Forecast of Subway Inbound Passenger Flow based on LSTM Model and BP Neural Network

Jiaming Jia*

School of Human Settlements and Civil Engineering, Xi'an Jiaotong University, Shaanxi, China

* Corresponding Author Email: jiajiajia@stu.xjtu.edu.cn

Abstract. Passenger flow prediction for rail transit is an extremely important research topic. This paper constructs a long-short-term memory model, and proposes a simple optimization method. At the same time this paper constructs a backpropagation neural network model and adjusts the size of the hidden layer through testing. Within 15 days, swipe card data from a randomly chosen tube station in a city is subjected to resampling, normalization, and other data preparation techniques. The processed data is then split into an 80% training set and a 20% test set. The root-mean-square error test analysis is carried out on the three types of models constructed to judge the fitting effect of the data. The conclusion is that the BP neural network model is relatively easy to build a shallow network structure, which is typically less than or equal to 3. Additionally, the data fitting effect outperforms both the LSTM model and the straightforward optimization approach. Especially for passenger flow fluctuations in a short period of time, the BP neural network can have good prediction ability.

Keywords: LSTM, BP, passenger flow data, root mean squared error.

1. Introduction

With the rapid increase in traffic flow, vehicle congestion has become an important problem hindering urban travel and development. Therefore, the establishment of intelligent transportation systems is the general trend. To address the issue of traffic congestion, several cities have implemented intelligent transportation systems. The forecast data of short-term traffic flow provides data support for travelers to arrange travel plans reasonably and for traffic departments to control traffic in time. Accuracy of short-term forecasts is important, and the low operation cost and high accuracy of prediction results are the main research directions of many scholars.

The same sort of traffic passenger flow forecast with time intervals of hours, days, months, and even years is completely distinct from the prediction of short-term traffic passenger flow, which has a prediction time span of no more than 15 minutes. In addition, the traffic flow estimation with a maximum 15-minute time frame offers significant research value [1]. Generally, short-term traffic prediction can be divided into three directions, prediction models based on traditional mathematical statistics, machine learning and deep learning. An improved short-time traffic flow forecasting model based on the Autoregressive Integrated Moving Average, also known as ARIMA algorithm has been used in conventional forecasting experiments proposed by Yang DL [2]. Xie et al. comprehensively considered the factors affecting climate and temperature and built a multiple linear regression model to predict bus passenger flow [3]. Chen et al. proposed a linear regression model to predict passenger flow results considering the spatiotemporal correlation between subway passenger data [4]. Among them, regression analysis model is also a widely used traditional statistical forecasting model, and the autoregressive moving average model is the most widely used. For example, Qkutani built ARIMA model in 1984 and applied it to urban traffic control system.

Guo et al. employed a support vector machine model to foresee the flow of transit users as an element of a machine learning approach. They created a suitable model using AFC data analysis and a PSO-SVM model to predict passenger flow at subway stations [5]. To forecast short-term rail transit passenger flow, Xu et al. developed a random forest method [6]. In order to anticipate the outgoing passenger flow at train stations, Qian et al. took into account a number of contributing parameters and built the matching decision tree forecasting model [7].

In terms of short-term prediction based on deep learning, Zhang et al. have developed a relatively long short-term memory network (LSTM), a gated recurrent neural network (GRU), a recurrent neural network (RNN), a convolutional neural network (CNN) algorithm, and a graph convolutional network (GCN) that have been excavated and applied to short-term passenger flow prediction successively [8-10]. Among them, LSTM was used as the optimization model of RNN, and Feng constructed the CNN-LSTM combined model [11]. In order to determine the ideal values of the LSTM hyperparameters, Zeng et al. developed a combined model to forecast the short-term passenger flow of urban rail transportation. They introduced the decomposition method CEEMDAN and the enhanced particle swarm optimization algorithm IPSO [12]. To research very precise short-term passenger traffic forecasting, LSTM is frequently integrated with other algorithm models as a representative example of deep learning.

This study trains and predicts the flow of people of multiple subway stations using the LSTM algorithm model and the backpropagation neural network structure, and it computes the root mean square error. It proposes the corresponding optimization method and model combination based on the card records of the train station data from 2019-1-1 to 2019-1-15 organization of the text.

2. Method

2.1. LSTM Introduction

The LSTM model is a variant of RNN model, which has a "gate" structure. Through the logic control of the gate unit, the data is decided to be updated or discarded, which overcomes the shortcomings of RNN that the weight is too large, and it is easy to produce gradient disappearance and explosion, so that the network can converge better and faster, and can effectively improve the prediction accuracy. The basic concept behind LSTM is to use flexible, controlled self-loops to create routes that enable changes to flow continuously over a long period of time. Specific structures are shown in Figure 1.

