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A study on short-term traffic speed prediction of highway based on multilayer perceptron machine and historical flow data

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Abstract Highway networks are expanding and traffic congestion problems are gradually emerging. Accurate prediction of highway traffic speed is of great significance to traffic management and scheduling, and it is a key means to alleviate congestion and improve operational efficiency. In this study, a short-term traffic speed prediction system for highways is constructed based on the multilayer perceptual machine model and historical flow data. By analyzing the toll data of Chongqing Yuxiang Expressway in 2018 and the traffic speed data from 2023 to 2024, the spatial and temporal distribution characteristics and regular fluctuation patterns of traffic flow are revealed. The study adopts the multilayer perceptron model to establish the mapping relationship between the traffic flows of relevant road sections, introduces the BP algorithm for model training, and evaluates the prediction effect by the average relative error and the mean coefficient of parity. The experimental results show that the R^2 value of the constructed multilayer perceptron model reaches 0.837, which is 0.158 higher than that of the traditional RNN model and 0.089 higher than that of the GRU model, and the prediction accuracies are improved by 0.012 and 0.034 compared with those of the RNN and the GRU, respectively, which effectively captures the cyclic change characteristics of the traffic speed, and it is of great value to be applied in the support of decision-making of traffic management. The study confirms that the spatial and temporal features embedded in the historical flow data are of great value for short-term traffic speed prediction, and the short-term traffic speed prediction method based on multilayer perceptron can provide a scientific basis for highway traffic management.

Index Terms multilayer perceptron, historical flow data, highway, traffic speed prediction, spatio-temporal features, BP algorithm

I. Introduction

In recent years, with the rapid development of intelligent transportation technology, vehicle speed prediction has begun to receive attention. In order to realize the traffic “knowable, measurable, controllable, serviceable”, to make accurate prediction of vehicle speed is the key link of the traffic management system, so vehicle speed prediction is an important part of the intelligent transportation system [1]-[3]. Vehicle short-term speed prediction allows highway managers to perceive the time and location of traffic congestion in advance, and take corresponding control means to improve the efficiency of highway use [4], [5]. At the same time, the establishment of data models for highway short-term speed prediction can also provide travelers with real-time effective road network information, so as to avoid congested road sections in order to choose the ideal travel route [6]-[8]. However, due to the complex spatio-temporal dependence of vehicle speed, its prediction is a challenging task [9].

With the continuous deepening of traffic prediction research, a large number of methods with high prediction accuracy have emerged, which are mainly categorized into parametric and nonparametric models [10]. Parametric models take the regression function as the premise, determine the parameters through the processing of raw data, and then realize traffic prediction according to the regression function [11]. Traditional parametric models have simple algorithms and are easy to compute, however, these models are based on the smooth assumption and do not truly reflect the uncertainty and nonlinear characteristics of the traffic state and are easily affected by random events such as traffic accidents [12]-[14]. Nonparametric modeling successfully solves these problems by automatically obtaining statistical regularities with only enough historical data [15]. Therefore, it is of great significance to construct short-term traffic speed forecasts for highways that are adequate to cope with complex and dynamic spatial correlations.

Traffic congestion has become an important factor restricting urban development and affecting people's quality of life, especially in the highway system, accurate prediction of short-term traffic speed is of great significance for improving traffic operation efficiency and reducing traffic accidents. Highway traffic flow has complex nonlinear dynamic characteristics and is affected by many factors, including traffic flow, weather conditions, road conditions and driving behavior. Traditional traffic prediction methods mainly rely on statistical models and time series analysis, but these methods are often difficult to effectively capture the complex nonlinear relationships in traffic data. In recent years, deep learning technology has shown strong potential in the field of traffic prediction, and its powerful feature extraction and pattern recognition capabilities have made it a hotspot in traffic prediction research. In particular, multilayer perceptron (MLP), as a basic deep learning model, has been widely used in the field of transportation due to its flexibility and adaptability. Highway traffic flow presents obvious spatial and temporal distribution characteristics, and there are significant differences in traffic conditions at different times and on different road sections, which provides a rich data base for deep learning-based prediction methods. Effective use of the spatial and temporal characteristics contained in the historical traffic data to build an accurate traffic speed prediction model has important practical value for optimizing traffic management, improving road utilization efficiency and reducing traffic accidents. The main challenge of highway traffic speed prediction is how to deal with a large amount of heterogeneous traffic data from multiple sources and how to construct a prediction model that can accurately capture the spatial and temporal evolution of traffic flow. Most of the existing studies focus on a single data source or a simple model structure, which is difficult to fully reflect the complexity of the transportation system. In addition, most studies lack interpretable analysis of the prediction results, which limits the application value of the models in practical traffic management.

