International Journal of Multidisciplinary Research and Publications
ISSN (Online): 2581-6187

Carbon Emission Prediction Using CNN-LSTM

Feng Li, Yujun Hu, Lingling Wang*
School of Management Science and Engineering, Anhui University of Finance and Economics, Bengbu 233030, China
*Corresponding author: wll@aufe.edu.cn

Abstract— *In order to achieve energy structure change and green low-carbon transition as soon as possible, the schedule and roadmap of total carbon emission control need to be formulated as early as possible and continuously improved in the process of transition development. However, the ability to obtain prediction models with high accuracy from the temporal characteristics of historical data needs to be improved urgently. In this paper, a CNN-LSTM-based CO2 emission prediction model is constructed and empirically tested using Chinese data from 2009 to 2019 to calculate and predict the carbon emission intensity and per capita carbon emission in 2023 and 2033, and the validity and feasibility of the model is confirmed by comparing with the carbon emission intensity in 2010.*

Keywords— *Carbon emission intensity; LSTM; Sparrow search algorithm; prediction.*

I. Introduction

Under the guidance of the national policy of "striving to reach the peak of carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060", it is urgent to control carbon emissions. As the level of urbanization increases year by year, from 0.3 in 2009 to 0.9 in 2008, the carbon emissions have been fluctuating [1]. The high or low labor force of a city, urbanization development, the proportion of GDP occupied by each industry and the development of industrial structure may cause the rise of carbon emissions, while the optimization and rectification of environment and transportation may suppress carbon emissions [2].

In the literature [3], the factors that are closely related to carbon emissions were investigated using the grey relational prediction method using principal component analysis to extract data and thus reduce redundancy, and a long and short-term memory network was built to predict the carbon emissions of a region for a future period. We used back propagation neural network (BPNN) and Gaussian process regression (GPR) to compare LSTM methods.In the literature [4], an ARIMA-BP neural network model was developed to predict carbon emissions and a validation model was established, and the carbon emission intensity was decreasing year by year under the prediction framework of LSTM neural network model, which was a great progress compared to a decade ago. The literature [5] studied the causal relationship between carbon dioxide (CO2EFFCO) emissions from fossil fuel combustion only and local economic development in some Western and Asian countries using annual time series data for the period 1990-2016. The results showed a causal relationship between GDP per capita and CO2EFFCO in these countries.

For example, scholars have studied the calculation and modeling methods of CO_2 emissions [6-7], the influencing factors of haze [8-10], carbon emission intensity [11-12] and performance [13], etc. Among them, scholars are now widely concerned with the intensity of carbon emissions, which as an important element of environmental performance assessment, can be divided into two categories: individual elements and all elements. The literature [14] used carbon emissions per unit of energy consumption as an important basis for assessing the performance of developing countries; the literature [15] studied the total carbon emissions in the Japanese region were studied, and the ratio of total CO_2 emissions to GDP was defined as CO_2 productivity; some other single-factor indicators were then developed, such as CO_2 emissions intensity[16], CO_2 emissions per capita[17], and cumulative emissions per capita from industrialization[18].

Based on the above exploratory research work, this paper aims to combine CNN-LSTM neural network model to study the carbon emission intensity and per capita carbon emission in Chinese cities, to make long-term evolution and development trend prediction, and then to provide basis and suggestions for formulating scientific low-carbon sustainable development policies.

II. Relevant Work

By comparing the availability of data needed for the various methods and the characteristics of carbon emission calculation, this paper will use the carbon emission factor method to measure the carbon emissions of energy consumption in China. Let the oxidation rate of all fuels be 100%, and the calculation method of fuel combustion CO2 provided in the IPCC Guidelines.

A. Carbon emission factor selection

By comparing the availability of data needed for the various methods and the characteristics of carbon emission calculation, this paper will use the carbon emission factor method to measure the carbon emissions of energy consumption in China. Let the oxidation rate of all fuels be 100%, and the calculation method of fuel combustion CO2 provided in the IPCC Guidelines.

$$C_E = \sum_{i=1}^{n} E_i \times S_i \times \alpha$$

where C denotes the total carbon emission of energy consumption (million tons); E denotes the consumption of the ith energy source (million tons or billion cubic meters); S denotes the carbon emission factor of the ith energy source (tons of carbon/ton of fuel or tons/million cubic meters of gas); and is the conversion factor of carbon and CO2 with a value of 44/12.