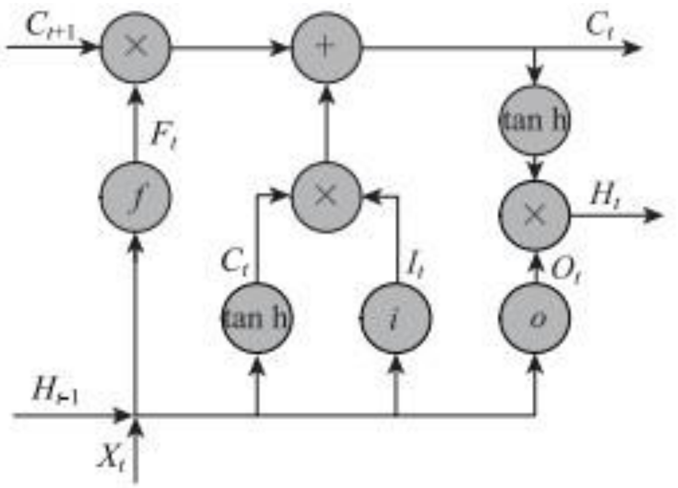

Fig. 1 LSTM Memory Cell Structure [13]

2.2. Back Propagation Introduction

Backpropagation Neural Network (BP) is a common Artificial Neural Network model used to solve supervised learning problems. It is a kind of forward-feedback artificial brain that modifies the network's weight and bias to reduce the discrepancy between its expected and real results.

The layers of input, hidden, and output are made up by a BP neural net. The Backpropagation technique underpins the training of BP neural networks. It calculates the errors between the output and the actual output, propagates those mistakes from the output layer to the hidden layer, and then adjusts the network's weights and biases. To maximize network performance, this procedure employs the gradient descent technique to locate the local minimum of the error function.

3. Results and Discussion

3.1. Overview of the Data

The data comes from the swipe card information of a city metro rail transit. The file records the swipe time, entry and exit status, swipe type, and station ID of each subway station. The file records the data for 15 days from 2019-1-1 to 2019-1-15, and the card records exceed one million.

In this paper, a specific subway station is selected, and the data information of all inbound passenger flows in the station within 15 days is extracted and combined. A total of 412,111 entry card records are obtained within 15 days.

The research data are selected and merged in batches, and the non-research attributes of the data are eliminated. The data is resampled with 10 minutes as the time granularity, and the resampling results are saved into a new table. The information is shown in Table 1 and Figure 2.

Table 1. Resampled-10 Minutes

Column name	Style	Explanation
Time	String	Time to enter the subway station with your card
Number	Int	Passenger flow in 10 minutes