In this study, based on the historical flow data of Chongqing Yuxiang Expressway, we deeply analyze the spatial and temporal characteristics of traffic flow and construct a short-term traffic speed prediction model based on multilayer perceptron. Firstly, the original data are preprocessed to solve the problems of data redundancy, missing and error; secondly, the traffic flow characteristics are analyzed from both time and space dimensions to reveal the cyclic change rule and spatial correlation of traffic speed; then the prediction model is constructed based on multilayer perceptron and trained and optimized by BP algorithm; finally, the effectiveness of the proposed method is verified by comparing it with the traditional RNN and GRU models. By introducing multidimensional features and optimizing the model structure, this study aims to improve the accuracy and robustness of traffic speed prediction, provide scientific basis for highway traffic management and decision-making, and promote the development and application of intelligent transportation system.

II. Characterization of the study area and historical flow data

II. A. Definition of the study area

Chongqing expressway is a general term for the ring road highway in the main city of Chongqing, the highway between the main city of Chongqing and the neighboring cities (including the districts and counties of Chongqing and the neighboring cities outside of Chongqing), and the highway between the districts and counties within Chongqing Municipality. In recent years, Chongqing Municipal Expressway has been developing rapidly, with the mileage of the expressway reaching 3,065 kilometers by the end of 2022.

Chongqing section of Yuxiang Expressway is one of the important rays in the main skeleton of “three rings and eighteen shoots” highway network, starting point is located in Hong'an Town, Xiushan County, and ending point is in Jieshi Town, Banan District. Yuxiang Expressway from Hunan to the direction of the main city of Chongqing, the route has passed through Xiushan, Youyang, Qianjiang, Pengshui, Wulong, Nanchuan, Banan, Nanchuan is only 75 kilometers away from the main city of Chongqing, less than an hour's drive, Nanchuan, the town of the south of Chongqing into the south of Chongqing, “1 hour economic circle”, accelerating the south of the urban and rural areas in the south of the pace of urban and rural integration. However, with the people's living standards continue to improve, the demand for travel continues to increase, the rapid growth of highway traffic flow, Yu Xiang high-speed traffic congestion, traffic accidents and other issues have gradually attracted the attention of the relevant departments. In this paper, the section of Nanhuan Interchange-Shuanghekou Interchange is taken as a test channel to carry out the research on the spatial and temporal characteristics of traffic flow as well as the prediction of traffic speed.

II. B. Overview of historical flow data

The data used in this paper comes from the 2018 Chongqing highway toll data provided by the Chongqing Municipal Traffic Operation Monitoring and Emergency Dispatch Center. The toll data contains a total of 20 fields, detailing information such as license plate number, vehicle type, entrance toll station point, exit toll station point, and toll collector.

II. C. Data pre-processing

II. C. 1) Raw data processing

In the process of analyzing highway radar speed measurements containing only useful fields, it was found that there were three main types of anomalous problems in the data: data redundancy, missing data, and data errors.

(1) Data redundancy

Data redundancy means that the same record is stored repeatedly in the system. Theoretically, each piece of data should exist independently, but data redundancy is caused by possible errors in the process of data collection, transmission and storage. Before analyzing and mining massive data, increasing data independence and reducing data redundancy can save a lot of storage space and improve database computing efficiency. Data redundancy is generally handled by directly deleting duplicate data records.

(2) Missing data

When there are missing values in the data, the first thing you need to do is to analyze the missing data rate. If the data missing rate is small, then consider directly deleting the missing data; if the data missing rate is large, then you need to use the average filling method, k-neighborhood filling method or maximum likelihood filling method to fill in the missing values.

