Research on logistics volume prediction model based on ARIMA-LSTM

Nannan Lin[1, *], Yuan Yuan[2], Hongzhan Li[3]

[1]Department of Industrial automation, School of Beijing Institute of Technology, Zhuhai, China, 519000

[2]Department of Materials and Environment, School of Beijing Institute of Technology, Zhuhai, China, 519000

[3]Department of Applied Science and Civil Engineering, School of Beijing Institute of Technology, Zhuhai, China, 519000

*Corresponding author: 2543715236@qq.com

Abstract. At present, the line volume prediction problem in the cargo transportation problem is very important, if the line volume prediction in the parcel emergency transportation and structure optimization problem in the e-commerce logistics network is not handled well, it may lead to unreasonable allocation of logistics resources, logistics congestion, parcel delays, and even loss. Meanwhile, in order to increase the transportation efficiency of logistics network, this paper proposes an ARIMA-LSTM prediction model. Through data analysis and processing, it is found that the data is characterized by time series data. For this reason, this paper firstly uses the ARIMA model to predict the cargo volume, and finds that it can only predict the linear part of the cargo volume well. Secondly, the LSTM model is used for prediction, and contrary to the ARIMA model, it is found that the LSTM model can better capture the information of the nonlinear part of the cargo volume; finally, this paper combines them to construct the ARIMA-LSTM model, and finally compares the prediction effect of these three models by using the MAE, MSE, and R2, and it is found that the prediction effect of the ARIMA-LSTM model is the best, and the MAE is 0.5. The ARIMA-LSTM model was found to be the best. The MAE is 0.00042, the MSE is $3.08e^{-08}$, and the R^2 is as high as 0.89.

Keywords: LSTM model, ARIMA-LSTM prediction, cargo volume forecasts.

1. Introduction

The emergency dispatch and transportation of parcels in e-commerce logistics network is a major challenge faced by the current logistics industry. Due to the rapid development of e-commerce business and consumers' high requirements for delivery speed, logistics companies need to deal with the impact of various emergencies, such as weather and traffic, on logistics while ensuring efficiency. The volume of e-commerce logistics network is affected by holidays and promotional activities, and the amount of users' orders will fluctuate significantly. With the frequent occurrence of large-scale unexpected events, the logistics site will be temporarily or permanently suspended, which will increase the processing pressure of other logistics sites. The emergency logistics network can realize the safe and efficient transportation of emergency materials to the disaster area. It plays an important role in the rescue process [1].

Among them, line cargo volume prediction is the key link to solve the problem of emergency transportation. Through the analysis of historical data, the possible future logistics demand and line situation can be predicted, so as to make preparation for scheduling in advance and ensure the smooth logistics. However, the accuracy of line prediction is affected by many factors, such as the integrity of data, the accuracy of prediction model, etc., which is also an important problem to be solved in the current logistics industry. In this study, the line freight volume data of a logistics network is taken as an example, and a line freight volume prediction model based on ARIMA-LSTM is constructed based on the spatio-temporal characteristics of freight volume data and the composite characteristics of linear and nonlinear.

2. The basic funamental of ARIMA-LSTM prediction model

2.1. ARIMA prediction model

The ARIMA(p, d, q) model is called the autoregressive integrated moving average model, where p is the autoregressive term; d is the number of differences when the time series is smoothed; Q is the number of moving average terms. This model combines autoregressive (AR) and moving average (MA) to transform non-stationary time series into stationary interseries, and then regresses the lagged values of the dependent variable, the current lagged values of the random error term, and the lagged values into the created model[2]. If the researched time series Q(t) is non-stationary, then a stationary time series can be obtained through appropriate dif\u0002ferences in the standard ARIMA model[3].

$$F_t = \mu + \sum_{i=1}^{p} \gamma_i F_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{1}$$

Where F_t is the current value; μ is the constant term; γ_i is the autocorrelation coefficient; $\varepsilon_t$is the error term; The θ_i is the coefficient of the error term. The process of ARIMA(p,d,q) model is shown in Figure 1.