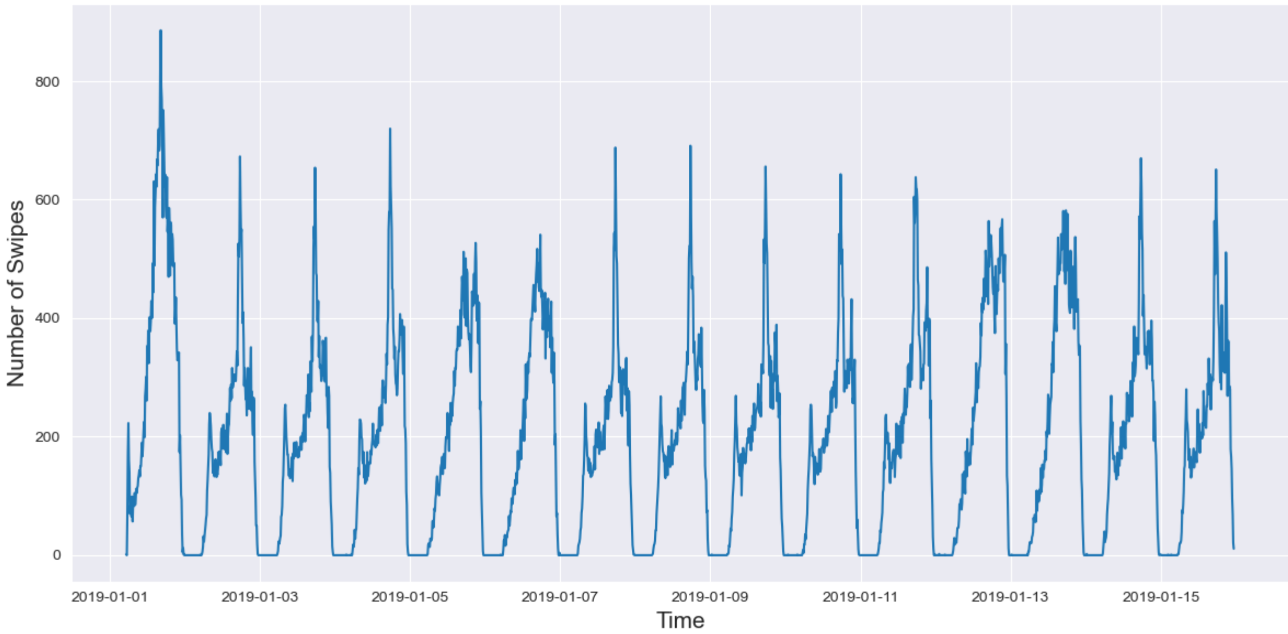

Fig. 2 Subway Card Swipes at Station 10 (Resampled - 10 minutes)

By pre-processing the data, it is possible to figure out that the subway is a crucial instrument for urban train traffic and that the daily arrival traffic exhibits the features of distinct cyclical changes in time, with regular variations in the day as a time cycle.

3.2. Construction of LSTM Prediction Model

All of the data collected over a 15-day period were split into two groups: twenty percent for the experimental group and eighty percent for the set that was used for training. The input of the model was the actual passenger flow in every 10mins in the training set, and the output was the passenger flow in the test set time series. The time step was set to 10 and 30 single training iterations were performed. The loss function values are shown in Figure 3.

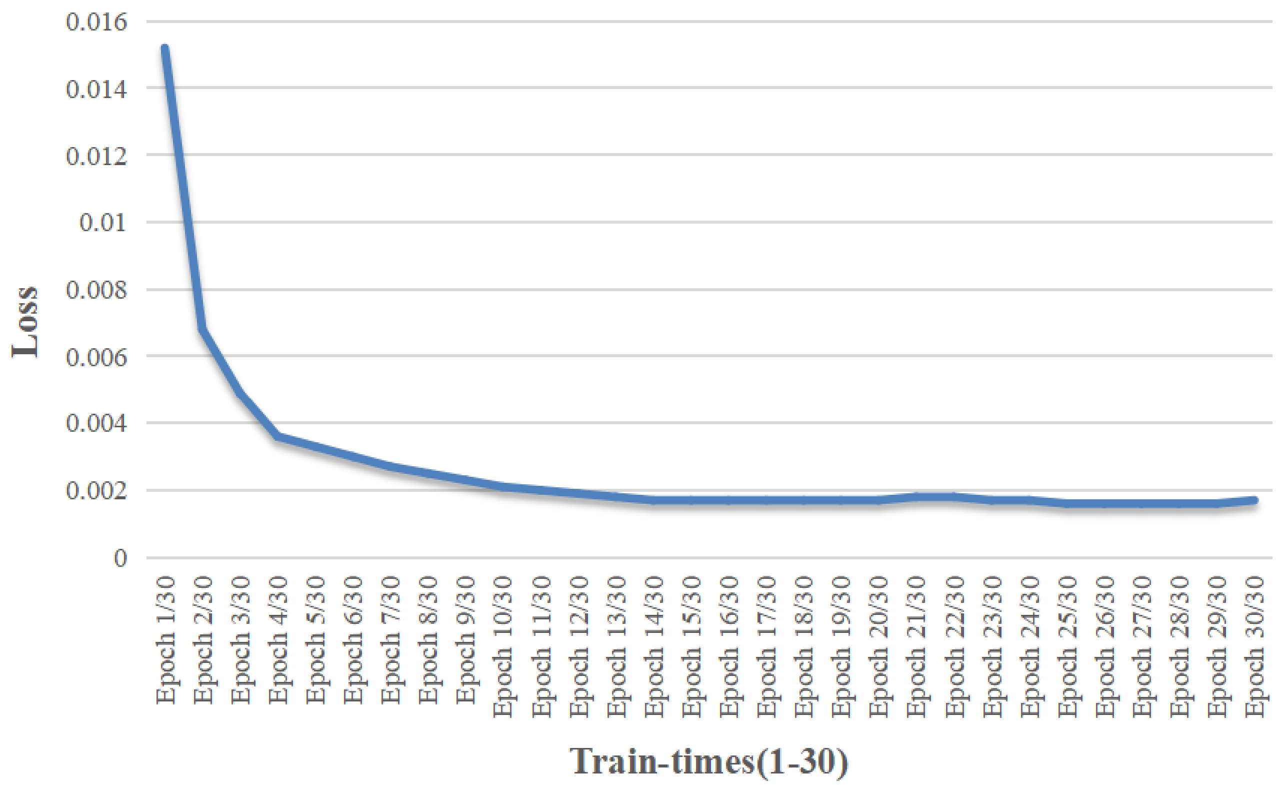

Fig. 3 Loss-Results

In this study, it can be observed that the LSTM model exhibits continuously decreasing Loss values during training. Loss function is widely used in machine learning to measure the difference between the predicted result of a model and the actual label, and the continuously decreasing Loss value means that the model's ability to fit the training data is gradually increasing.

