A prediction model of buses passenger flow based on neural networks

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Abstract. With the popularization of smart buses, the ways to obtain buses operation information are becoming increasingly diversified, and passenger flow prediction based on big data information has also emerged. In this work, Principal Component Analysis (PCA) and error Back Propagation (BP) neural networks were combined to propose a prediction model of short-term buses passenger flow on the basis of PCA-BP neural networks. Firstly, the PCA method was adopted to reduce the dimensionality of the indices of buses passenger flow and improve the input nodes of the BP networks. Secondly, the fully trained network was employed to predict the buses passenger flow. More specifically, the passenger flow data set pair of the 17th bus in Guiyang on November 29, 2019 was used to carry out the PCA-BP neural networks model test. The test results indicated that the predicted passenger flow of each time period was very close, and the passenger flow prediction error in most time periods was very small. Besides, the relative error could achieve a satisfactory fitting effect, which was able to provide a reliable basis for bus dispatch. We found that the proposed PCA-BP neural networks model had high prediction accuracy and prediction performance. Therefore, it is expected to be used as a model for final short-term passenger flow prediction.

1. Introduction

In the actual operation of buses, there is a low handling capacity during the flat peak and low peak periods, which leads to low utilization rate of resources, thus greatly increasing the operating cost of the bus company [1]. In order to avoid this situation, most bus companies take measures to increase the departure interval between peak and low peak periods. However, this measure will affect the quality of bus services, and then form a vicious circle, which is not conducive to the long-term development of bus routes. With the development and application of big data and artificial intelligence technology, bus passenger flow prediction has become an important basis for formulating bus dispatch plans to thereby realize intelligent bus dispatch, improve bus service quality, and reduce the costs of buses operating. Consequently, predicting passenger flow is a necessary prerequisite for formulating bus dispatching plans. On the other side, determining the departure interval is a vital task for dispatching buses, which has a huge impact on the number of buses, the cost of the bus companies, and the level of bus service.

Taking the characteristics which include randomness and nonlinearity of buses passenger flow into consideration [2], the main methods used by scholars to predict buses passenger flow contain time series analysis, neural networks, and so on. [3, 4]. In this respect, some literature [5] proposed a direct prediction model of urban rail transit station passenger flow based on LS-SVM to solve the problem of medium and long-term passenger flow prediction. Nevertheless, the accuracy of the overall dispatch is difficult to guarantee and the prediction accuracy has room for improvement. As one of the most
mature prediction models, neural networks can perfectly solve the problem of nonlinear characteristics in the prediction of passenger flow. The references [6] put forward a method of predicting buses passenger flow by neural networks with a basis of quantum genetic algorithm-learning vector quantization (QGA-LVQ) to predict traffic flow changes, which solves the short-term traffic flow prediction problem and achieves a good accuracy. However, it is still not able to complete the prediction of bus passenger flow. Back-propagation Network (BPN) is one of the typical representatives of neural networks methods. BP neural network is multi-layer feedback networks with strong self-adaptation, and capabilities of self-learning, anti-interference, and outstanding nonlinear mapping. It is suitable for solving nonlinear problems in passenger flow prediction. Besides, it has the advantages of simple structure, high training efficiency and few setting parameters. On the contrary, the BP neural network has the disadvantages of long training time and unsatisfactory convergence performance as well. At the same time, it is easy to fall into a local optimal solution during networks training.

In response to the above problems, this study adopted principal component analysis (PCA) to reduce the dimensionality of buses passenger flow data and improve the input nodes of the original BP network by selecting principal component features, and then proposed a short-term buses passenger flow prediction model according to PCA-BP neural networks. This model not only simplified the structure of the network of training, but also increased the convergence speed and develop the prediction accuracy of networks.

2. Buses Passenger Flow Prediction Model Based on PCA-BP Neural Network

The sample data used in this study is the route of 17th bus in Guiyang which is as presented in Fig. 1. The bus passenger flow data is from November 1, 2019 to November 29, 2019 for a total of four weeks, of which there are 21 days of data on weekdays and 8 days of data on weekends. This study only predicted the passenger flow on weekdays. Moreover, the daily operating hours of this line are from 06:30 in the morning to 21:30 in the evening. Accordingly, in order to facilitate passenger flow prediction, the daily operating time was divided into 60 minutes as time intervals, so that there were 16 time periods in each working day.

