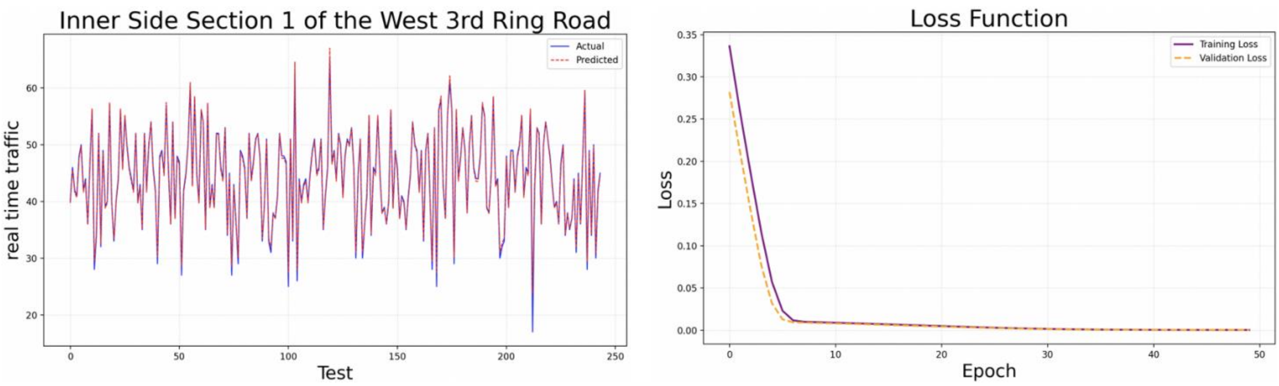

Fig. 4 Forecast Result of Inner Side Section 1 of the West 3rd Ring Road

As Figure 4 shows, the inner side section 1 of the West 3rd Ring Road has a large amount of traffic during peak and peak hours, and the traffic operation needs to be improved, the average traffic volume reaches 45veh/min, compared with other road sections, congestion is more obvious, the traffic capacity of the road section is poor, from the perspective of prediction results, due to the large number of samples, the prediction accuracy is higher and the convergence speed is faster.

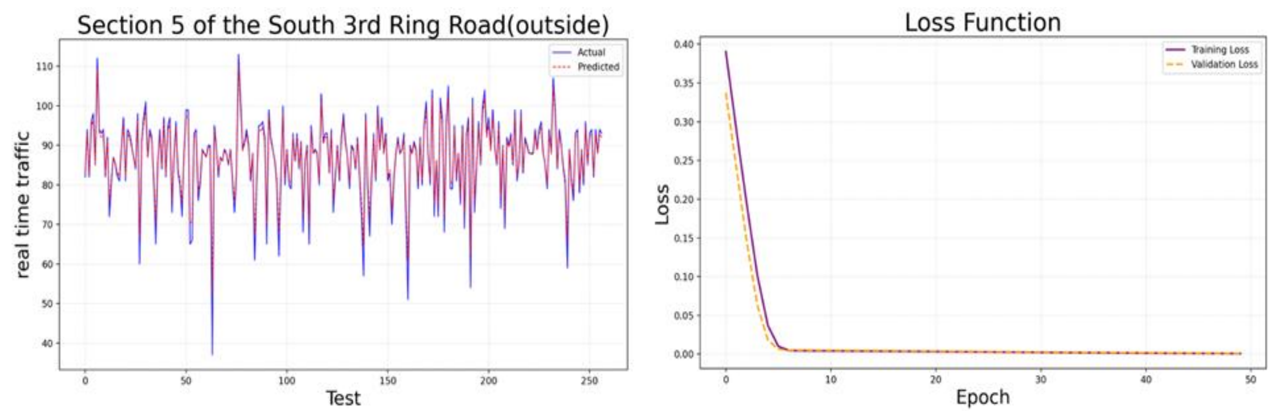

Fig. 5 Forecast Result of Section 5 of the South 3rd Ring Road (Outside)

As Figure 5 shows, the section 5 of the south 3rd Ring Road(outside) is the most congested section of the whole line, with an average traffic volume of 90veh/min, high saturation of traffic operation, and is the key section of expressway transformation, from the perspective of prediction accuracy, it can reflect the overall traffic operation of this section, with high accuracy and fast convergence speed.