It can be concluded that the model's capacity to match the training information is gradually enhanced, which provides a solid foundation for further research and application of LSTM models. The trained model is matched with actual data, and the specific visualization results are shown in Figures 4, 5, and 6.

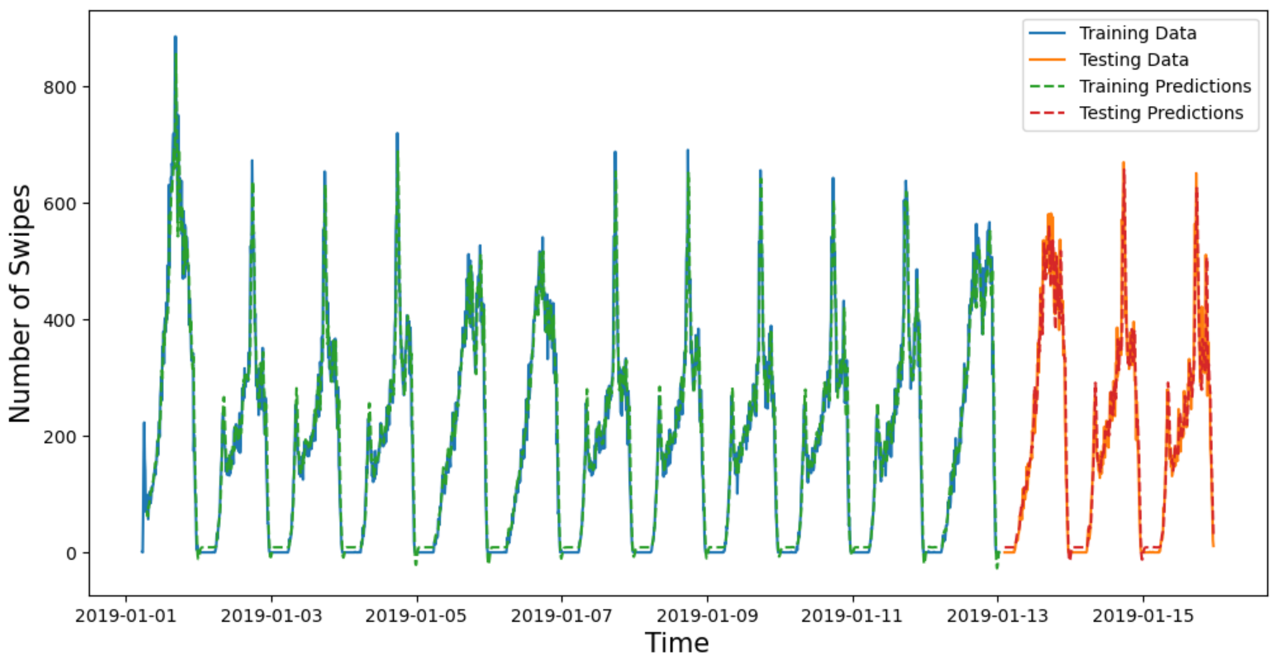

Fig. 4 LSTM Prediction-Actual Data

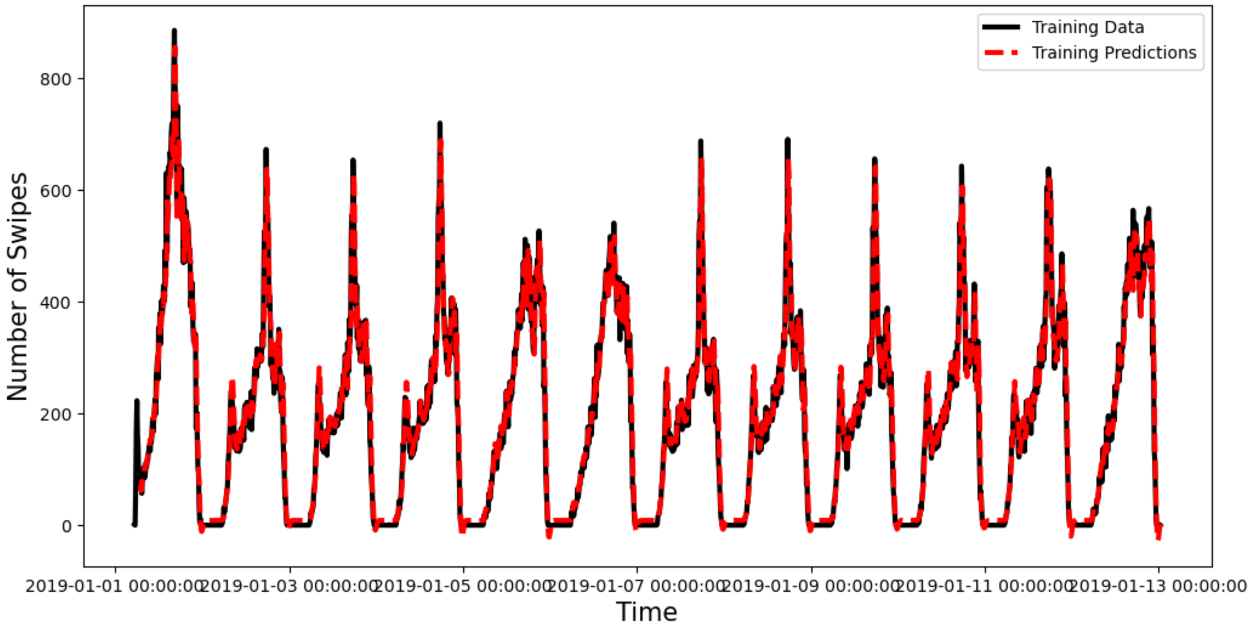

Fig. 5 LSTM Prediction-Training Data

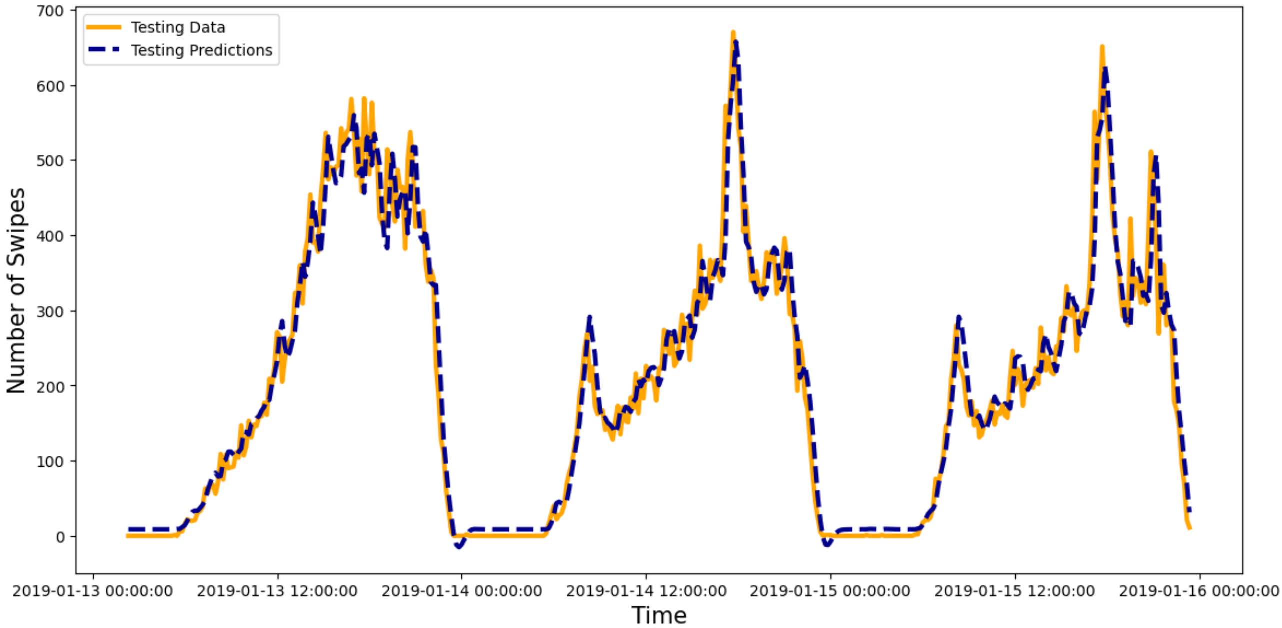

Fig. 6 LSTM Prediction-Testing Data

Through the images, it is clear that while the LSTM model performs well in terms of the general trend of people movement prediction, the model itself has a negative situation. It does not accurately reflect the actual phenomenon and is only partially accurate in terms of prediction adaptation. Instead, it is best to ignore local fluctuations and focus on the overall forecast.

3.3. Model Evaluation

It can be seen that the model constructed by LSTM has a good fitting effect. At the same time, the root mean square error of the model is calculated, which is 35.79 for the training set and 38.72 for the test set. Figure 7 evaluates the 90% confidence interval, and the predictions are mostly within the range.

