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Research Article

Construction and Analysis of Urban Traffic Noise Prediction Model Based on PSO Algorithm and BRF Network Structure

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Due to the current nonlinear traffic noise and changing natural environment, accurate prediction of traffic noise has become a major challenge. In order to improve the accuracy of traffic noise prediction, this paper constructs a short-term traffic noise prediction model based on PSO algorithm and BRF network structure. The model can predict the noise state of future traffic according to historical traffic information. Particle swarm optimization (PSO) network is used for short-term traffic prediction to deal with the problems of low accuracy and long-time consumption. A BRF (one-dimensional convolution)-PSO short-term traffic noise prediction model is proposed. BRF method is used to extract the spatial features of traffic noise and compared with PCA (principal component analysis)-PSO model and PSO model. The results show that the prediction accuracy of BRF-PSO model is 2% higher than that of PCA-PSO model and 6% higher than that of PSO model, which proves the effectiveness of BRF-PSO model. This study provides a technical reference for the short-term traffic noise prediction of intelligent city and the effective improvement of urban traffic environment.

1. Introduction

In many densely populated cities, the increase in the number of cars has increased traffic congestion, which occurs during daily peak hours in first tier cities (Hong et al.) [1]. At the same time, economic development and integration have increased the use of vehicles, making the pressure on urban traffic volume system increase year by year. If the traffic noise problem cannot be solved in time, there will be more serious traffic congestion (Meng) [2]. Intelligent transportation system can effectively solve this problem by adopting scientific and efficient methods. Through the intelligent transportation system, the reasonable scheduling of vehicles and the optimal planning of driving routes can be realized (Xu et al.) [3]. Through the analysis of real-time vehicle driving data, the status of traffic systems in different regions is constantly adjusted, congestion is reduced, vehicle exhaust emissions are reduced, and urban traffic is kept healthy (Chen et al.) [4]. In order to better serve the people, it is necessary to improve the efficiency and accuracy of noise prediction.

Time-based short-term traffic noise prediction can be studied at a fixed monitoring point. Through different model algorithms, the data of the monitoring point is predicted and analyzed, and the advantages and disadvantages of different algorithms in prediction are obtained. The traffic noise is analyzed and predicted by extracting the features on the traffic space. The accuracy and efficiency of prediction are improved, and the analysis of traffic space-time domain is realized at the same time (Rui and Qinming) [5]. It is not necessary for the KNN algorithm to establish parameter and function mapping relationships when it comes to short-term traffic noise prediction problems. The traffic noise status similar to the current status is found from the historical traffic noise database and is predicted by the historical status similar to the current status (Zhang and Zhang) [6]. In summary, based on the deep learning KNN algorithm and traffic space-time prediction analysis, the smart city short-term traffic prediction model is constructed and analyzed.

This paper is mainly divided into three parts. The first part introduces the data cleaning method. By analyzing a variety of traffic data modes and synthesizing different traffic

noise modes, a data processing model based on KNN algorithm is constructed. The second part uses different feature selection methods to select the experimental data and explores the construction of short-term traffic noise prediction model based on deep learning. Finally, in the short-term prediction of traffic noise, the temporal and spatial characteristics of traffic are analyzed and considered. In addition, the model and algorithm are analyzed experimentally.

2. Related Work

From 1962, related research on traffic noise began to appear, and since then, a large number of research scholars have been pouring in from year to year. You et al. studied short-term traffic noise prediction algorithm based on ARIMA model, adopting the initial estimation of parameters by the moment estimation method [7]. Tang et al. proposed a real-time traffic noise prediction model based on Kalman filter theory. Through the traffic noise collected by the coil detector, the traffic noise in the future period of the section was predicted [8]. Rui et al. argued that nonparametric methods can produce better results than those with parameters and nonparametric methods had a better processing power for obtaining spatiotemporal relationships and nonlinear effects [9]. Wang et al. proposed a comprehensive algorithm based on nonparametric regression for short-term traffic noise prediction and event detection and improved the traditional nonparametric regression algorithm in two aspects, and the prediction effect was improved to some extent [10]. In Lei et al.'s nonparametric traffic noise prediction model, various statistical theories were not needed. The data was put into the network for training, and then the unknown data was predicted. It was found that that in this type of model, the number of network layers and weights need to be adjusted, and the network weights are continuously adjusted through training errors until the error is lower than the set threshold [11]. With respect to the issue of traffic noise forecasting, Aslan compared statistical methods with machine learning methods. The experimental results show the advantages of machine learning methods [12]. Wang et al. established a fuzzy neural network algorithm to process nonlinear traffic data. The research found that there is a clear advantage over the statistical-based approach [13]. Qin et al. proposed an algorithm model of support vector machine. Through BP neural network, the traffic noise at the intersection was predicted [14]. Stolpe proposed a short-term traffic noise prediction method based on multi-agent theory. According to the nonlinear time series prediction method, an improved method model under the multi-agent model was proposed. It was found that the prediction result of this method is better than that of the traditional method and the prediction error changes more smoothly [15].