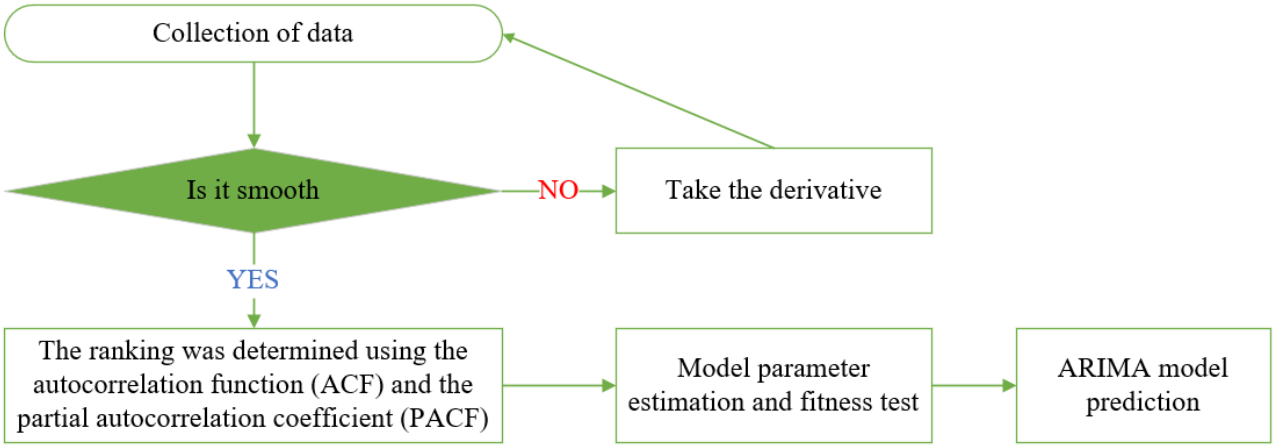


Figure 1. ARIMA predict flow chart

2.2. LSTM prediction model

LSTM (Long Short-Term Memory) is a special type of Recurrent Neural Net work (RNN). In 2005, ALEX improved it and put it into application [4]. It solves the problem of gradient explosion and gradient disappearance in the process of long sequence training of RNN. That is, when the number of layers of the network increases, the perception ability of subsequent nodes to the previous node decreases, and the phenomenon of forgetting the previous information will occur over time[5][6].

On the basis of RNN, LSTM adds a memory unit to each neural unit in the hidden layer: the information transmission band is called "unit state", and uses structures such as forgetting gate, input gate and output gate to control the stored information on the time series[7]. In this way, LSTM can dig deeper into the underlying patterns between data, making predictions more accurate and reliable. The LSTM model neural network is shown in Figure 2.