II. C. 2) Traffic volume data processing

Real and accurate traffic volume data is the foundation and key to carry out the research on spatio-temporal characteristics of traffic flow and OD flow prediction. In order to reduce the impact of traffic volume anomalies on traffic speed prediction, highway traffic volume data is further analyzed on the basis of completing the cleaning of the original data anomaly problem. Figure 1 shows the speed change of some traffic speeds on the highway in 2022, with the horizontal coordinate indicating the month and the vertical coordinate the speed. As can be seen from the figure, the speed change has a certain regularity. There is a big difference between some daily traffic speeds from October to December and other months, such as the hourly traffic speed of Nanpeng-G65 Banan is more than 90km/h, which is more than one times of other months, while the hourly traffic speed of Nanchuan-Daguan is greatly decreased and tends to be close to zero. In addition, the black circle marking part indicates that there are sporadic outliers in daily traffic volume during other months.

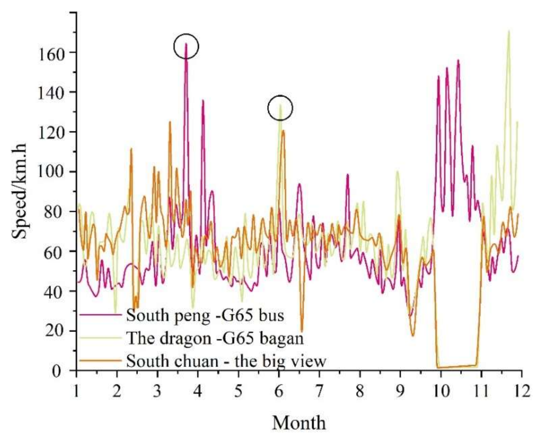


Figure 1: Traffic speed changes in the highway

II. D. Spatial and temporal characterization of historical flow data

II. D. 1) Temporal characterization

Figure 2 shows the weekly change pattern of total traffic volume of an exit, which can be seen that the traffic volume at night from 2:00 to 4:00 is the trough period, and the peak period is from 8:00 a.m. to 5:00 p.m. in the daytime, with no obvious morning and evening hump pattern. The exit flow itself shows a stable cyclic pattern, with similar changes in traffic volume during each cycle, and the flow at moment t has some correlation with the historical flow.

Export traffic flow in addition to the historical cyclical characteristics, but also associated with the import flow, in order to analyze the relationship between the flow changes between an OD pair, for a single OD pair, the extraction of imports and exports of 24-hour flow data (here the import flow data is only for a specific O to a specific D of the import flow), the two flow trend pattern as shown in Figure 3, from which it can be seen that the same OD pair of flow time distribution patterns are similar It can be seen that the same OD pair has similar traffic distribution pattern in time, but shows a certain asynchrony, that is, there is a time surplus in the distribution of export and import traffic, and the pattern of change of export traffic lags behind that of import traffic, and the size of the lag time is related to factors such as travel time between OD paths, distance, and road conditions.

