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Prediction of national carbon emission efficiency based on ARMI-Convolution LSTM*

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Abstract

In this paper, convolutional long and short term neural network model(LSTM) and ARIMA model are used to fit and forecast China's carbon emission efficiency, and the weights of the two in the combined prediction are set to different values to observe the optimal fitting results and predict the future trend. First of all, in terms of prediction accuracy, the results show that the prediction accuracy of the long-term and short-term neural network model and the time series ARIMA model is less than the combined prediction accuracy. Compared with each single prediction, the combined prediction not only considers the complementarity of linear and nonlinear, but also considers the combination of mathematical model prediction and influencing factor prediction, which makes the prediction result more practical significance. Finally, the analysis results have certain enlightenment significance for the future trend.

Keywords

Convolutional long and short term neural networks; ARIMA; Carbon efficiency, CLC number: F222.1.

1. Introduction

Since the "Double carbon Goal" was put forward, relevant researches on the screening of influencing factors and the prediction of carbon emission have been carried out one after another. The research on carbon emission prediction is mainly divided into two directions: one is to analyze various factors affecting carbon efficiency through the analysis of influencing factors, so as to predict the change trend of carbon efficiency; the other is to establish a mathematical prediction model, use the data to directly analyze the change rule of carbon emission efficiency, and predict the future carbon emission efficiency.

Early studies in China mostly focused on the first direction, such as studying the relationship between energy consumption and energy production and carbon emission [1][2], so as to predict carbon emission. With the passage of time, more and more factors affecting carbon emissions have come into the view of scholars, so the prediction of carbon emissions also starts from multiple influential factors, such as manufacturing [3], tourism [4], transportation [5], green economy development [6], etc. Theoretical results show that relevant research has provided guidance for the development of enterprises and cities to a certain extent. However, this kind of prediction is highly dependent on related factors. Currently, the world is in a great change unseen in a century, and the economic and political environment is very unstable. The result of predicting carbon emission efficiency by a single influencing factor is good, but when compared with the reality after a period of time, sometimes there will be a large deviation. However, when multiple influencing factors are combined for linear analysis, a more serious multicollinearity problem will occur. Therefore, for a long time, the direction of relying on the analysis of influencing factors to predict carbon emission efficiency has been gradually downplayed by

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scholars, and the direct prediction of carbon emission efficiency has been changed from the perspective of target variables.

In the establishment of econometric model for prediction, there are great disputes and problems in determining explanatory variables. Because a single explanatory variable cannot fully explain the cause of the change of the explained variable, and when the explanatory variable is affected, its explanatory ability is greatly reduced, and the stability of the model is reduced. When multiple explanatory variables explain the explained variable, its stability is improved, the prediction accuracy is improved, and the prediction effect is better. However, the possibility of multicollinearity is increased at the same time, and the actual interpretation status of each explanatory variable to the explained variable is more difficult to distinguish, and the effect of a change of an explanatory variable on the overall change cannot be precise. Therefore, scholars have introduced many financial time series forecasting methods into the prediction of carbon emission efficiency in recent years. At present, the mainstream prediction models include gray prediction [7], ARIMA [8], super-efficiency SBM model [9] and some prediction models of machine learning and deep learning, and the results show that the robustness of direct prediction has been improved. For example, the grey prediction model GM (1, 1) is used to forecast the carbon emissions of Zhejiang Province from 2022 to 2025. The results show that the agricultural carbon emissions and carbon emission intensity of Zhejiang Province show a downward trend [10], and it is further concluded that Shaoxing, Hangzhou, Jiaxing and Huzhou are cities with low emission and high efficiency, while Wenzhou is cities with high emission and low efficiency. For example, LSTM (Long and Short term memory neural network) is used to forecast AQI [12], which improves the prediction accuracy and enhances the generalization ability.

However, due to the different modeling mechanisms and angles of information presentation of various models, a single model has certain limitations in reflecting data information, and has the defects of not high enough prediction accuracy and wide enough application range. Therefore, in recent years, scholars have adopted more combined forecasting methods when predicting carbon emission efficiency. For example, in literature [11], Sha Emin et al., based on the combined prediction model theory, adopted the method of Fu The optimal combined forecasting model was established for different weight coefficients of grey Verhulst model, Logistic model and Gompertz model. The results showed that the prediction accuracy and reliability of the combined forecasting model were significantly higher than that of the single forecasting model, which had obvious advantages and could predict the traffic carbon emissions more accurately.