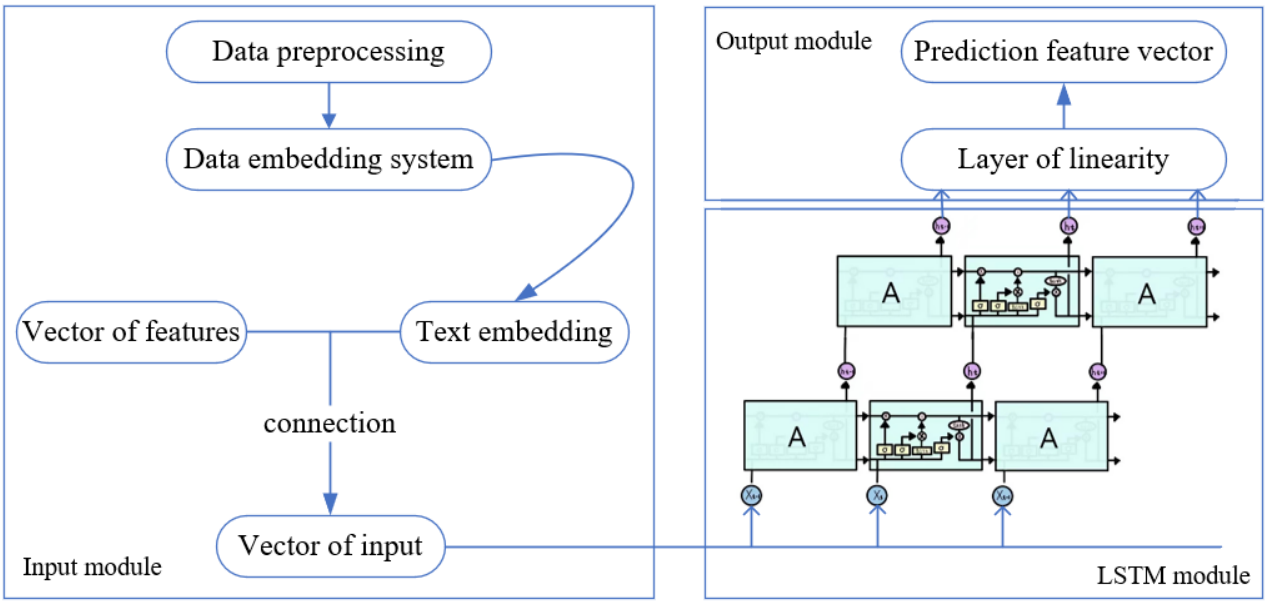


Figure 2. Schematic diagram of LSTM neural network

The calculation formula of input gate i_t, forget gate f, output gate o_t, memory cell update state C_t and hidden gate h_t is as follows[8].

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{4}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{5}$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \tag{6}$$

$$h_t = o_t tanh(C_t) \tag{7}$$

Where σ is the Sigmoid activation function; b_i、b_f、b_o and b_c represent the corresponding bias of different gates respectively; W_i、W_f、W_o and W_c are the corresponding full values of different gates respectively; x_t represents the input of the current node; h_t represents the output of the current node; $\tilde{C}_t$ represents the candidate value vector in the calculation process; C_{t-1} is the memory update state of the previous node.

2.3. ARIMA-LSTM combined prediction model

The change law of cargo volume with time is complex and diverse, including both linear trend and nonlinear trend, so it is difficult to fully fit the prediction by only using a single model. Based on this idea, this paper constructs a combined model [9]. The process of the model is shown in Figure 3, and its mathematical description is as follows.

$$y_t = L_t + N_t \tag{8}$$

Suppose that the sequence data is y_t, where L_t describes the linear component in the sequence data and N_t represents the nonlinear component in the sequence data. The modeling process of the combined model is as follows.

(1) The ARIMA model is first used to model the series data and obtain the predicted values of its linear components. The nonlinear component is then included in the residuals.

(2) After the residuals are obtained, they are modeled using the LSTM model to obtain the predicted values of the nonlinear components.

(3) Finally, L_t and N_t are added to obtain the final forecast.

$$e_t = y_t - \hat{L}_t \tag{9}$$

$$\hat{N}_t = f(e_{t-1}, e_{t-2}, \text{dots}, e_{t-m}) + \varepsilon_t \tag{10}$$

$$\hat{y}_t = \hat{L}_t + \hat{N}_t \tag{11}$$

Where e_t represents the residual error containing nonlinear components, $\hat{L}_t$ is the predicted value of ARIMA model, $f(\cdot)$ is the relationship function established by LSTM model, and ε_t is the random error.

In order to ensure the prediction accuracy of the LATM model for the residual error of the ARIMA model, this paper adopts the iterative prediction method, that is, the prediction of the sequence value at each next moment is made on the new model after the change of the predicted value at the previous moment, rather than using the test data to predict the sequence value at each future moment.