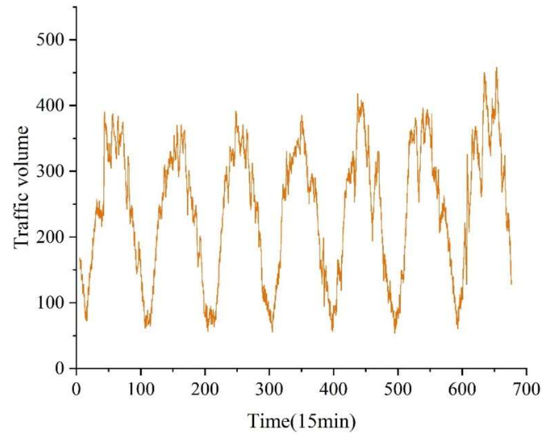


Figure 2: The export flow sequence is distributed week

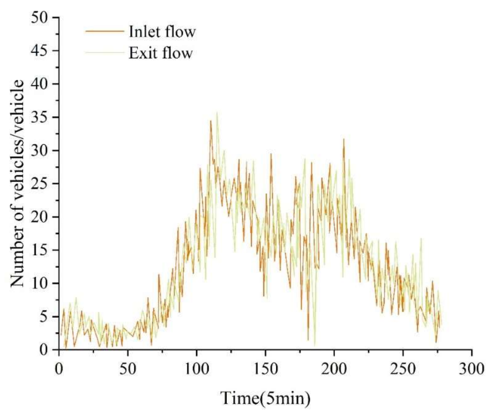
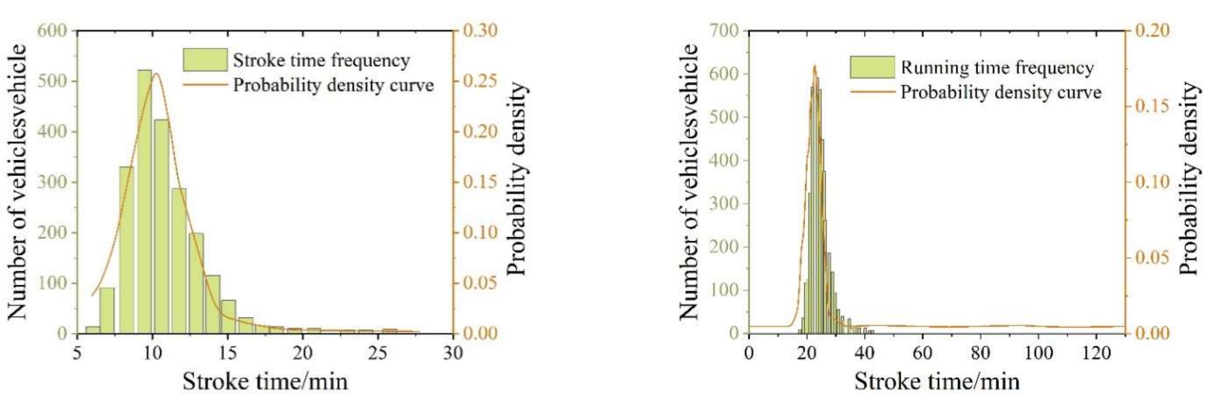


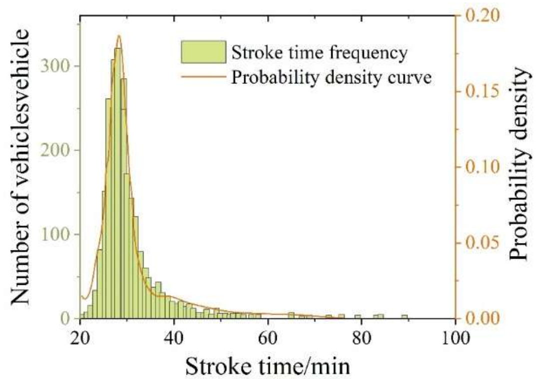
Figure 3: Import flow and export flow time surplus relationship

In order to analyze the time difference between different ODs, the vehicle travel time data of three OD pairs with distances between toll stations of 18km, 27km and 40km were selected, and the distribution of vehicle travel time is shown in Fig. 4, which shows that there are obvious differences in the size of the travel time of different OD pairs, and the three travel times are mainly concentrated in the ranges of 8min-12min, 19min-23min, and 33min-35min, even if the individual vehicle travel time of the same OD is not the same, the overall gamma distribution. The export flow rate is affected by the import flow rate, so the vehicle time of import and export is also an influencing factor in the prediction of an export flow rate.



(a) 18km

(b) 27km



(c) 40km

Figure 4: Different od travel time distribution

The above is to analyze the travel time distribution of import and export from the perspective of individual vehicles, it can be seen that there are obvious differences in the travel time of vehicles, which is caused by the differences in the characteristics of vehicles by drivers and vehicles themselves. From the overall point of view, the vehicle traveling environment between an OD pair is the same, and the vehicle travel time presents stability, and the distribution of the vehicle entry and exit moments of an OD pair is shown in Fig. 5, which shows that the overall import-export time relationship presents a stable linear distribution, i.e., the vehicles imported from a certain moment basically reach the exit station after a stable travel time, and thus the average time of the vehicles between the OD pairs can be approximated as the time surplus.