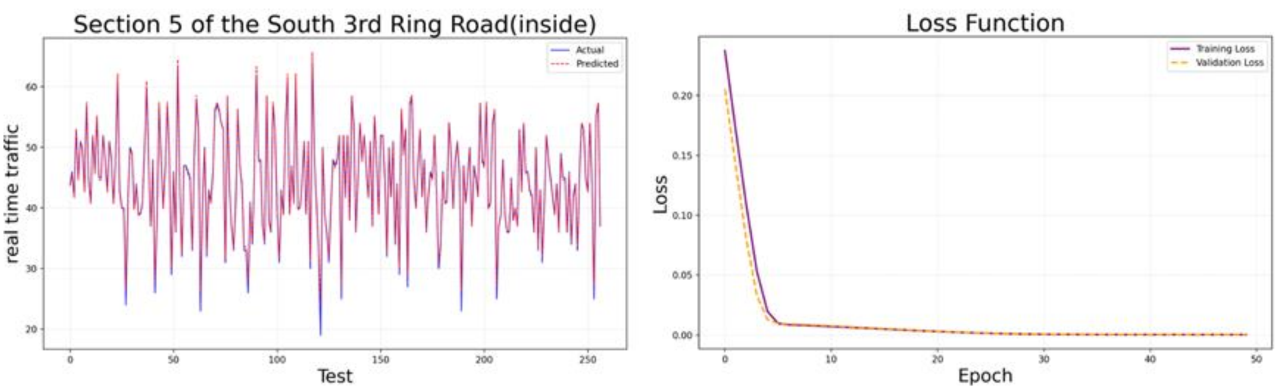

Fig. 6 Forecast Result of Section 5 of the South 3rd Ring Road (Inside)

As Figure 6 shows, the traffic volume of section 5 of the south 3rd Ring Road(inside) is about 35veh/min during peak hours, 45veh/min during peak hours, and the maximum traffic volume reaches 68veh/min, which is the same key reconstruction section as the fifth section of the South Third Ring

Road (outside) and the first section of the West Third Ring Road (inside), which has a large sample number, high prediction accuracy, fast convergence speed, and can reflect the overall traffic operation.

3.1.2 Average speed prediction

Based on the existing data, the LSTM model is used to predict the average speed of the morning and evening peaks and the flat peak hours of the study section as shown in Figure 7.