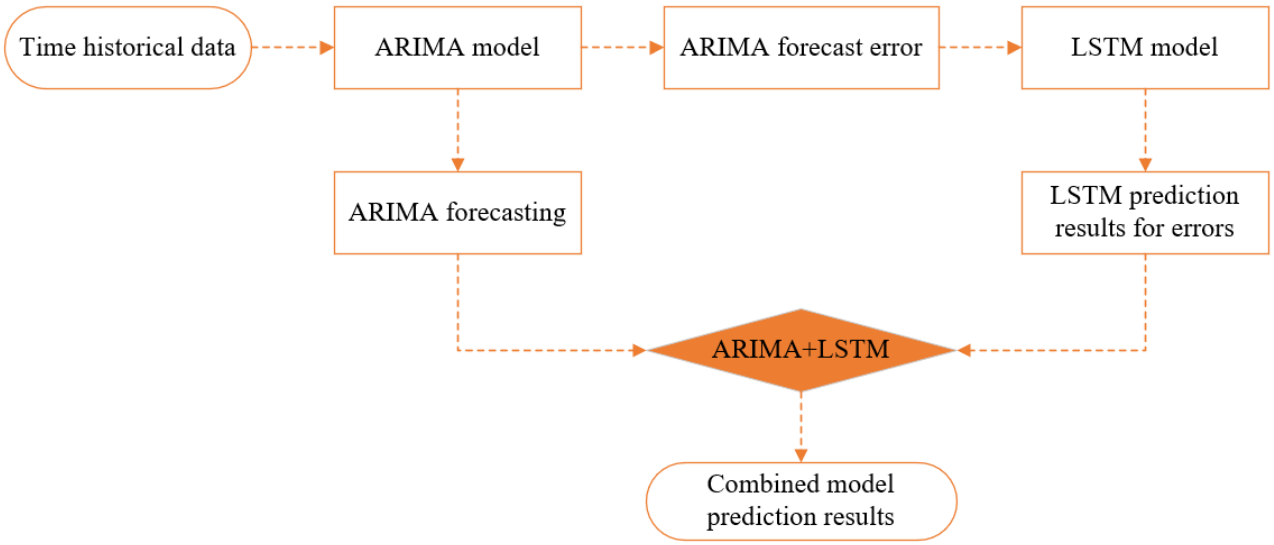


Figure 3. Flow chart of ARIMA-LSTM prediction

3. Results

In order to verify the accuracy, feasibility and effectiveness of the ARIMA-LSTM model, this paper selects the daily cargo volume data of three lines in a logistics network from 2021-01-01 to 2022-12-31 as input. The data set is divided into training set and test set[10]. The training set is used for model learning, training and parameter tuning, while the test set is used to evaluate the prediction effect of the ARIMA-LSTM model.

3.1. The establishment of error index model

In this paper, MAE, MSE and coefficient of determination are used to evaluate the prediction effect, and the calculation formula is as follows.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \overline{y}_i| \tag{12}$$

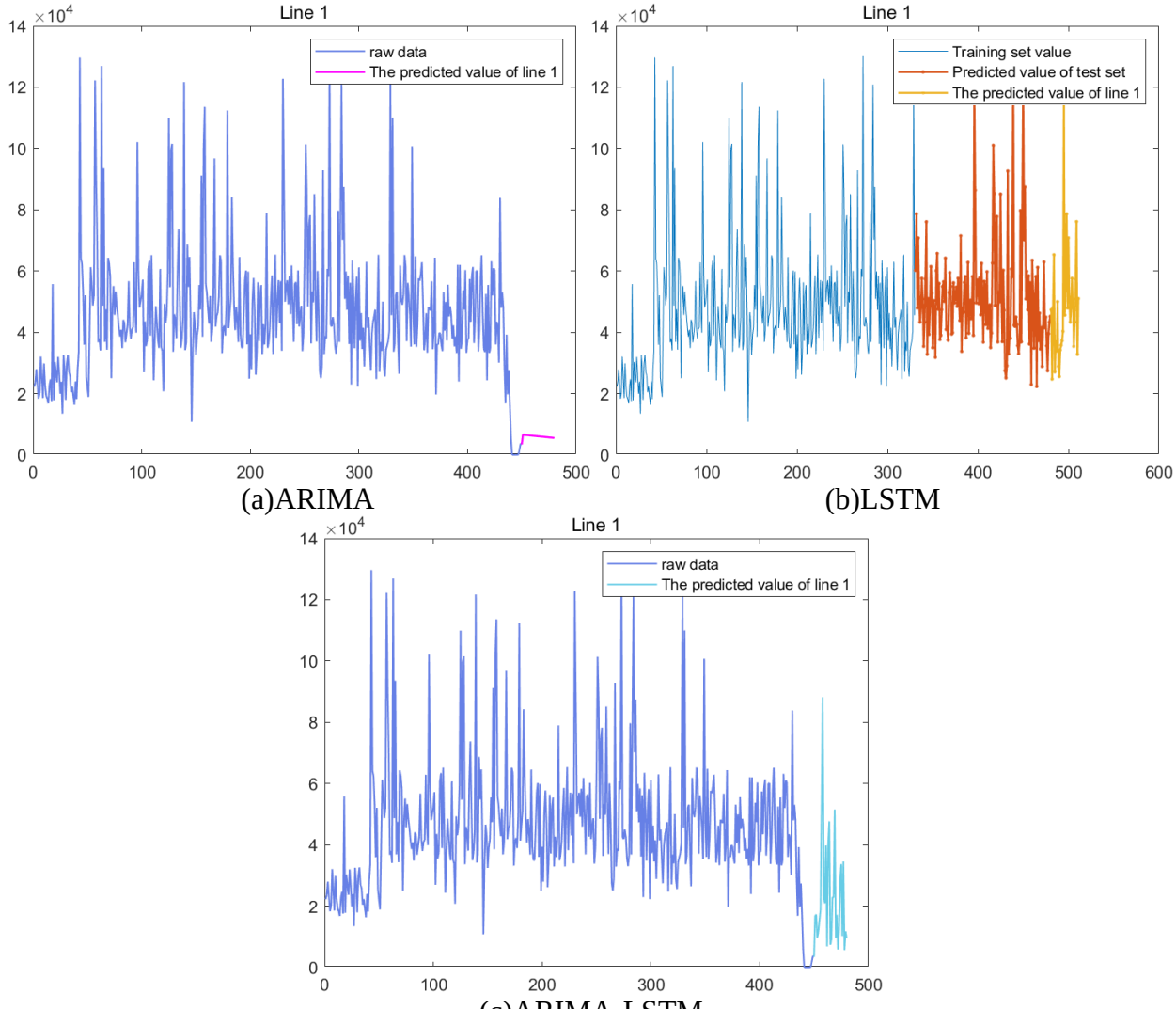
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y}_i)^2 \tag{13}$$