According to the above research by Chinese and foreign scholars, the research on traffic noise mainly includes traffic noise pattern matching, traffic noise forecasting, traffic time series mining, traffic congestion, and intelligent transportation system. At present, due to the increasing size of urban transportation networks and the increasing traffic data, a large amount of traffic data cannot be handled well by traditional traffic noise prediction models. Deep learning has powerful modeling capabilities, and its multilayer, multi-node network structure has the advantage of processing big data.

3. Construction of Short-Term Traffic Noise Prediction Model in Smart City

3.1. Traffic Data Processing Method Based on KNN Algorithm. The KNN model is mainly used for sequence matching of traffic states. After digging into the mode of traffic noise, special mode prediction and mining are performed by means of distance measurement, such as finding an abnormal traffic sequence in which a traffic accident occurs or finding a traffic state under special weather [16].

The KNN algorithm is also used in the classification problem to calculate the distance between the target sample and all categories of data in a specific feature space and select the nearest K classifications. Finally, the K category that has the largest number is calculated. In addition to the classification function, the KNN algorithm can also perform regression calculations. By finding the K known samples closest to the destination sample and assigning the average of the K known samples to the sample, the value of the target sample can be determined. When KNN is used as a regression prediction, it is suitable for dynamic processes of uncertainty and nonlinearity. The method used is a nonparametric regression calculation method. The KNN method can be used in the process of regression prediction. And the most important part is the choice of K value. When the K value is too small, it is considered that the current state is related to the value of the previous smaller time period, and underfitting is easily generated in the model [17]. While the K value is relatively large, it means that the current state is related to many states, and it is easy to produce overfitting.

When the KNN regression model is applied to the short-term traffic noise prediction problem, compared with other regression prediction methods, the KNN algorithm does not need to establish parameters or establish a function mapping relationship. The traffic noise status similar to the current status is obtained from the historical traffic noise database, and the current traffic noise status is predicted. As long as the amount of historical data is large enough, the relationship between input and output can be automatically found by the model. In order to improve the accuracy of short-term traffic noise prediction, it is necessary to select the K value. At present, there are many ways to select the K value. Some scholars have proposed to minimize the L2 Risk method to select the K value, as shown in the following formula:

$$k = \text{argmin}_k \left(\frac{1}{\text{num} \cdot d \cdot T1} \sum_{s=1}^{\text{num}} \sum_{i=1}^{T1} \sum_{j=1}^{d} \left| V_{\text{true}}(i, j) - V_{\text{predict}}(i, j) \right|^2 \right). \tag{1}$$

Among them, s represents the sth detector. num is the number of valid detectors. i represents the ith time period. T_1 is the number of all prediction periods. j indicates the jth day. d is the predicted number of days. V_{true} represents the real traffic noise. V_{predict} represents the predicted traffic noise. The change of traffic state is random and uneven. Therefore, when k historical states similar to the current state are determined, the mean value is taken as the traffic noise predicted value at the next moment. The specific form is as shown in the following equation:

$$\widehat{V}(t+1) = m_n(x) = \frac{1}{k_n} \sum_{i=1}^{k_n} V_i(t+1). \tag{2}$$

Among them, $\widehat{V}(t+1)$ represents the predicted traffic noise at time $t+1$, and $V_i(t+1)$ represents the traffic noise at the K historically identical state $t+1$. For the new research data collected, the original traffic data needs to be screened and visualized as a whole. When a missing value is found in the data, the missing data needs to be effectively populated. There are many ways to fill missing data. One of the simpler and more intuitive methods is to use the mean for data filling. For example, 13 : 45 and 13 : 55 timestamps collected by a sensor have a corresponding traffic noise, and there is no traffic noise data at 13 : 50. The average value of the traffic noise data corresponding to the 13 : 45 and 13 : 55 time-stamps can be calculated as the traffic noise value of 13 : 50, so as to achieve the purpose of filling the missing value. Data protocol can make the data format tidy. In order to reduce the impact of different orders of short-term traffic data on the prediction results and improve the calculation speed of the computer, data normalization is a very important step in the short-term traffic noise prediction process.

3.2. Intelligent City Short-Term Traffic Noise Prediction Model Based on Deep Learning.

Feature selection based on mutual information is a common method of feature selection through information theory, which is widely used in classification regression problems. Mutual information feature selection is generally used to determine which category a feature word belongs to. If a particular feature word belongs to a certain class, the feature word and the mutual information amount of this class must be the largest. In the method of mutual information feature selection, it is not necessary to assume the relationship between feature words and categories, and the method can be used as a match between text classification features and categories. Meanwhile, mutual information also has a certain feature selection when calculating the correlation between timings. It is possible to filter information with high correlation and information with low correlation. Traffic noise belongs to time series data, with high dimensionality and large data volume. According to the characteristics of traffic data, through the selection of mutual information features of

traffic data, the purpose of reducing the dimension of traffic noise data is achieved. The processed traffic noise data is placed in the PSO model.

In the MIFS (mutual information feature selection)-PSO model, the threshold of mutual information calculation is first set, and the mutual information value MI between traffic data is calculated. After selecting the traffic characteristics whose mutual information value is greater than the threshold, the selected data features are placed in the input layer of the PSO model. Finally, the weight of the network and the parameters of the model are adjusted. The overall flow of the MIFS-PSO model is shown in Figure 1.

In Figure 1, the traffic noise data is reduced by MIFS, and the mutual data of the current T time traffic data and the previous time traffic data is calculated. By setting the threshold of the mutual information, the traffic data at the time when the correlation with the T time is relatively strong is selected and reorganized, and then the recombined data is brought into the PSO model for short-term traffic noise prediction. After the data passes through the hidden layer and the output layer, it is judged whether it meets the termination condition. When the termination condition is not met, the model network weight adjustment is performed until the termination condition is met.

3.3. Determination of Experimental Model for Short Traffic Noise Prediction Based on Spatiotemporal Characteristics.

The BRF-PSO short-term traffic noise prediction model involves the construction of the BRF model convolutional layer and the pooling layer, the PSO model network layer number, and the parameter adjustment of the two models. In the experiment, mean relative error (MRE) is used to determine the number of network layers of BRF. The MRE expression is as shown in the following formula:

$$\text{MRE} = \frac{1}{N} \sum_{n=1}^{N} \frac{|y_n - \widehat{y}_n|}{y_n} \times 100\%. \tag{3}$$

Among them, y_n is the true value, $\widehat{y}_n$ is the predicted value, and n is the number of data points of the traffic noise. By setting different number of convolution layers, the value of MRE is calculated, and the result is shown in Figure 2.