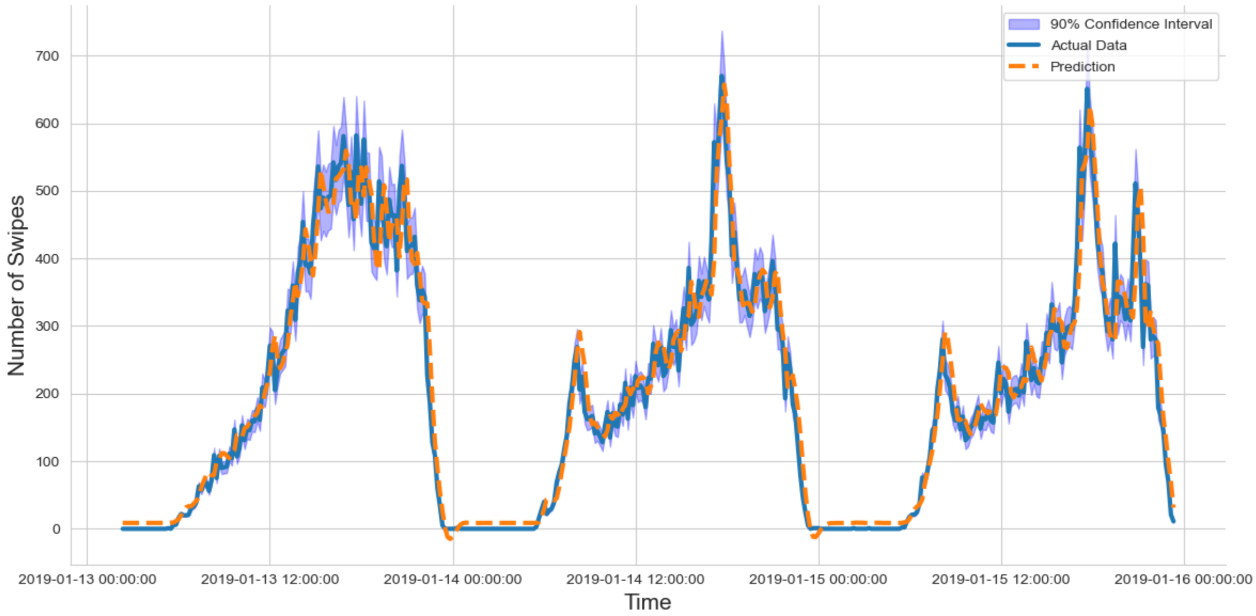

Fig. 7 LSTM Prediction with Confidence Interval

The prediction results of LSTM have good accuracy, but the training results have negative values, which is not in line with reality, so it needs to be optimized. In view of the periodic negative phenomenon in LSTM training results, the model was optimized in combination with the actual passenger flow data of subway card swiping. By adjusting the output range of the model, a certain activation function was used to limit the output range to ensure that the predicted result would not be less than zero. By using the Rectified Linear Unit (ReLU), it sets negative values to zero, thus ensuring that the output is never less than zero. After the activation function is added, the model image is shown in Figure 8.