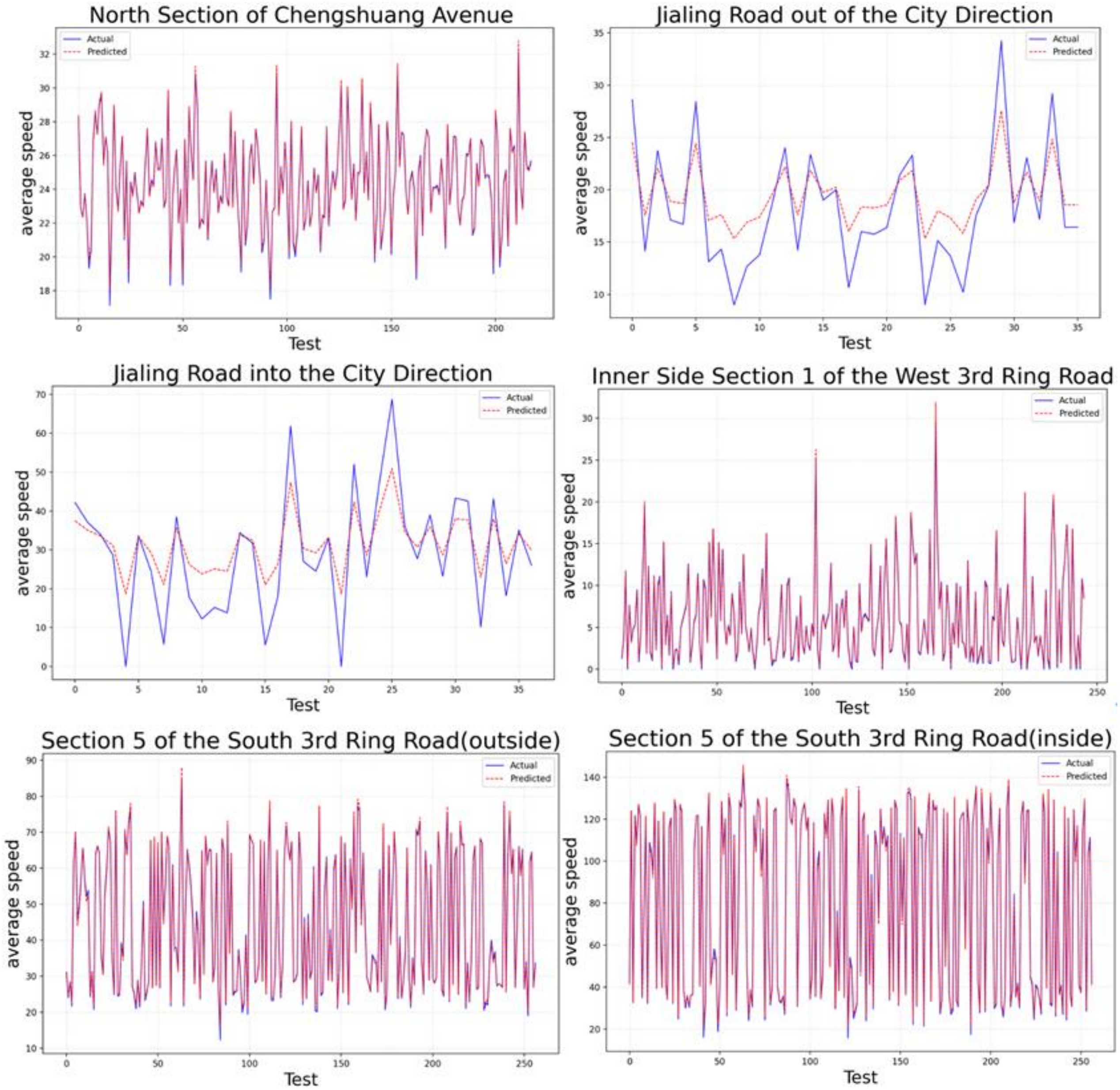

Fig. 7 Forecast Result of Average Speed

3.2. Analysis of Prediction Results

In order to reflect the accuracy of the LSTM prediction model and intuitively reflect the difference between the LSTM prediction results and the actual traffic, the following representative performance indicators are selected to evaluate the accuracy of the model, including root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y_i}-y_i}{y_i}\right| \times 100\% \quad (4)$$

In formula, $\hat{y_i}$ indicates the value of the prediction result, y_i indicates the actual value, n indicates the number of experiments, RMSE is the result of squared mean square deviation, the smaller the value, the higher the accuracy of the model. MAE characterizes the average deviation between the predicted results and the actual values. MAPE stands for the degree of relative deviation, and the smaller the value, the higher the accuracy of the model. The results of the three indicators for traffic flow and speed prediction are as Table 2 and Table 3 follows.

Table 2. Evaluation of Traffic Flow Prediction Results

Road	RMSE	MAE	MAPE
North Section of Chengshuang Avenue	0.432	0.351	7.238
Jialing Road(out of the city direction)	4.469	3.466	76.768
Jialing Road(into the city direction)	5.221	4.528	73.761
Inner Side Section 1 of the west 3rd Ring Road	0.689	0.443	1.245
Section 5 of the South 3rd Ring Road(outside)	1.591	0.991	1.343
Section 5 of the South 3rd Ring Road(inside)	0.692	0.425	1.195

Table 3. Evaluation of Speed Prediction Results

Road	RMSE	MAE	MAPE
North Section of Chengshuang Avenue	0.299	0.209	0.936
Jialing Road(out of the city direction)	3.299	2.825	19.092
Jialing Road(into the city direction)	7.651	5.951	inf
Inner Side Section 1 of the west 3rd Ring Road	0.213	0.163	inf
Section 5 of the South 3rd Ring Road(outside)	0.833	0.646	1.794
Section 5 of the South 3rd Ring Road(inside)	1.576	1.207	2.458

The data collected in the direction of Jialing Road in and out of the city is less than seven days, so the error is relatively large, and from other results, the model has high accuracy, which can provide a strong basis for analyzing and predicting traffic congestion and other traffic phenomena.

Based on the comprehensive traffic survey and macro traffic model data of Chengdu and the prediction results of LSTM traffic conditions, the current peak hour traffic volume of Chuan-Zang Road (Central-Third Ring Road) is about 3252pcu/h. During peak hours, the traffic flow is large, and the road sections before and after some signal-controlled intersections are congested, and the traffic operation is poor.