Few studies have been conducted on the prediction of ARIMA model and Long Short Term Memory network (LSTM) model. ARIMA model is one of the typical time series prediction models, which belongs to linear prediction model. LSTM is a new forecasting model in recent years, which has been applied in various fields by many scholars. For example, Zhao Xingyu et al. used the prediction method of the mixed model of time convolutional network and long short term memory network to predict the power load. The results show that the algorithm can predict the change of actual load data more accurately than other common prediction algorithms, and all evaluation indicators are better than other prediction methods. It can provide a timely and effective basis for the electric power department to improve the efficiency of power scheduling and make maintenance plans [11]. In the process of application, this model not only incorporates a variety of influencing factors into the model, but also effectively avoids the problem of multicollinearity. It is now a popular choice for scholars in empirical forecasting.

LSTM is evolved on the basis of recurrent neural network (RNN), in order to solve the long-term data dependence problem of RNN, but the defects still exist in this aspect. In order to improve the capability of LSTM, nn module in pytorch is used in this paper to establish convolutional LSTM, which makes the training accuracy more accurate and the prediction

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results more convincing. At the same time, compared with many deep learning prediction models, LSTM can incorporate relevant explanatory variables that have a greater impact on the prediction target into the model, making the prediction results not only more accurate, but also more practical. At present, the existing researches mainly use LSTM and convolutional neural network separately. ARIMA and LSTM models are predicted first, and then convolutional neural network is used for analysis. At present, the existing studies mainly use LSTM and convolutional neural network separately, and first make prediction by LSTM model, and then make analysis by convolutional neural network [16] .

In this paper, convolutional long short-term memory neural network is directly established for prediction. However, overfitting often occurs when LSTM network is used to predict time series with linear relationship [12]. Therefore, in this paper, linear time series prediction model ARIMA model is organically combined with LSTM model, which not only enhances the representation of linear relationship in data, but also improves the accuracy of prediction to a certain extent. In this paper, ARIMA-LSTM convolutional neural network combined prediction model is proposed to fit and predict China's carbon emission efficiency by using seven indicators, including the proportion of the secondary industry in GDP, energy consumption and fixed investment growth rate.

2. Model construction

2.1. ARIMA (2,1,2) Model building

The ARIMA model is one of the most commonly used linear models for time series analysis, which is mainly suitable for shortterm analysis and prediction. Figure 1 shows the change trend of China's carbon emission efficiency from 1997 to 2020 of the time series data. It can be seen from Figure 1 that the series Non-stationary series. In order to be able to use the time series ARIMA prediction model, the raw data needs to be processed and tested as follows:

First, the ADF test is performed on the data to judge the stationarity of the data. The results are shown in Table 1.

Table 1. ADF test results

test statistics	First-order difference ADF test statistic	Test critical value		
		1%	5%	10%
t statistic	-5.240648	-3.769597	-3.004861	-2.642242
p	0.0004			

It can be seen from the test results in the table that China's carbon emission efficiency is stable under first-order difference, and the difference d is determined to be 1. The white noise test results of this sequence show that this sequence is not a white noise sequence, so it can be modeled.

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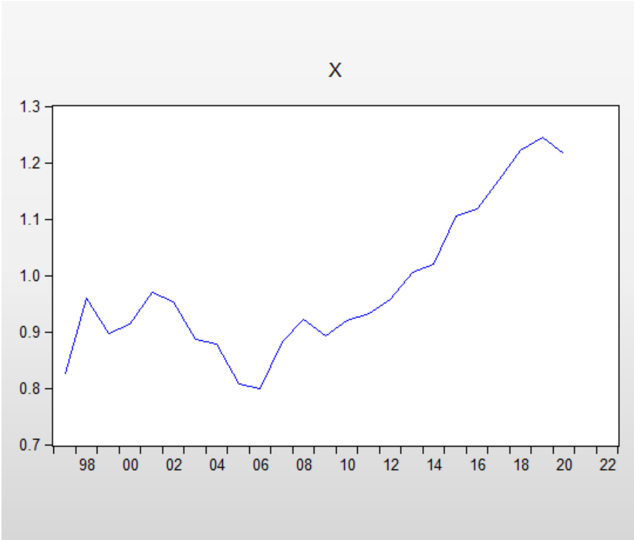

Figure 1. Trend chart of China's carbon emission intensity from 1997 to 2020

Then, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Schwarz Criterion (Schwarz Criterion) are used. SC) to determine the specific constant terms in the model -- trend terms, intercept terms or no constant terms, and get the results as shown in the table.