As can be seen from Figure 2, the dimension of the convolution layer is set to 1. Traffic noise data is simple text data, so the BRF dimension is set to 1. The BRF network is set to 3-layer full convolution, and each convolution layer is provided with 30 convolution kernels. The length of the first two convolution kernels is 3, while the length of the last convolution kernel is set to 2. Because the short-term traffic volume data dimension is relatively low, the pooling layer does not work in the model. The traffic noise data matrix is extracted by the special BRF model for spatial feature extraction, and the data of the upstream sensor with large influence is selected as the input of the PSO model. Compared to the time-based PSO model, all input forms of the
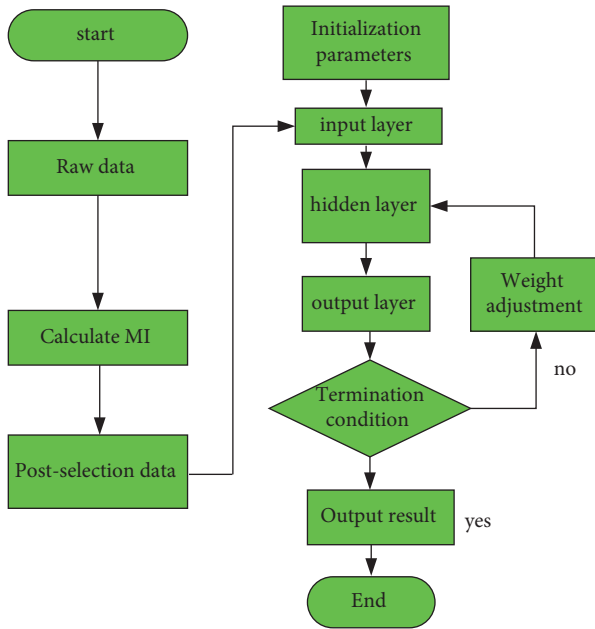
Figure 1: MIFS-PSO model workflow diagram.

Figure 2: MRE values under different convolution layers.

spatiotemporal based PSO model change from a sequence to a matrix of sequences. Through the forgotten gate of PSO, the information on the time characteristic of the traffic noise data is extracted by the input time series matrix, and finally the traffic noise data of the next moment is acquired by linear regression.

4. Experimental Design and Analysis

4.1. Source of Experimental Data. The highway performance monitoring system of the California Department of transportation provides researchers with historical traffic data of California. This includes annual traffic data collected from 39000 traffic sensors in major cities such as California. The traffic data can be stored online in the database of the detection station by selecting different acquisition frequencies such as 5 min or 1 h. For any section of the highway, traffic information such as traffic noise, vehicle speed, and vehicle occupancy rate of each lane can be collected by the deployed traffic sensors. The data used in the experiment is the traffic data for the two-month business days of 2017/08 and 2017/11 collected by the ID = 1201100 sensor and traffic noise data for 2017/08 working days collected by ID = 773281 sensor. The data sampling frequency is 288 traffic data points per 5 minutes per day. In order to speed up the running time required for the study, the sampling frequency of the data is converted into 96 traffic noise data points per day for 15 minutes. The sensor with the ID = 773274 is tested on the traffic noise data of the second lane collected on 2017/08/01, and the sampling frequency of the data is converted from 5 min to 15 min data conversion.

4.2. Algorithm Experiment and Result Analysis. The adjustment of PSO short-term engineering cost prediction model involves network model parameters such as excitation function, network layer number, and step size. Since the
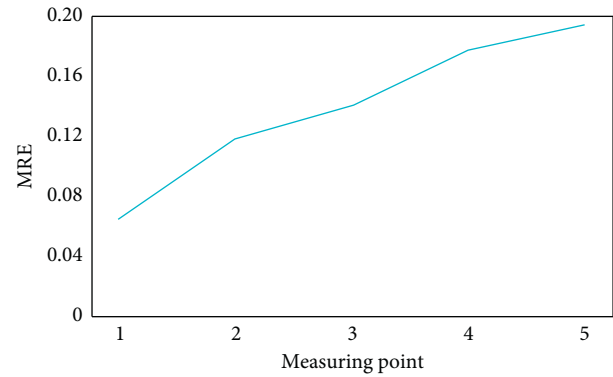
purpose of the experiment is short-term engineering cost prediction, the excitation function adopted in the experiment is a linear regression function, and the regression calculation is performed by the predicted data. When the model is adjusted, the length of each input time series and the number of layers of the network are adjusted separately. The experimental results are as follows. In the optimal step length experiment, the step size experiment is carried out using the engineering cost data collected by the ID = 1201100 sensor in 2017/08. The step size of the PSO model is set to 1, 2, ..., 10, and the corresponding root mean square error and average absolute percentage error are calculated. The results are shown in Figure 3.

It can be seen from Figure 3 that when the step size of the PSO model is increased from 1 to 10, the calculated RMSE and MAPE values are increased first, then decreased, and finally increased. When the step size is increased, more engineering cost data from the previous moment is taken into account in the model. In theory, it should have a better effect. However, when the input length is greater than 8, the values of MAPE and RMSE begin to increase. It can be seen that when the input length is increased to a certain extent, overfitting occurs, which increases the generalization error of the model. In this model, the length of the input engineering cost sequence is set to 8, the input length of the network input layer is selected to be 8, and the length of the input data is selected in the form of a sliding time window. The engineering cost data is used as an input every 8 moments; that is, the rated length of the matrix is set to 8 to train the engineering cost model.