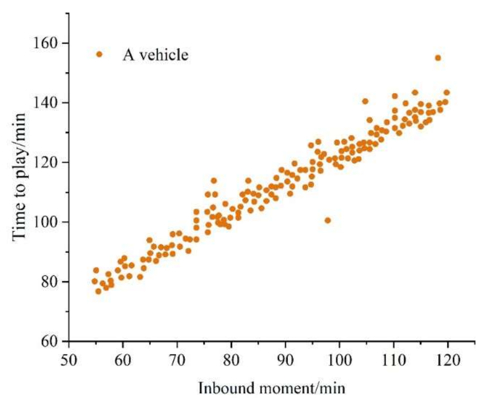
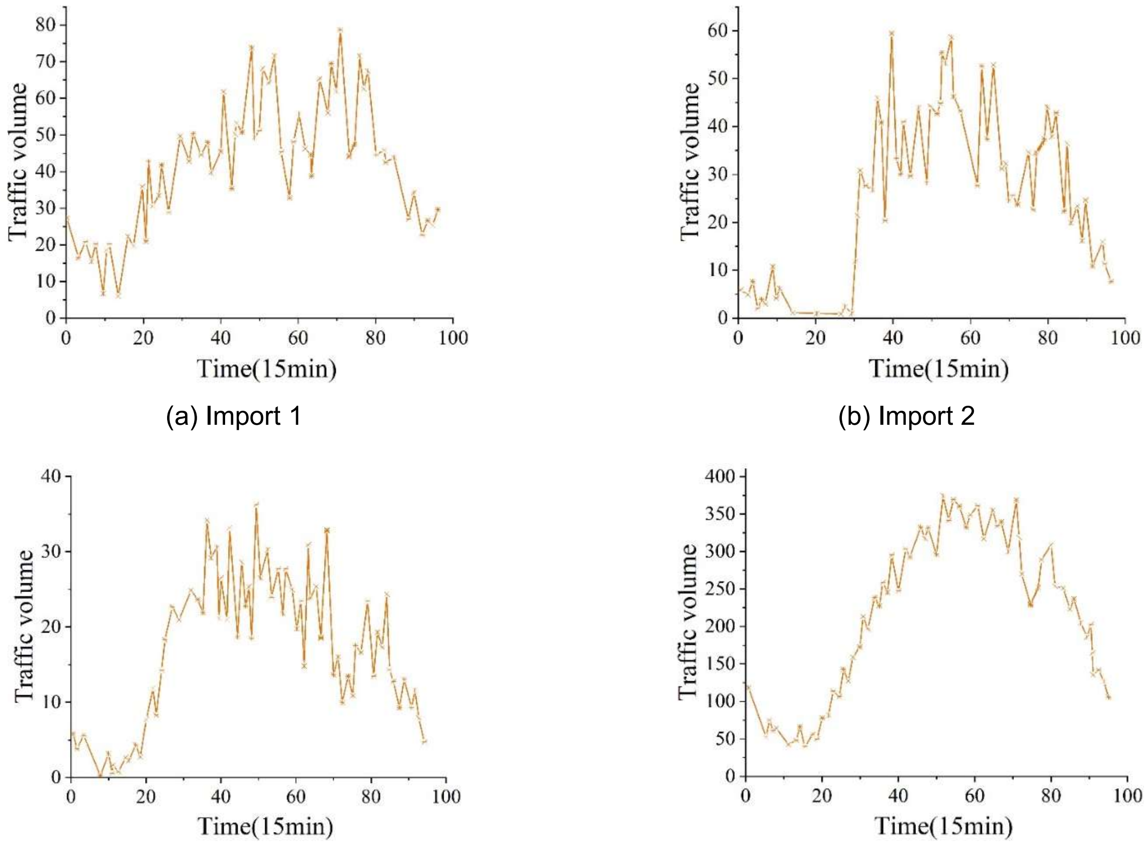


Figure 5: The distribution of vehicle import and export time

II. D. 2) Spatial characterization

In order to analyze the relationship between the flow trend of the exit and the flow trend of each import, the 24-hour flow data of one exit and three associated imports are extracted, and their respective distribution patterns are shown in Fig. 6, from which it can be observed that the flow change trend of each inlet is different, and there is a big difference between the import and export flow trends, and there is a spatial correlation characteristic of the flow rate and export flow rate of each inlet, which is similar to the same time period of different road sections. This is similar to the spatial correlation characteristics of traffic flow in the same time period of different road sections. Before predicting the flow at the exit station, the import flow with strong spatial and temporal correlation can be screened out to provide a data basis for the prediction.