Table 2. Information criteria judge the form of the model

	Trend and intercept	Intercept	None
AIC	-3.334450	-3.247717	-3.271635
BIC	-3.185672	-3.148531	-3.222042
HQ	-3.299402	-3.224352	-3.259953

By comparing AIC, BIC and HQ information criteria, it can be seen that the ARIMA model does not contain constant terms.

Finally, through correlation and partial correlation analysis, the ARIMA(2,1,2) model with p as 2, d as 1 and q as 2 can be established based on the sequence data.

2.2. LSTM model construction

As can be seen from the change trend chart of China's carbon emission efficiency from 1997 to 2020 in Figure 1, there is a nonlinear trend of China's carbon emission efficiency, and the common time prediction models are basically linear prediction models. In order to make up for the defects of the linear prediction model, this paper introduces a nonlinear prediction model - long short-term memory neural network. The neural network prediction model is a kind of nonlinear prediction model which is widely used nowadays. It is often used in the prediction of nonlinear data.

The Long Short Term Memory network (LSTM) model is a neural network model for learning and predicting long-term sequential data, which is developed on the basis of recurrent neural network. Its structure is shown in the following figure:

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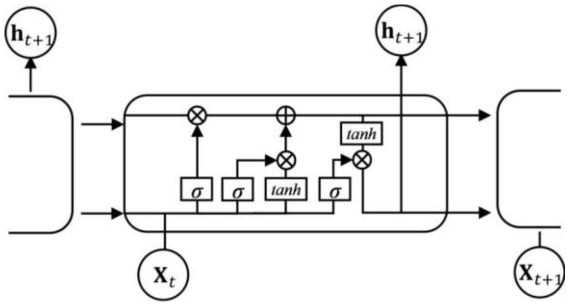

Figure 2. LSTM model structure diagram

The LSTM has three gates to protect and control the cell state: the forget gate, the input gate, and the output gate. A gate is a structure that allows information to selectively pass through, and the LSTM removes or adds information to the cell state through a variety of carefully designed gates. Among them:

The forgetting gate is determining what information to discard from the cell state, done by layers made up of sigmoid functions that describe how little of each part can pass through.

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

Where σ represents the sigmoid function, W_f represents the elements of the weight matrix, and b is the bias coefficient.

The input gate determines what new information to input into the cell state. The first part is the sigmoid layer, which to update Is a value. The second part is the tanh layer, which produces new pending values.

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

$$C_t = f_t * C_{t-1} + i_t * tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

Where i_t is the value of the input gate at the current time, W_i is the cyclic weight, C is the cell state, sigmoid function and tanh function determine the updated value and create a new candidate value vector respectively.

The output gate determines the value to be output, and the sigmoid function determines the part to be output, which is multiplied by the cell state transformation with tanh to output the required information.

$$O_t = \sigma(W_O \cdot [h_{t-1}, x_t] + b_O) \tag{4}$$

$$h_t = O_t * \tanh(C_t) \tag{5}$$

O_t indicates the output gate, and h_t indicates the current time output.

Therefore, a long short-term memory neural network (LSTM) model was built to predict China's carbon emission efficiency data from 1997 to 2018, and the prediction performance was tested with the data from 2019 and 2020.

The convolutional LSTM network model is mainly composed of two parts: First, the input data passes through the convolutional network, and the data features are extracted and dimensionality reduced through convolution and pooling operations; The data processed by the convolutional network is input into the LSTM network, and the forgetting gate, input gate and output gate in the LSTM network adjust their own parameters through continuous iterative training of a large number of data, so that it can learn the time fitting relationship between data from the data information extracted by the convolutional network, so as to carry out effective dynamic modeling of the input and output data of the predictive time series. Finally, the trained data is fitted through the convolutional LSTM network to output the predicted value through the fully connected neural network.

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3. Empirical analysis

3.1. Data selection

In this paper, the ratio of China's per capita GDP (yuan) to carbon emission (million tons) during 1997-2020 was used to establish carbon emission efficiency index, and ARIMA model and LSTM model were used to forecast.