2.1. Data preparation

When selecting the input and output data of the networks, the obtained data was limited and the data of adjacent weeks and adjacent months was not able to be used. Due to the continuous sunny days in November, the weather information was not included in the input variables as well. Therefore, it was decided to select the buses passenger flow data of the first 20 working days of the 17th bus line in Guiyang from November 1, 2019 to November 29, 2019, and input the passenger flow of the first 3 time periods of each day to predict the passenger flow of the next time period. The daily data was arranged in a rolling manner. Lastly, the prediction result is to output the passenger flow of 16 time periods in a day.

2.2. Data normalization

The neural networks require the input data to be normalized within a certain range, which can reduce the order of magnitude between the data and prevent the difference of the magnitude from causing excessive errors. It usually chooses the maximum and minimum method to unify the data between. The formula of this method is:

\[ x_k' = \frac{x_k - x_{\min}}{x_{\max} - x_{\min}} \]

Where, \( x_k \) is the current input data, \( x_{\min} \) is the minimum value of all input data while \( x_{\max} \) is the maximum value of all input data.
2.3. The construction of PCA-BP neural networks prediction model

After the data was processed, a short-term buses passenger flow prediction model based on PCA-BP neural network was constructed. The basic idea was to first use the principal component analysis method to reduce the dimensionality of the buses passenger flow indices, develop the input nodes of the BP network, and secondly use the fully trained networks to predict the buses passenger flow. The specific implementation steps are as follows:

2.3.1. PCA feature extraction. PCA-based feature extraction is a multivariate statistical method. Its principle is to use the idea of dimensionality reduction to convert multiple related indices into a few independent comprehensive indices, namely to replace and reflect more original information with fewer indices. These selected few independent aggregate indices are the main components of the original multiple indices. The principal component analysis processing method is to first process the multivariate parameter matrix. The essence is to perform a coordinate rotation in the N-dimensional space, but does not change the structure of the original sample data, thus to obtain the principal components which are still a linear combination of the original data, and they are not related to each other. This can explain the information contained in the original variable to a large extent. In addition, it is necessary to select some of the most critical principal components according to the standard, which will greatly simplify the multidimensional problem of the original data.

2.3.2. BP Network Design. Then, BP network will be considered from the following four aspects:
(1) Design the basic structure of the neural networks, including determining the number of layers, the number of nodes, and the transfer function of the networks;
(2) Set initial parameters, including initial weights and thresholds, learning rate, maximum number of training steps, etc.;
(3) Train the networks and select the training function in advance according to the actual situation of the sample;
(4) Simulate the networks, determine the BP network and complete the design through the performance comparison of different parameters in the training process. Although the error can be reduced and the accuracy can be improved with the increase of the number of network layers, the neural networks are becoming more and more complex, and the training time of the networks will be longer and longer. Any mapping from N-dimensional to M-dimensional can be completed by a three-layer forward network. As a result, based on the theory that a three-layer neural network can approximate any nonlinear function, this study adopted a three-layer network structure which is present as Figure 2.

![BP three-layer network structure diagram](image)

After confirming the number of layers and structure of the BP network, the following step is to start to set the initialization parameters. The learning rate value ought to be controlled within the range of 0.01-0.8. If the rate is too small, the convergence speed will be slow and the training time will be also too long. However, if the rate is too fast, the system will be very unstable. Generally, in order to ensure the stability of the system, it is usual to choose a relatively small rate. On the other side, reasonable initial weight and threshold selection are also extremely important. The initial weight is generally a small random number. Larger selections will easily lead to saturation and then occur stagnation. The random value is generally chosen in the range of (-1,1). Although it is hoped to get a smaller error, it is also necessary to select an appropriate value based on the actual situation. According to the number of input variables and output variables, it was determined that the input layer of the network contains 3 neurons and the output layer contains 1 neuron. Besides, trial algorithm was used to decide how many neurons the hidden layer contains. When the number of neurons was 13, the error of the network is minimized, so 13 was adopted as the final number. Meanwhile, the transfer function of the hidden layer was set to tanh and the transfer function of the output layer is set to purelin, and then it selected trainscg as the training function of the networks. At the same time, the necessary network parameters is installed. More specifically, the learning rate is set to 0.01, the maximum step size is set to 1000, and the target error accuracy is set to 0.00010.

2.4. Selection of training data
Choosing appropriate training samples for training the PCA-BP neural network model contributes to improve the prediction performance of the model. The selection of samples generally has the following principles:
(1) The selected samples should be representative to ensure that there are samples corresponding to faults with different occurrence frequencies;
(2) The selected samples should be extensive, to ensure that there are enough samples to make sure that all situations will occur;
(3) The selected sample should be compact to thereby prevent the sample from generating singular input.