(a) Import 1

(b) Import 2

(c) Import 3

(d) Import 4

Figure 6: The export and its associated 24h flow distribution trend

III. Short-term highway traffic speed forecasts

III. A. MLP applicability

Multilayer Perceptron (MLP) is extended from single-layer perceptron, and the network structure contains input, hidden and output layers, which is a commonly used deep learning model. Due to the existence of one or more hidden layers in the structure, MLP has strong self-adaptive, self-learning and fault-tolerant capabilities, and can solve the nonlinear differentiable problems to which single-layer perceptron is not applicable, and has been widely used in the fields of regional logistics demand forecasting, regional road network size prediction, etc [16]. According to the theory of urban road traffic flow, there is a complex nonlinear relationship between road section flow and its influencing factors, which is difficult to be modeled and calculated by simple models. Therefore, this paper uses the MLP model to establish the mapping relationship between the relevant road section flows.

III. B. Model Variables and Training

III. B. 1) Model variables

The flow rate of the relevant road sections is the result of the mutual coupling of multidimensional factors such as urban morphology, road network layout characteristics, and spatial and temporal characteristics of regional traffic flow, and presents the phenomenon of correlation of the flow rate of road sections in space. Therefore, under the premise that the flow rate of key road sections in each group of relevant road sections is known, the key point of predicting the flow rate of the remaining road sections in the same group is how to describe the correlation between the key road sections and the predicted road section flow rate, and use this to construct the mapping relationship between the flow rate of relevant road sections. The essence of the correlation of roadway flow is the existence of a continuous flow of traffic dependent on the roadway network, so the topology of the roadway network is the most important factor affecting the correlation of roadway flow. At the micro road segment level, the number of lanes of the predicted road segment reflects its physical characteristics, and the length of the shortest path reflects the distance between it and the key road segments; at the macro road network level, the degree of the predicted road segment, the median, and the degree of compactness and centrality reflect the degree of importance of the road segment in the road network in terms of the number of connected road segments, the probability of the occurrence of the shortest paths in the road network, and the accessibility to the other road segments, respectively.

III. B. 2) Model training

After normalization of the sample data, the BP algorithm [17] is used for MLP model training. The learning process of the BP neural network consists of two parts: forward propagation of information and back propagation of error, and the core idea is to apportion the resulting error to all units in each layer through back propagation.

(1) Information forward propagation process

Let $a_i^{(1)} = x_i$ be the input value (activation value) of the neuron in layer 1, then the activation value of the next layer is:

$$\begin{cases} a_i^{(1)} = x_i \\ a_j^{(l+1)} = f(z_j^{(l+1)}) \\ z_j^{(l+1)} = \sum_{i=1}^{n} W_{ji}^{(l)} a_i^{(l)} + b_j^{(l)} \end{cases} \tag{1}$$

where, x_i is the data input value of neuron i node in layer 1 of the sample data; $a_i^{(l)}$ denotes the output value of node i in layer l; $z_i^{(l)}$ denotes the activation value of node i in layer l; $W_{ji}^{(l)}$ is the link weight parameter between node i in layer l and node j in layer $l+1$; $b_j^{(1)}$ is the link weight parameter between node j in layer $l+1$; $b_j^{(1)}$ is the node j in layer $l+1$ intercept term; f is the sigmoid activation function with expression $\varphi(x) = \frac{1}{1+e^{-x}}$.

(2) Error back propagation process

$$C(W,b) = \frac{1}{2} \sum_{i \in outputs} \| y_i - a_i \|^2 \tag{2}$$

where, y_i is the sample data output layer i node flow true value; a_i is the sample data output layer i node flow output value.