3.3. Road Plan Renovation Design

In the recommended plan, the main line from the ring to the third ring road adopts two-way 6 lanes, the elevated starts 120m outside the Changyi intersection, crosses the third ring road, and goes down in front of Julong Road, enters the underpass tunnel, covering a section of 995 meters, and sets up an elevated crossing of Chengshuang Avenue again to connect to the toll station of the main line of Chengle Expressway. The elevated section of the road underpasses through the tunnel section. Set up butterfly fully interchange interchanges at the third ring road node.

3.4. Traffic imulation and Evaluation

3.4.1 Current design simulation

Based on the current layout of the old Chuanzang Road and the roads along it, VISSIM software is used to simulate the current road network, current design simulation in VISSIM as figure 8 shows.

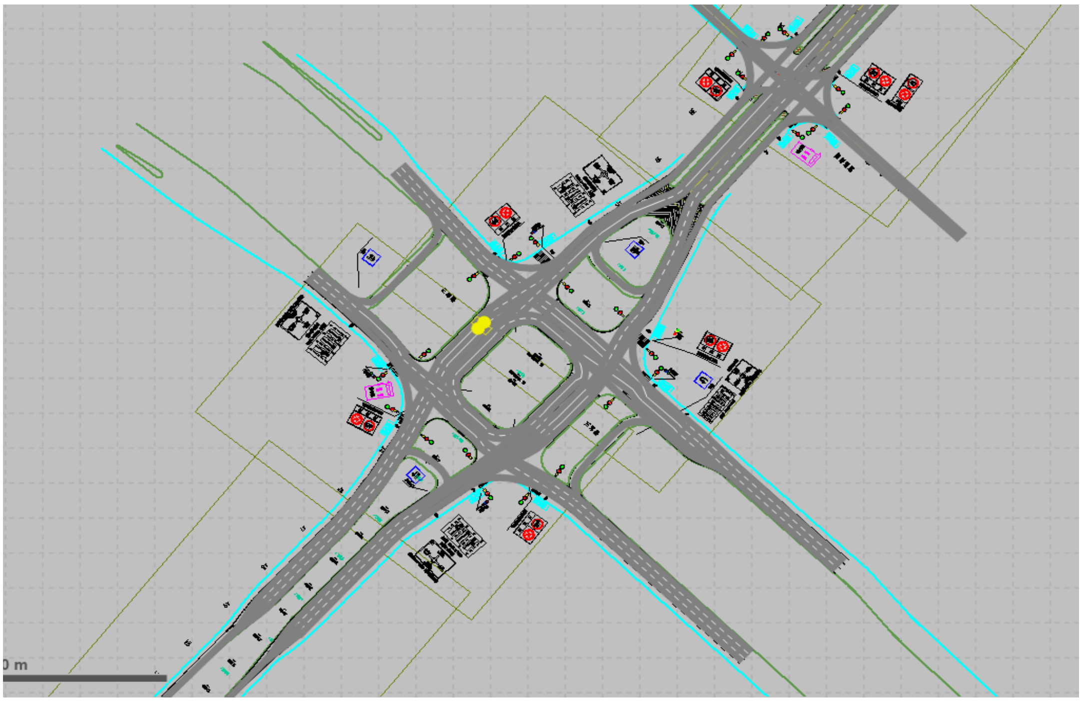

Fig. 8 Current Design Simulation in VISSIM

The actual traffic flow data on the main line within one hour (17:30-18:30) monitored by the radio frequency identification is used as vehicle input, and the node function is used to evaluate the congestion situation of the third ring road. The main evaluation index selects the average delay time of the vehicle and its corresponding delay level. The longer the average delay time of the vehicle, the more serious the congestion situation in the area where the vehicle is located. The simulation of the current road in VISSIM (Figure 8) and the list of results are shown in Table 4.

Table 4. Result List Base on Current Design

ID	Average Vehicle Delay	Oil Consumption	Pollutant Discharge
1	77.51	0.074	7.427
2	131.88	1.272	126.827
3	139.53	0.385	38.401
4	0.81	0.276	27.558
5	0.74	0.402	40.051
6	0.37	0.355	35.392
7	68.79	0.375	37.38
8	97.02	0.368	36.709
9	0.07	0.188	18.777
10	0.29	0.028	2.832

3.4.2 Optimal design simulation

In order to facilitate the rapid travel of transit traffic and ease the conflict between intra-city traffic and transit traffic, the scheme of bridge and bridge came into being. The Central to the Third Ring Road section adopts the bridge scheme, and an interchange is set up at the Third Ring Road. From the Third Ring Road to the main toll station, the original Chengshuang Avenue Bridge Yulong Road to Wensheng section will be optimized as a underpass tunnel, covering 995 meters (K2+505~K3+500), and Chengshuang Avenue is still connected to the Chengle high-speed main line toll station by cross-line bridge. The improvement plan is drawn in VISSIM (Figure 9) and the list of results after improvement is shown in the Table 5 below.