The traditional way of measuring carbon emissions is based on three fossil fuels: coal, oil and natural gas. Although it is

Feng Li, Yujun Hu and Lingling Wang, "Carbon Emission Prediction Using CNN-LSTM," *International Journal of Multidisciplinary Research and Publications (IJMRAP)*, Volume 5, Issue 6, pp. 30-35, 2022.

relatively easy to obtain data and there is no complicated calculation process, this calculation method may cause large errors in the measurement of carbon emissions and does not take into account the proportion of carbon content of different energy types. and the differences that exist between the carbon emission factors. This error can be largely avoided if, we subdivide this energy type to calculate the respective carbon emission factors. The heat map of carbon emissions generated by different energy types is shown in Figure.

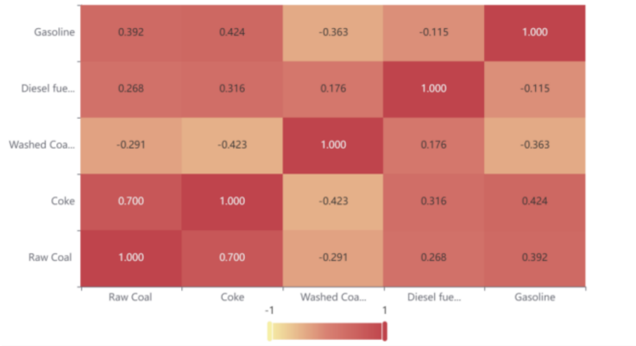

Fig. 1. Related energy heat map.

It can be seen that the correlation coefficient between coke and kerosene is larger at 0.700, and the correlation coefficient between washed coal and diesel is small, and the correlation coefficient of their carbon emissions is only 1.176.

B. Related Studies

Today, more and more scholars have paid attention to the country's environmental pollution problem. We analyze the current state of domestic and international research, and the main methods used to predict carbon emissions include model prediction, machine learning, and analytical research.

In the literature [19], through the STIRPAT model, which has a significant impact on the peak, it was found that if the carbon intensity decreases at a slower rate with economic and social development, it will take longer to reach the peak. Meanwhile, if emissions are to peak earlier, carbon intensity should decrease faster than socio-economic development. According to the current development trend, 2020-2045 should be the time to reach the peak if the carbon intensity decreases reasonably while the economic and social development is maintained. Therefore, we should keep the carbon emission intensity decreasing so that the carbon emission peak can occur as soon as possible, and for this purpose the future focus should be on increasing the use of clean energy and reducing energy consumption. The literature [20] combined multiple linear regression models to plot the historical carbon emission curves of each province, and found that 2002 is a carbon emission dividing line, within the two time periods before and after it, there are great differences in the changes of carbon emissions in each province and region. Based on this, a logistic multiple linear regression model is constructed to predict the growth of carbon emissions, and the sample data are eight years of carbon emissions data, and the carbon emissions of each province and region in China are predicted from 2011 to 2020.In the literature [21], by building a combined APIMA-BP neural network model, the data structure of the time series of carbon emission intensity was decomposed into linear and nonlinear residual components, and the trend of carbon emission intensity in China was comprehensively analyzed and predicted.In the literature [22], a gray correlation model was used to make short-term predictions of carbon emissions. Based on the results of the study, the strategies of developing low carbon economy, improving energy efficiency and developing non-fossil energy sources to reduce carbon emissions were proposed. The model test results showed that the prediction accuracy was level 2, and the correlation, mean squared error ratio and probability of small errors were level 1. Wang et al [23] further analyzed the carbon emission efficiency of various industrial sectors in China from an industrial perspective using the DEA method, and found that the carbon emission performance of light industries was generally higher than that of heavy industries. Xi et al [24] used the IPAT model to predict the future peak of carbon emissions in Jiangxi Province by regressing the time series data of Jiangxi Province for the last 15 years. It was found that if the economic and social development is maintained with a reasonable decrease in energy intensity and carbon emission intensity, the peak arrival time in Jiangxi province is about between 2032 and 2035.

In recent years, due to the strong learning and data processing ability of neural network models, they are capable of mining the complex nonlinear relationships behind the data, and there is no special requirement on the number of samples used, and the structure design has greater flexibility. Therefore, neural network models have, become a major method for time prediction [25-26] and are widely used in the field of forecasting.