According to the three principles mentioned above, it is necessary to consider collecting buses passenger flow samples at different times, and the samples must be representative, effective, and accurate. Consequently, this model picks the data of the first 20 working days as training data and inputs it into the model for training, and selects the data of the last working day on November 29 as test data to verify the usability of the model.

when the neural network model is built, the training data is input into the network for training, and the training process is terminated as soon as the stopping conditions are met.

3. Experimental Test and Results Analysis

For the propose of testing the trained PCA-BP neural networks prediction model, the sample data of the passenger flow of the 17th bus lines in Guiyang on November 29, 2019 was selected as the training network and re-input. Based on the trained network model that was obtained in the previous section, the test data was entered to obtain model prediction results. Then, it denormalized the results and indicated them in the form of a line chart. Figure 3 presented the prediction results of the PCA-BP neural network model by comparing the predicted value of the model with the true value.

![Figure 3. The line chart of the predicted results](image)
In the process of testing the PCA-BP neural network model through the passenger flow data which was set on November 29, 2019, the data of the previous 3 time periods at 6:30, 7:30, and 8:30 on the day is input to predict the buses passenger flow in next time period at 9:30, and the date is rolled to predict hourly. The output result is the buses passenger flow of 16 time periods of the day which is as presented in Figure 3 and Figure 4. The red solid dots in Figure 3 represent the predicted value based on the PCA-BP neural networks prediction model, while the blue hollow dots represent the true value of passenger flow. Through observation, it can be seen that the predicted passenger flow trend is roughly consistent with the real trend, which indicates that the PCA-BP neural networks prediction model can be applied for short-term bus passenger flow prediction. Figure 4 shows a more intuitive relative error and presents the error between the predicted value and the true value at each moment. Specifically, the relative error calculation formula is as follow:

\[ RE = \frac{y(t) - \hat{y}(t)}{y(t)} \]

In the formula, \( y(t) \) is the true value obtained by the current network model, and \( \hat{y}(t) \) is the predicted value of passenger flow.

In the experimental test results in Figure 3, the passenger flow prediction error in most time periods is very small, and the prediction errors in multiple time periods such as 10:30, 11:30, 14:30 and 15:30 are all around 5 people. It is also determined by the relatively stable passenger flow during this time period. The relative error in most of the time periods presented in Figure 4 can also achieve satisfactory fitting results, which can provide a reliable basis for bus scheduling. On the other side, in the three time periods of 6:30, 12:30, and 18:30, the absolute value of the relative error is comparatively large but only around 0.05. The reason why the relative error engendered may caused by the data set which was originated from Friday, November 29, 2019. Since, it was a Friday, the travelers could increase suddenly after the work of the day, and they probably took inter-city leisure travel and visited relatives and friends. The experimental test results mentioned above indicate that the passenger flow data predicted by the PCA-BP neural networks model are consistent with the actual passenger flow change trend, which means that the neural network model can be used as the final short-term buses passenger flow prediction model, and its prediction accuracy and prediction performance are relatively better. Realizing the short-term prediction of public transportation passenger flow can provide valuable information for decision makers in the public transportation industry.
system, so that they can reasonably adjust the operation plan according to the prediction results, which has great practical significance for the management of the entire public transportation system.

4. Summary

By obtaining and analyzing historical passenger flow data, this study analyzed and judged the development trend of passenger flow of bus lines, and then made reasonable capacity arrangements to better meet the demands of urban residents for transit trip. As one of the representatives of nonlinear intelligent models, the neural networks method is preferable for nonlinear and complex traffic flow prediction. In this respect, this study established a prediction model based on PCA-BP neural networks for bus passenger flow prediction, which not only simplified the network training structure, but also improved the convergence speed and prediction accuracy of the networks. First, the PCA method was used to reduce the dimensionality of the buses passenger flow indices to improve the input nodes of the BP network. Second, the fully trained network was applied in predicting the buses passenger flow. The experimental test results displayed that the relative error of most time periods was very small, and achieved a satisfactory fitting effect, which can provide a reliable basis for the next hour's buses dispatch. It showed that the prediction model based on PCA-BP neural networks proposed in this study had high prediction accuracy and good prediction performance, and accordingly can be used as the final prediction model of buses passenger flow.

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