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{14}$$

Where n is the total number of selected samples, y_i is the actual value of the cargo volume, and $\hat{y}_i$ is the predicted value of the cargo volume.

3.2. Analysis of experimental results

The prediction results of ARIMA and LSTM models are shown in Figure 4. It can be seen from Figure 4 (a) that the ARIMA model is not very accurate in predicting the volume of goods, which is particularly obvious in the upward trend of the volume of goods. However, the ARIMA model is still able to capture the trend of daily cargoes variation of the line well, which means that it is able to predict the linear part of cargoes well. It can be seen from Figure 4 (b) that compared with the ARIMA model, the LSTM neural network model improves the prediction accuracy of cargo volume and can well capture the fluctuation of cargo volume. It can be concluded that the LSTM model can better capture the information of the nonlinear part of the cargo volume, and it can be found that its prediction accuracy will get higher and higher over time with the increase of the training set. It can be seen from Figure 4 (c) that the ARIMA-LSTM model combining linear and nonlinear prediction results has good accuracy and stability, and can better meet the changes of cargo volume in actual scenarios.

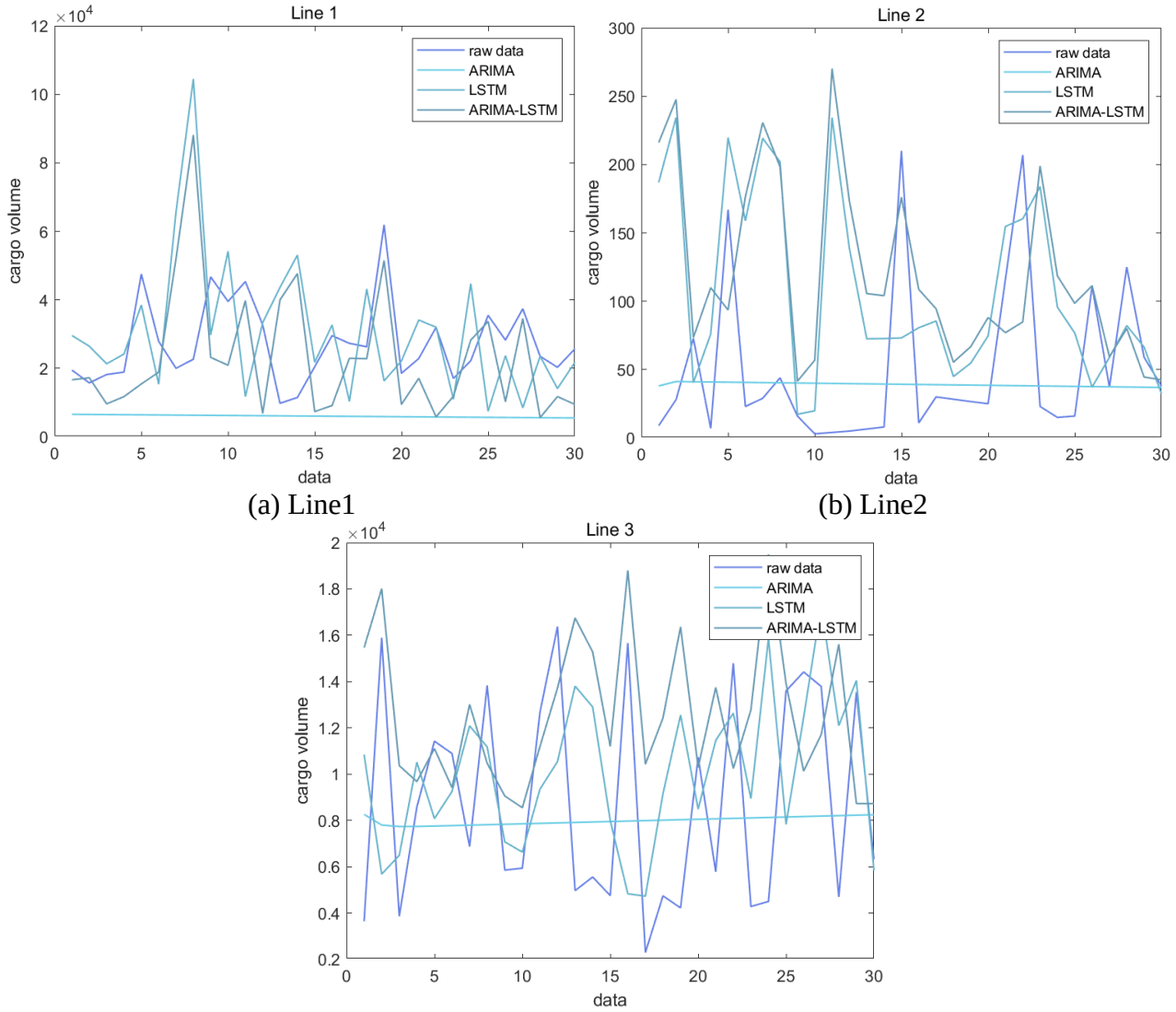


(a)ARIMA (b)LSTM

(c)ARIMA-LSTM

Figure 4. Model prediction results

In order to more intuitively compare the prediction accuracy of the three models, the error between the real value and the predicted value among the models is compared, and the predicted value of each model of the three lines is calculated, as shown in Figure 5. It can be seen from Figure 5 that the ARIMA-LSTM model has the best fitting degree and the highest prediction accuracy between the predicted value and the real value, and the LSTM model has a better fitting effect than the ARIMA model.



(a) Line1 (b) Line2

(c) Line3

Figure 5. Line forecast value