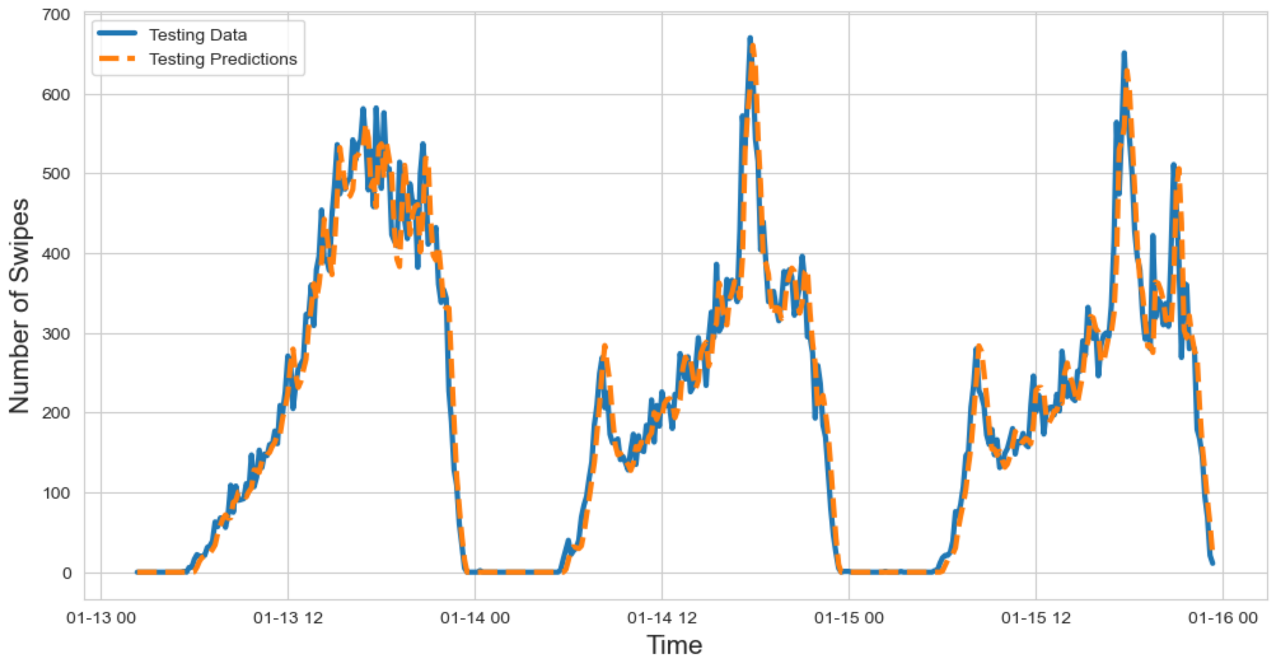

Fig. 8 LSTM Prediction with Output Limiting

The root-mean-square error of the test set also decreases to 38.17. It is obvious that output limiting has enhanced the model's forecast accuracy and made it more useful.

3.4. Construction of BP Prediction Model

Necessary pre-processing and preparation of data, including transforming time series into timestamp labels, data normalization, constructing features and target variables, are consistent with the pre-preparation work of LSTM model construction.

Because of the simple input of influencing factors, the author constructs a neural network with two hidden layers, adjusts the parameters, conducts error analysis, and sets (50, 50) to the optimal parameters of hidden_layer_sizes, with a smaller root-mean-square error when there are 50 neurons in each hidden layer. The Rectified Linear Unit (ReLU) performs well in practice and is chosen as the activation function. With the actual data from 13 to 15 days as the test data, mean absolute error, mean squared error, and root mean squared error can be obtained. And Figure 9 provide further details. In Table 2, the comparison of the three models' root-means-square mistakes is presented. They make fewer mistakes as a result, and their performance eventually improves.

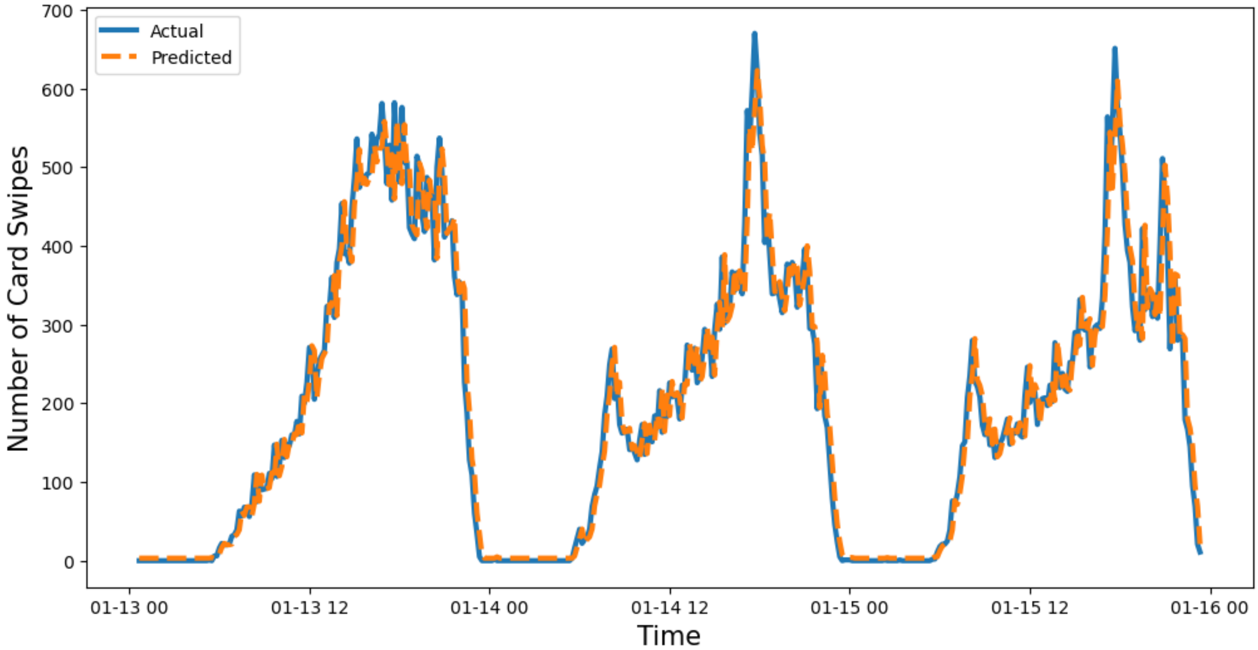

Fig. 9 BP Prediction-Testing Data

Table 2. Models - Error Test Results

Models	Mean Squared Error	Root Mean Squared Error
LSTM	1499.59	38.72
Output Limiting-LSTM	1456.77	38.17
BP	1355.97	36.82