The optimization objective is to determine W (weights) and b (bias) so that the loss function $C(W,b)$ is minimized and the model output flow prediction value will be more and more close to the true value. The iterative formulas for W and b are given below:

$$\begin{cases} W_{ji}^{(l)} = W_{ji}^{(l)} - \alpha \frac{\partial C(W,b)}{\partial W_{ji}^{(l)}} \\ b_j^{(l)} = b_j^{(l)} - \alpha \frac{\partial C(W,b)}{\partial b_j^{(l)}} \end{cases} \tag{3}$$

where, α is the learning rate and takes the value range (0, 1].

(3) Effectiveness evaluation

In order to verify the accuracy of the prediction model, the model prediction effect is comprehensively evaluated using the average relative error (MRE) and the homogeneity coefficient (EC). Among them, MRE reflects the degree of deviation of the model predicted value from the actual value; EC reflects the fit between the model predicted value and the actual value, and a value greater than 0.85 indicates a good fit.

$$\begin{cases} \mathrm{MRE} = \left[\sum_{i=1}^{n} (| y_i - y_i^{'} | / y_i) \right] / n \\ EC = 1 - \left[\sqrt{\sum_{i=1}^{n} (y_i - y_i^{'})^2} / (\sqrt{\sum_{i=1}^{n} y_i^2} + \sqrt{\sum_{i=1}^{n} y_i^{'2}}) \right] \end{cases} \tag{4}$$

where, y_i is the measured value of the i nd test sample; is the predicted value of the i rd test sample; n is the number of test samples.

IV. Analysis of data source results

IV. A. Data sources

The data sources include daily highway vehicle speed values, weather, temperature, and passenger volume from January 1, 2023 to October 31, 2024 in Chongqing Municipality. The decomposition of the bus speed series from a certain three-week period is shown in Figure 7. The bus speed has obvious cyclical characteristics, the cycle length of about 7 days, that is, the trend of daily speed changes in each week is similar; in addition, by the holiday travel and other factors, the speed of the two vehicles show some abnormal fluctuations, abnormal high values mainly in the home office and the Spring Festival holiday, the abnormal low values mainly appeared in the day before the long vacation.