In the optimal network layer experiment, the engineering cost data collected by the number 10 = 1201100 sensor in 2017/08 is used to carry out the network layer experiment, and the number of layers of the PSO model is set to 1, 2, ..., 5 layers. By comparing the values of RMSE and MAPE calculated under different models, and the results are calculated as follows.

As can be seen from Figure 4, when the single layer of the PSO network layer is selected, the calculated RMSE (root mean square error) and MAPE (mean absolute percentage error) values are the smallest. Therefore, the PSO model selection single layer structure is determined. The SVR model is trained using the best parameters c and g obtained. The training time series is selected in the form of sliding time
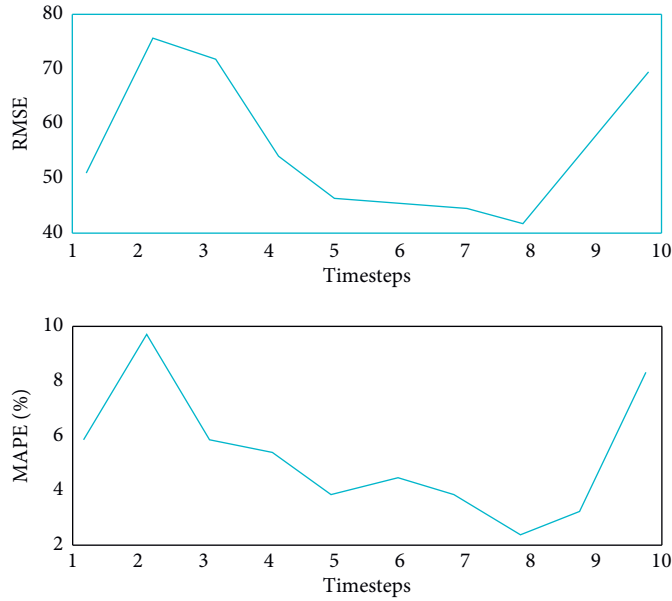
FIGURE 3: RMSE and MAPE values for PSO model with asynchronous size.

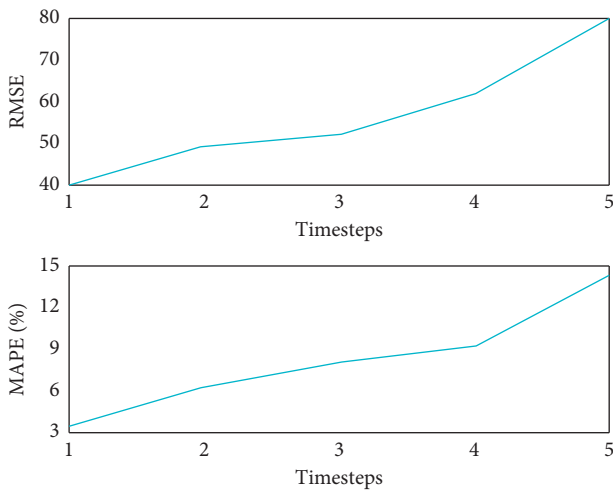FIGURE 5: Comparison of raw and predicted data.

FIGURE 4: RMSE and MAPE values for PSO models with different layers.

window. Each of the six engineering cost data points is used as a model input, the engineering cost data is modeled, and the test data is tested and predicted by the trained regression model. The predicted engineering cost data is denormalized to obtain the predicted true value, and the regression prediction result and the real engineering cost data are visualized to obtain the short-term engineering cost prediction result, as shown in Figure 5.

The trained model parameters c and g are saved, the test data is put into the trained network model to obtain prediction data, and the predicted value and the true value of the last day of the test data are visualized. The result is shown in Figure 6.