China is still in the primary stage of socialism, the development of secondary industry still accounts for a large proportion in China's national economy, and the development of secondary industry is an important source of carbon dioxide emissions in China. The empirical results show that there is no inevitable causal relationship between fixed asset investment, economic growth and carbon dioxide emissions, but increasing China's fixed asset investment will reduce carbon dioxide emissions. Liquefied petroleum gas (LPG) is an important gas in China. Its main components are alkanes and alkenes, which produce a lot of carbon dioxide when burned.

Compared with other neural network prediction models, LSTM has the advantage that it can not only make long and short term prediction, but also make a long and short term prediction Explanatory variables are added in the forecasting process, so seven explanatory variables are selected in this paper, including the proportion of secondary industry income in GDP (%), fixed asset investment growth rate (%), liquefied petroleum gas supply (10,000 tons), total energy consumption (10,000 tons of standard coal), electricity consumption (billion KWH), coal consumption (10,000 tons) and private automobile ownership (10,000 units).

The data are from China Statistical Yearbook and China Energy Statistical Yearbook, and the carbon emission inventory is compiled according to the latest energy data revision (2015) of the National Bureau of Statistics of China. Due to different methods, the results obtained by the apparent emission accounting method and the department method are sometimes slightly different, but the overall effect is the same.

Table 3. National data on relevant indicators from 1997 to 2020

Year	Proportion of the added value of the secondary industry in GDP	Growth rate of total investment in fixed assets	Total LPG gas supply Municipal area	Total energy consumption Living consumption
	%	%	Ten thousand tons	Ten thousand tons of standard coal
1997	47.1	8.85	578.6	14677.15
1998	45.8	13.9	797.29	14779.82
1999	45.36	5.1	761.2	16695.05
2000	45.54	10.26	1053.71	16695.05
2001	44.79	13	981.83	16183.07
2002	44.45	16.89	1136.39	17162.46
2003	45.62	23.8	1126.35	19764.66
2004	45.9	23	1126.71	22768.41
2005	47.02	22.3	1222.01	27572.9
2006	47.56	20.5	1263.66	27765.16
2007	46.88	21.3	1466.77	30813.9
2008	46.97	22.2	1329.11	31898.32
2009	45.96	25.7	1340.03	35173
2010	46.5	20.4	1268.01	36469.63
2011	46.53	20.1	1165.83	39584
2012	45.42	18	1114.8	42306

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2013	44.18	16.9	1109.73	45531
2014	43.09	13.5	1082.85	47211
2015	40.84	8.6	1039.22	50461
2016	39.58	7	1078.8	54336
2017	39.85	6.2	998.81	57459
2018	39.69	5.9	1015.33	60436
2019	38.59	5.1	1040.81	61709
2020	37.84	2.7	833.71	64380
Year	Electricity consumption (physical quantity) living consumption	Coal consumption (physical quantity) domestic consumption	Private vehicle ownership of cars	Carbon emission efficiency
	100 million kilowatt hours	Ten thousand tons	Ten thousand vehicles	Yuan / 100 million tons per person
1997	1213.15	9498.3	358.36	0.826134
1998	1294.5	9081	423.65	0.959102
1999	1360.78	8758.42	533.88	0.897466
2000	1451.95	8456.96	625.33	0.913877
2001	1609.23	8410.25	770.78	0.970688
2002	1771.42	8412.64	968.98	0.952586
2003	2058.04	9004.71	1219.23	0.886269
2004	2384.49	9768.2	1481.66	0.877629
2005	2884.81	10038.97	1848.07	0.806868
2006	3351.58	10036.34	2333.32	0.79839
2007	4062.71	9760.61	2876.22	0.882955
2008	4396.1	9147.61	3501.39	0.921339
2009	4872.16	9121.95	4574.91	0.892398
2010	5124.63	9159.17	5938.68	0.920247
2011	5620.06	9212.06	7326.79	0.931863
2012	6218.96	9253.44	8838.6	0.958262
2013	6989.16	9289.83	10501.68	1.004199
2014	7176.1	9303.22	12339.36	1.019258
2015	7565.21	9627.13	14099.1	1.104934
2016	8420.6	9491.52	16330.22	1.117982
2017	9071.57	9282.52	18515.11	1.169848
2018	10057.55	7714	20574.93	1.220941
2019	10637.21	6547	22508.99	1.244391
2020	11396.48	6283	24291.19	1.215409

3.2. Empirical results

3.2.1. ARIMA regression and prediction results

The regression results based on ARIMA(2,1,2) model are shown in the table.