In order to accurately evaluate the prediction effect of the model, the error comparison of each model is shown in Table 1. Table 1 shows that the ARIMA-LSTM model has the smallest prediction error and the highest fit and accuracy. Combined with the model prediction chart and error table, it can be concluded that the ARIMA-LSTM model has the best prediction effect and provides effective data basis for the realization of cargo transportation arrangement.

Table 1. Errors

Model	MAE	MSE	R^2
ARIMA	0.00267	6.08e-06	0.5
LSTM	0.00103	4.12e-06	0.76
ARIMA-LSTM	0.00042	3.08e-08	0.89

4. Conclusions

Aiming at the problem of route prediction in cargo transportation, this paper firstly adopts ARIMA model and LSTM model to predict the route respectively. Finally, through the prediction effect of these two models, it can be found that the prediction effect of ARIMA model on cargo is not very accurate. However, the ARIMA model is still able to capture the trend of daily freight volume variation of the line well, indicating that it can predict the linear part of freight volume well. However, the prediction effect of LSTM model is better than that of ARIMA model, which can well capture the fluctuation of cargo volume. Therefore, the LSTM model can better capture the information of the nonlinear part of the cargo volume. Finally, in order to capture the information of both linear and nonlinear parts, the ARIMA-LSTM model is constructed in this paper, and the prediction results of this model can be seen to be more accurate and stable through the prediction effect diagram. Finally, in order to more obviously highlight the predictive ability of the model, this paper uses MAE, MSE and R2 to judge the predictive ability of the model. Through the comparison of the three models, it is finally obtained that the MAE and MSE values of the ARIMA-LSTM model are the smallest, and R^2 is larger than the other two models, up to 0.89. It shows that the model can accurately predict the route, and can help logistics companies to plan and adjust the transportation route in advance, reduce unnecessary waiting and transfer time, so as to improve logistics efficiency.

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