4. Conclusion

After completing the training process, the LSTM model demonstrates commendable performance in terms of overall data fitting. However, certain unrealistic situations arise, and the model's local volatility prediction does not exhibit satisfactory accuracy. To address these limitations, an innovative approach called the Output Limiting-LSTM model is proposed. This model not only enhances the realism of the data fitting process but also effectively diminishes the root mean square error (RMSE) outcomes. The Output Limiting-LSTM model introduces a novel mechanism to refine the predictions by constraining the output values within predefined limits. By incorporating this limitation during the training phase, the model exhibits improved fidelity in capturing realistic patterns and mitigates the occurrence of unrealistic situations. Consequently, the local volatility prediction is enhanced, leading to more accurate results.

Furthermore, the BP algorithm, which outputs classification information through forward propagation signal, error calculation, output back propagation error, weight adjustment, and a continuous iterative optimization process, has shown excellent performance in shallow network structures. In the present study, actual passenger flow data from a city over a period of 15 days was utilized. Specifically, data from a single subway station was crawled and merged after preprocessing tasks such as resampling. The resulting dataset comprises only 2125 data points and is characterized by a relatively small data volume and simple input influence factors, making it suitable for constructing a shallow network structure.

In this scenario, the BP neural network model offers several advantages, including ease of construction and a good fit. Particularly in the context of local prediction, the data trained by the BP neural network model exhibits a superior fit to the actual subway station passenger flow fluctuations. Notably, the prediction results for small-scale fluctuations within local time intervals are highly accurate. Moreover, the effectiveness of the BP neural network model, especially in the context of local prediction, is demonstrated using a real-world dataset from a subway station. These results contribute to the understanding of shallow network structures and their applicability to scenarios involving limited data amounts and simplified input factors.

References

[1] Guoguang He, Yu Li, Shoufeng Ma. Discussion on short-term Traffic flow prediction Method based on Mathematical model. Systems Engineering Theory & Practice, 2000, (12): 51-56.

[2] Donglong Yang. Research on short-term road traffic flow prediction based on ARIMA model. Electronic design engineering, 2021, 29(13): 38-42.

[3] Zhendong Xie, Xueqin Liu, Jincheng Wu, et al. Research on passenger flow prediction Model based on public transportation IC card data. Journal of Guangdong University of Technology, 2018, 35(01): 16-22.

[4] Dongyang Chen, et al. Research on Metro Passenger Travel Time Prediction Based on Passenger Flow Big Data Analysis and Support Vector Regression. Modern Urban Rail Transit, 2020, (09): 70-76.

[5] Guo Wen, Xiao Weizhou, Qin Feifei. Passenger flow prediction of Metro station based on Support vector Machine model. Hebei Industrial Science and Technology, 2019, 36(01): 31-35.

[6] Xu Wenxing, Zhang Yu. Short-term Passenger flow prediction of orbital stations based on Random forest algorithm. Journal of Wuhan University of Technology, 2012, 46(03): 406-410.

[7] Qian Huimin, et al. Sports events surrounding rail site based on AFC data of short-term passenger flow prediction. Journal of transportation engineering, 2020, 20 (6): 30-36.

[8] Zhang Yawei, Chen Ruifeng, LIU Xiaoyan. Door control loop of the neural network based passenger flow prediction. Journal of railway transportation and economy, 2022, 44(9): 96-102.

[9] Yang Liu. Application of Deep Learning in Transportation. Information Technology and Informatization, 2022, 263(02): 192-195.

[10] Zuo Tong, et al. Passenger flow prediction of urban rail transit stations based on deep fusion of spatio-temporal characteristics. Comprehensive Transportation, 2023, 45(05): 67-74.

[11] Feng Biyu. Research on short-term passenger flow prediction of urban rail transit based on CNN-LSTM combined model. East China jiaotong university, 2020.

[12] Zeng Lu, et al. Research on short-term Passenger Flow Prediction of urban rail Transit Based on CEEMDAN-IPSO-LSTM. Journal of railway science and engineering, 2023, 1-14.

[13] Li Gao-sheng, Peng Ling, LI Xiang, Wu Tong. Research on short-term passenger flow prediction of urban bus station based on LSTM. Journal of Highway and Transportation Technology, 2019, 36(2): 128-135.