At the same time, it is necessary to adjust the input length of the model. By performing a step-by-step experiment on the data, the length of the time series input in the
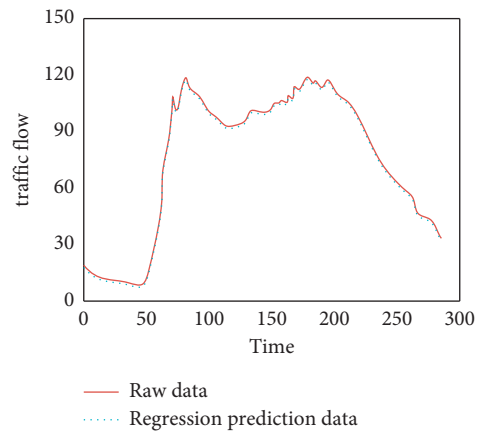
model is 6; that is, the step size is set to 6. Through the model training and saving, the predicted value of the last day of the test set is compared with the real value, and the result is shown in Figure 7.

By comparing the traffic data collected by the sensor with ID = 1201100 on working days in 2017/08 and 2017/11, as well as the engineering cost data collected by the sensor with ID = 773281 on the working day of 2017/08, short-time engineering cost prediction experiments are carried out. Among them, the sampling frequency is 5 min and the short-term engineering cost prediction is made for the above data with ARIMA, SVR, and PSO models, respectively. Then, the calculated MAPE and RMSE are compared. It can be seen from the results that the PSO model has the shortest running time, the prediction accuracy is 3% higher than that of the SVR model, and the prediction accuracy is 8% higher than that of the ARIMA model. The results show that the PSO model has a better effect on short-term engineering cost prediction than the other models.
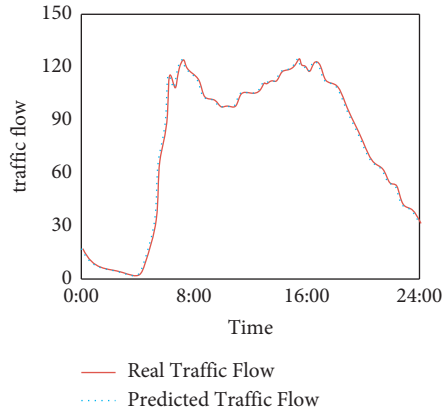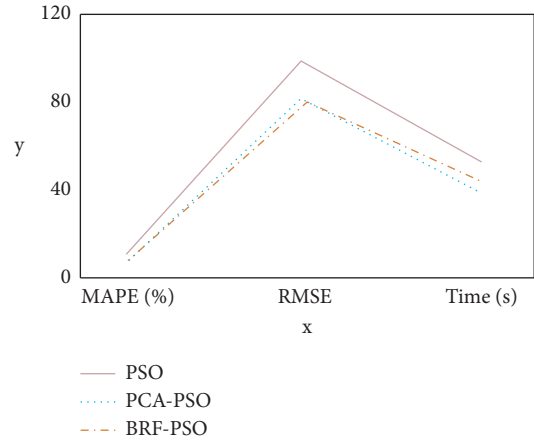
Figure 6: Comparison of raw and predicted data.

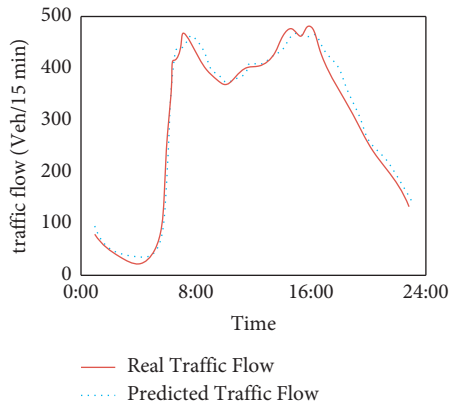Figure 7: A comparison of the predicted and true values of the month data with ID = 12011008.

Figure 8: Comparisons of different short-term project cost prediction models.

Figure 9: Comparisons of experimental results of 5 min sampling frequency.

Figure 10: Comparison of experimental results at sampling frequency of 15 minutes.

Comparing the engineering cost data of the working day collected by ID = 1201100 sensor in 2017/08 and 2017/11 and the traffic data collected by ID = 773281 sensor in 2017/08, we can see that PCA reduces the experimental data to 8 dimensions, while the mutual information feature selection method reduces the experimental data dimension to 14 and 16, respectively. The data after feature selection in two ways is used to predict the construction cost. The short-term engineering cost prediction is performed by MIFS-PSO, PCA-PSO, and PSO models, and the predicted values and real values are visualized. The result is shown in Figure 8.