Table 4. Eviews regression results and related statistics

	AR		MA	
Regression	AR(1)	AR(2)	MA(1)	MA(2)

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Coefficient	1.1568***[1] （0.0000）	-0.1568*** （0.0000）	-1.1968*** （0.0000）	-0.1971*** （0.0000）
Characteristic Root	0.16		0.20	

According to the data in the table, the feature roots of both the autoregressive term and the moving average term are less than 1 and the feature roots 。All are in the unit circle, that is, the time series is stable, the model is stable, regression can be performed and the results are meaningful. The p values of the regression coefficients are all 0.0000, so the coefficients in the regression results of AR(1), AR(2), MA(1) and MA(2) are all significant at the level of 1%. The fitting value, actual value and residual value of ARIMA(2,1,2) regression results by using Eviews software are shown in the figure below As shown below:

obs	Actual	Fitted	Residual
1998	0.13297	0.09336	0.03961
1999	-0.06164	0.06772	-0.12935
2000	0.01641	0.03333	-0.01692
2001	0.05681	0.03225	0.02456
2002	-0.01810	0.02811	-0.04621
2003	-0.06632	0.01777	-0.08409
2004	-0.00864	0.01126	-0.01990
2005	-0.07076	0.00284	-0.07360
2006	-0.00848	-0.00030	-0.00818
2007	0.08456	0.00162	0.08294
2008	0.03838	0.00344	0.03495
2009	-0.02894	0.00463	-0.03357
2010	0.02785	0.00697	0.02088
2011	0.01162	0.00628	0.00534
2012	0.02640	0.00745	0.01895
2013	0.04594	0.00878	0.03716
2014	0.01506	0.00925	0.00581
2015	0.08568	0.01260	0.07307
2016	0.01305	0.01206	0.00098
2017	0.05187	0.01544	0.03642
2018	0.05109	0.01614	0.03495

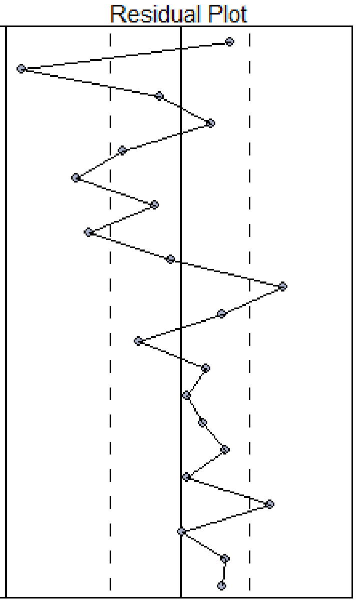

Figure 3. Regression result analysis graph from 1997 to 2018

As can be seen from the figure, the residual value of the prediction model is getting smaller and smaller, but the information in the figure also indicates that even if the model has a good regression effect, there has been a large deviation between the prediction result and the actual value. This is because the ARIMA model is a linear regression model, but the change of carbon emission efficiency is not linear, but fluctuates within a certain range. Therefore, it is difficult for this time series model to give accurate prediction results, and it can only predict the approximate results within a certain range. Using this model, the dynamic prediction results of carbon emission efficiency in 2019 and 2020 are 1.237748 and 1.255904 respectively, and the steady-state prediction results are 1.237748 and 1.255938 respectively. The prediction accuracy of the former is 5.34% and 3.33%, which is basically the same as but slightly lower than that of the latter. Therefore, we used the dynamic prediction results. As shown in Table 5.

3.2.2. LSTM regression, forecast results

Convolutional LSTM neural network model is a nonlinear forecasting model, which can make up for the problems of ARIMA (2,1,2) time series forecasting model in forecasting to a certain extent. In this paper, the data from 1997 to 2018 are selected as the training data, and the

*** indicates that the coefficient of the regression term is significant at the level of 1%; ** indicates that the coefficient of regression term is significant at the level of 5%; * indicates that the coefficient of the regression term is significant at the 10% level

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training results are shown in the following figure. As can be seen from the figure, the fitting line (red) fits the actual line (green) well.