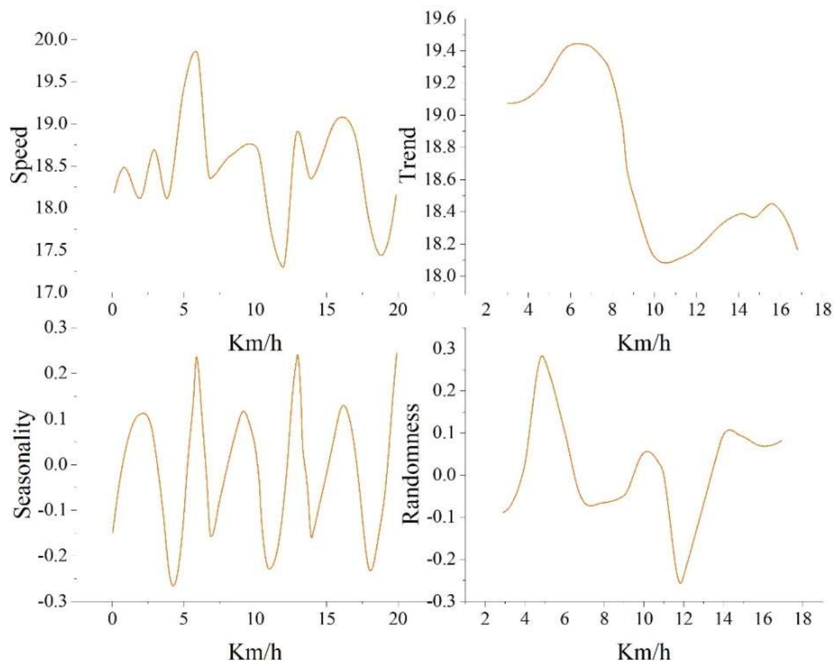


Figure 7: Bus speed sequence decomposition diagram

IV. B. Comparison of indicators

The evaluation metrics of the prediction performance of the model developed in this paper are compared with two other models, i.e., traditional recurrent neural network (RNN) and gated recurrent unit (GRU) as shown in Table 1. The accuracy of the model in this paper is improved by about 0.012 and 0.034 compared with the RNN model and GRU model, respectively, which indicates that the model in this paper is able to capture the actual situation more accurately. In terms of R2 value, the fitting degree of this paper's model is improved by 0.158 and 0.089 compared with the RNN and GRU models, respectively, which indicates that this paper's model is more capable of interpreting and fitting the actual data. It shows that this paper's model exhibits higher prediction accuracy, smaller prediction error, and stronger data fitting ability in highway speed prediction compared to RNN and GRU, and these advantages make this paper's model a potential tool for application in transit speed prediction.

Table 1: The model evaluation index is compared

Model	MAE	RMSE	R^2
This model	0.077	0.069	0.837
RNN	0.065	0.083	0.679
GRU	0.043	0.185	0.748

IV. C. Image Comparison

From the MLP model derived from the high-speed bus speed prediction value and the actual value of the change curve comparison shown in Figure 8, the figure of the model prediction results and the actual data, although in some of the speed fluctuations of the time point on the effect is slightly worse, but the overall trend of change is basically the same, and in some of the points of time and the actual data is very close to the model prediction performance is better.

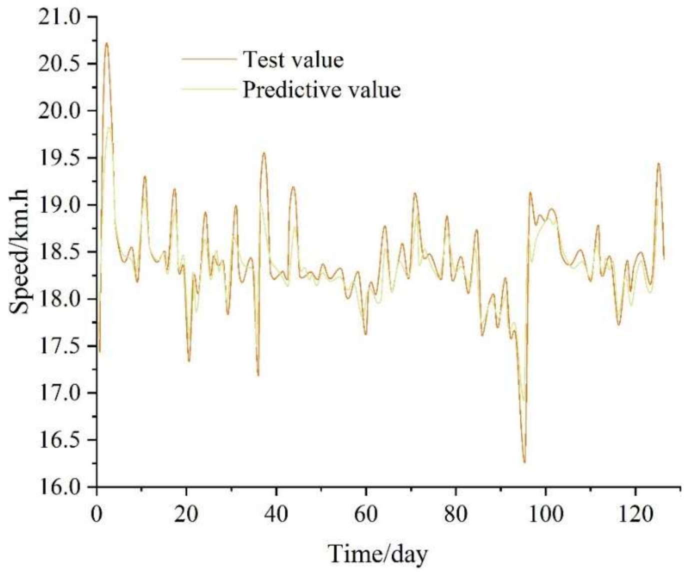


Figure 8: Comparison of vehicle speed prediction and actual value

V. Conclusion

The study draws the following conclusions by analyzing the traffic data of Chongqing Yuxiang Expressway and constructing the multilayer perceptron prediction model:

The traffic speed of the expressway shows obvious time-periodic characteristics, the cycle length is about 7 days, and there is a time-conformity relationship between the exit flow and the import flow, and the difference in vehicle travel time of OD pairs with different distances (e.g., 18km, 27km, and 40km) is obvious. The traffic speed prediction model constructed based on the multilayer perceptron outperforms the traditional model in terms of performance, and the predicted MAE index is 0.077, which is significantly better than that of the GRU model, which is 0.185. The model achieves 0.837 in the R^2 evaluation index, which is 0.158 higher than that of the RNN model, which indicates that the model has a stronger fitting ability for the trend of the change of traffic speed. The experiment shows that even at the time point when the traffic speed fluctuates greatly, the built model can still maintain the change trend that is basically consistent with the actual data, and it has good prediction stability.

The excellent performance of the multilayer perceptron model is mainly due to its strong nonlinear mapping ability, which can effectively capture the complex nonlinear relationship between traffic flow and its influencing factors. In addition, the application of BP algorithm enables the model to continuously optimize the weighting parameters through forward propagation and error back propagation to improve the prediction accuracy. This study has important reference value for highway traffic management departments, which can be used for traffic flow warning, congestion prediction and traffic accident risk assessment, providing data support for the development of scientific traffic management strategies and optimization of traffic resource allocation, thus improving the overall operational efficiency and safety level of the highway system.

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