Two evaluation indexes, MAPE and RMSE, as well as the running time results, are compared for short-time engineering cost prediction calculation by MIFS-PSO model, PCA-PSO model, and PSO model. It can be seen from the results that the computer running time is greatly reduced after the engineering cost is reduced by PCA and MIFS. When the PCA-PSO model is used for short-term engineering cost prediction, the accuracy of prediction is much lower. This shows that when the dimension is reduced by PCA, the relationship between the engineering cost and the time series is not taken into account, this leads to the neglect

of many important information, resulting in the accuracy and efficiency of prediction which is not high enough. After the dimensionality reduction of project cost through the method of mutual information feature selection, although the running time is not as much as that of PCA, the data with strong correlation in the time sequence of project cost is kept, and the predicted MAPE and RMSE are relatively small. Therefore, when the short-term engineering cost prediction is performed by the MIFS-PSO model, the accuracy and efficiency of the prediction are improved.

The spatial traffic noise data is set to a sampling frequency of 5 min and 10 min for data preparation. Through PCA, the spatial and temporal matrices of traffic noise are extracted by spatial features, and the spatial and temporal traffic characteristics of time-space traffic noise matrix are analyzed by BRF. Short-term traffic noise predictions are performed by using the PSO model, the PCA-PSO model, and the BRF-PSO model, respectively, and the root mean square error and the mean absolute percentage error are calculated. The calculation results are as shown in Figures 9 and 10.

It can be seen from Figures 9 and 10 that the accuracy of PCA-PSO and BRF-PSO model prediction is higher than that of PSO model, which illustrates the necessity of spatial feature extraction of traffic noise. The BRF-PSO short-term traffic noise prediction error is lower than the PCA-PSO prediction error, which indicates that the BRF model has advantages over the PCA method in spatial feature extraction. Although the time of BRF spatial feature extraction is slightly longer than PCA time, from the overall effect, BRF-PSO model is more suitable for short-term traffic noise prediction under space-time characteristics. In the above, the MIFS-PSO short-term engineering cost prediction model is mainly proposed. Firstly, PSO algorithm, SVR algorithm, and ARIMA algorithm are used to carry out multiple experiments on short-term engineering cost prediction. The experimental results show that PSO algorithm is superior in short-term engineering cost prediction. Then, the PCA and MIFS methods are used to select the engineering cost data collected by multiple groups of traffic sensors. The data after feature selection is put into the PSO model for multiple sets of short-term engineering cost prediction experiments. The experimental results show that the deep learning model PSO is efficient in short-term engineering cost prediction. The mutual information feature extraction method is used to select engineering cost data features, which is effective in short-term engineering cost prediction.

5. Conclusion

With the development of intelligent transportation, the transportation network is gradually becoming larger. At the same time, the ability of traffic data collection is getting larger and larger, and the collection methods are gradually increasing, which provides a rich data foundation for the study of short-term traffic noise prediction and also provides a guarantee for the improvement of intelligent transportation systems. Within this context, in this paper, based on the deep learning method, short-term traffic noise is predicted. Firstly, the PSO short-term traffic noise prediction model and the MIFS-PSO short-term traffic noise prediction model are constructed, and then the traffic noise characteristics are selected by PCA and MIFS, respectively. Besides, the time and space characteristics of the traffic field are analyzed, and the BRF model and BRF-PSO short-term traffic noise prediction model are introduced. Finally, short-term traffic noise prediction is compared by BRF-PSO model and PCA-PSO model. The results show that the PSO algorithm is superior to the short-term traffic noise prediction problem. The predictive performance of MIFS-PSO is better than the PSO model and the PCA-PSO model, while BRF-PSO has higher accuracy and speed in short-term traffic forecasting problems, and it is more advantageous. In the traffic noise forecasting system, the progress and speed of traffic noise forecasting can be improved by selecting superior algorithms, which in turn provides reference for urban traffic management. There are still some shortcomings in the research. Although the algorithm is tested, the algorithm is not used in actual traffic prediction, which is necessary to be done in the future.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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