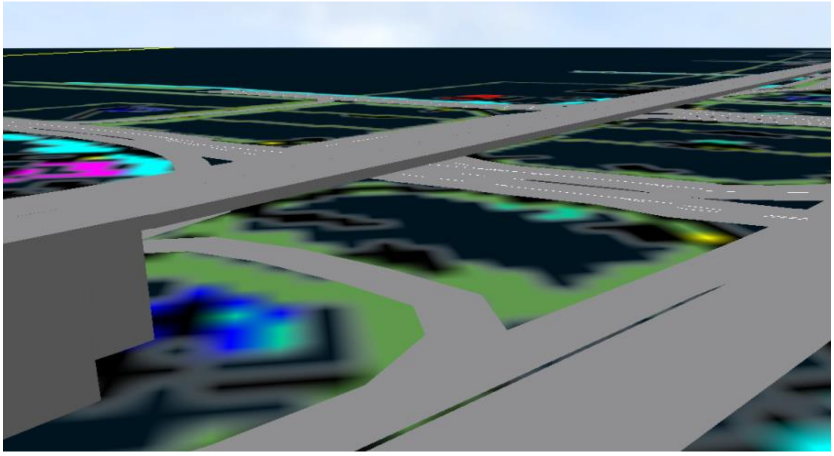

Fig. 9 Demonstration of the Bridge Scheme in VISSIM

Table 5. Result List Base on Optimal Design

ID	Average Vehicle Delay	Oil Consumption	Pollutant Discharge
1	51.7	0.178	17.72
2	74.68	1.659	165.37
3	53.07	1.045	104.16
4	0.99	0.253	25.2
5	0.7	0.686	68.38
6	0.68	0.555	55.31
7	91.3	0.888	88.56
8	90.41	0.792	78.93
9	0.13	0.23	22.96
10	30.18	5.308	529.25

3.4.3 Comparison before and after the optimization

According to the delay result data, the comparative analysis shows that after the transit traffic is separated from the intra-city traffic by viaduct, the travel efficiency of all kinds of traffic is significantly improved, and the congestion phenomenon of the third ring road is effectively alleviated. And the Average Vehicle Delay result, Oil Consumption result and Pollutant Discharge result are shown in the Figure 4,5 and 6 below respectively. Various indicators indicate that the retrofit scheme is more friendly to vehicle operation and the environment, the pair of traffic performance indicators before and after the renovation is shown in Figure 10, 11 and 12.