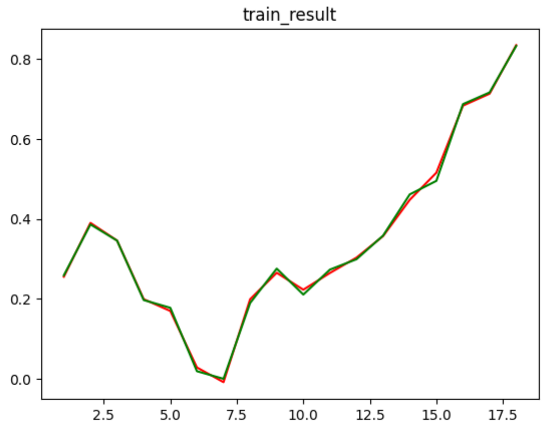

FIG. 4. LSTM training result fitting diagram

This training model is used to forecast the data of 2019 and 2020, and the results are 1. 178047147 and 1.183232794 respectively, with prediction errors of 5.33% and 2.65%, as shown in Table 5.

3.2.3. Combined prediction results

The ARIMA(2,1,2) model is a linear model, but the curve chart of carbon emission efficiency shows that although the overall trend of carbon emission efficiency in China from 1997 to 2020 is upward, it is not a function in the traditional sense. For the LSTM model, the amount of data of macroeconomic series data is less, coupled with the learning step of the model itself, the amount of data can be used is less. Therefore, in this paper, several linear combinations of ARIMA(2,1,2) model and convolutional LSTM model are obtained as follows. Firstly, based on OWA operator equal weight assignment, the ARIMA(2,1,2) model and the convolution LSTM are weighted by 50%, and then the biased weight assignment is 30%, 70% and 70%, 30% respectively. The prediction results are shown in Table 5 below.

Table 5. Prediction results

Model \ Year	2019	2020
ARIMA(2,1,2)	1.237748 -0.534%	1.255904 3.33%
Convolutional LSTM	1.178047 -5.33%	1.183232 -2.65%
Combined(50%，50%)	1.207898 -2.93%	1.219569 -0.62%
Combined(30%，70%)	1.219838 -1.97%	1.219568397 -3.42%
Combined(70%，30%)	1.195957403 -3.89%	1.205034156 -0.854%

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The combined analysis results of ARIMA(2,1,2) and LSTM show that the higher the weight of ARIMA(2,1,2) model, the lower the prediction accuracy, while the convolutional LSTM model with 50% weight has the highest accuracy, and the prediction accuracy of one and three combinations in 2020 is higher than that of single prediction. However, the combined prediction accuracy in 2019 was lower than that of ARIMA(2,1,2) model. The reason is that, on the one hand, ARIMA model has a high advantage in short-term forecasting, but the accuracy will be reduced in multi-period forecasting. On the other hand, the robustness of the ARIMA model is low, and when the predictor variables are impacted by the external environment, the prediction accuracy of the model will be reduced. In 2020, due to the sweeping of the novel coronavirus, the economy, society and environment are affected to varying degrees. Therefore, ARIMA(2,1,2) has a higher prediction accuracy in 2019, while a lower prediction accuracy in 2020.

4. Results and Analysis

In this paper, the convolutional long short-term memory neural network model and ARIMA model were integrated to establish the carbon emission efficiency index using the ratio of national per capita GDP to carbon emission during 1997-2020. Seven explanatory variables including the proportion of income from the secondary industry in GDP, growth rate of fixed asset investment, liquefied petroleum gas supply, total energy consumption, electricity consumption, coal consumption and private automobile ownership were selected for fitting prediction. The results of empirical analysis show that the combined prediction (50%, 50%) is better than the two single prediction ARIMA(2, 1, 2) and the convolutional long short-term memory neural network LSTM. Convolution LSTM makes up for the shortcomings of ARIMA model in the prediction of non-traditional linear change and multi-period prediction. The ARIMA model makes up for the deficiency of the convolutional LSTM in the requirement of data quantity. The combined prediction of the two models combines the advantages of the two models, and improves the accuracy and credibility of the prediction.

The model is used to predict the carbon emission efficiency in the next five years, and it is found that there will be a certain downward trend in the carbon emission efficiency. The reasons may be as follows: First, the worsening of regional wars and the more tense political and economic exchanges among countries and continents; Second, due to the lack of implementation of environmental governance, environmental deterioration was exacerbated, and economic development was put in a secondary position when the global economy fell into a downturn and China's economic growth slowed down. Third, due to the downturn of the global economy in the past few years, countries temporarily ignored environmental changes for the sake of rapid economic development in the short term. Therefore, the relevant authorities need to have a reasonable expectation of future changes in carbon emission efficiency, and to formulate reasonable responses to these assumptions.

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