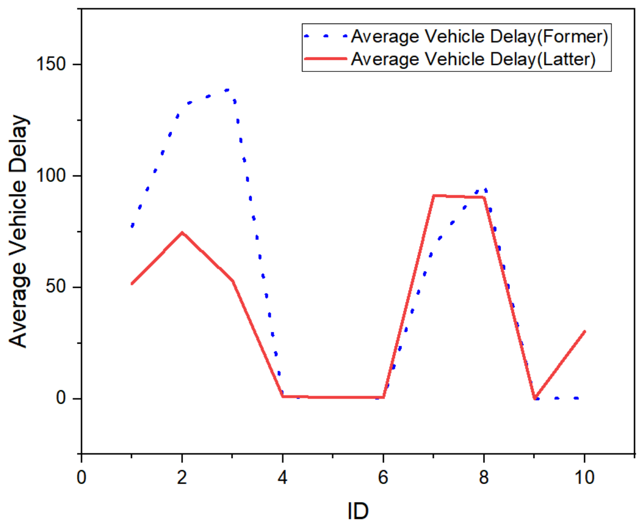

Fig. 10 Average Vehicle Delay Comparison

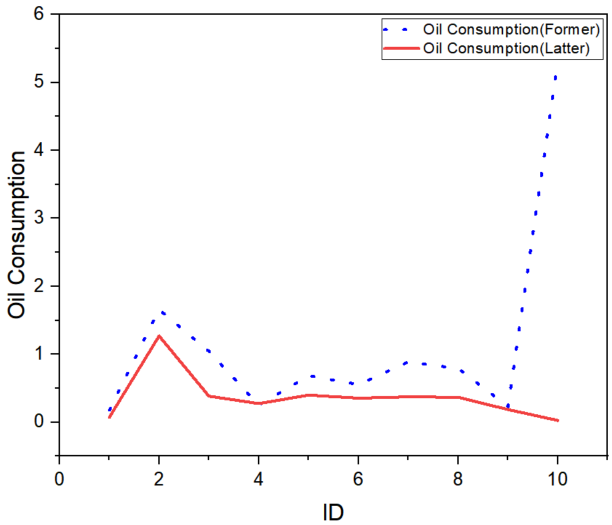

Fig. 11 Oil Consumption Comparison

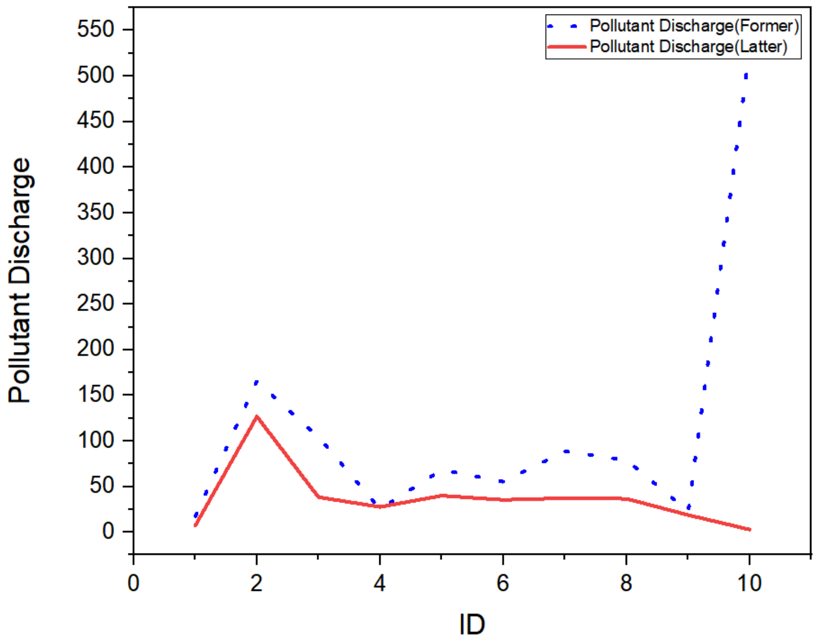

Fig. 12 Pollutant Discharge Comparison

According to the comparison of the number of vehicles at each intersection, it can be found that the traffic sharing of various traffic infrastructures decreases, the Average Vehicle Delay decreases by 23.82%, Oil Consumption reduces by 67.89%, and the Pollutant Discharge is down by 67.87%, which also shows that the construction of viaduct has an alleviating effect on the phenomenon of traffic gathering and queuing and congestion.

4. Conclusion

According to the traffic flow predicted by LSTM neural network of Long and Short Term Memory, This paper makes a simulation analysis of the expressway reconstruction intersections of Old Chuan-Zang Road. The feasibility and rationality of the expressway reconstruction scheme are verified by the improvement of traffic capacity and the reduction of average delay.

Old Chuan-Zang Road adopts the separation of main and auxiliary, and the main lane straddles or underpasses to ensure that transit vehicles can exit the city quickly, effectively improving the traffic capacity and reducing the average delay time. The straddle or underpass of the main lane can be selected according to the topography, surrounding land use and existing layout of road underground resources. The setting of full interchange at the intersection with the third Ring Road of the express road effectively alleviates traffic congestion during peak hours. In the next step, in order to avoid the traffic interference on the ground road, traffic control measures should be formulated on the ground road, and the setting of traffic lights along the road should be reduced as much as possible. The traffic flow predicted by LSTM neural network and VISSIM simulation analysis can provide a basis for determining the width of the main lane, the number of lanes and the interchange plan of important nodes, and provide a reference for the decision-making of the government and relevant functional departments.

In this paper, only the local intersection of the existing upgrading scheme of Old Chuan-Zang Road expressway in Chengdu is simulated and analyzed. Next, the scope of simulation analysis can be expanded, Quantitative analysis of capacity and average delays for all sections and intersections, The time sequence of construction implementation and the mode of traffic organization during construction are discussed, further explore the application of smart city super brain in the upgrading and transformation of expressways.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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