III. METHODS

A. LSTM Network Structure

The LSTM works with memory cells through input gates, forgetting gates, and output gates to enable better backward transmission of sequence information. 3 gates are designed to overcome the gradient disappearance problem in RNNs and to better capture longer dependencies in sequences, which is suitable for sequence information modeling like carbon emission prediction. The individual LSTM neurons are shown in the following figure.

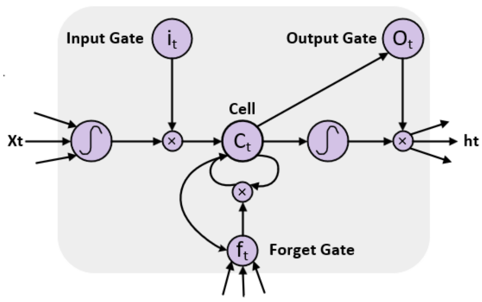

Fig. 2. LSTM cell structure.

The LSTM is a variation of the recurrent neural network model with additional functional parameters of hidden states and cell control. The LSTM can control the effective information of "cell states" through the structure of "gates" to retain the critical information and remove the unimportant content. The Sigmoid activation function layer outputs a probability value, which ranges from 0 to 1, describing how much of each sector can pass through, with 0 meaning "no messages are allowed to pass" and 1 meaning "all messages are allowed to pass". During the calculation of the transmission, there are two states of information transmission ct (cell state), and h^t (hidden state). Where h^t in the recurrent neural network is equivalent to c^t here. the formula for a certain time step is shown below.

$$z = \tanh(w \odot (x^t + h^{t-1}))$$
$$z^i = \sigma(w^i \odot (x^t + h^{t-1}))$$
$$z^f = \sigma(w^f \odot (x^t + h^{t-1}))$$
$$z^o = \sigma(w^o \odot (x^t + h^{t-1}))$$
$$c^t = z^f \odot c^{t-1} + z^{fi} \odot z$$
$$h^t = z^o \odot \tanh(c')$$
$$y^t = \sigma(w'h')$$

where, z^i、$z^f$is the vector obtained by multiplying the feature vector by the weight matrix, the meaning of $\odot$ the operator is peer matrix on both sides, each time step is divided into three stages, respectively, the forgetting end, the selection memory and the output end, through the calculation of z^f, screening the information of c^{t-1} the last state, the unimportant information will be forgotten, so as to achieve the selection memory, using z^i, control x^t, which is the new incoming parameter information of the training process that is selected for memory, such as the carbon emission data vector, and finally the output gated "double carbon" economic difference to obtain a better prediction model.

In the specific operation, the LSTM neural network model is used to make rolling pane projections of total carbon emissions at the national level as well as carbon emissions from residential consumption, and combined with the expectation of China's GDP growth rate from 2023 to 2033, the final derivation estimates the national carbon emission intensity in 2033.

B. *Sparrow Search Algorithm to Improve LSTM Accuracy*

SSA is a novel optimization algorithm inspired by hemp anti-predatory behavior sparrow foraging, proposed by Jiankai Xue [27]. Compared with the traditional algorithm, the sparrow search algorithm has easy implementation, simple structure, fewer control parameters, and stronger local search capability can improve the accuracy of LSTM. The algorithm outperforms traditional algorithms such as particle swarm algorithm and ant colony algorithm on some benchmark functions.In the sparrow search algorithm, individuals are divided into finders, followers and vigilantes, and each individual position corresponds to a solution. From the algorithm setting, it can be seen that vigilantes account for 10%-20% of the population, while discoverers and followers are dynamic, one individual becoming a discoverer necessarily means that another individual will become a follower. According to the division of labor, the discoverer mainly provides the foraging direction and area for the whole population, the follower follows the discoverer to forage, and the vigilant is responsible for the monitoring of the foraging area. During the foraging process, resources are obtained by constantly updating the positions of the three species.

Discoverer location updated to：

$$x_{ij}^{t+i} = \begin{cases} x_{ij}^t * exp(\dfrac{-i}{\alpha * MaxCycle}), R_2 > ST \\ x_{ij}^t + QL, R_2 > ST \end{cases}$$

where Max cycle denotes the number of evolutions of the algorithm; Q is a random number obeying the standard normal distribution; L denotes a 1 × d matrix with all elements being 1; R2 and ST denote the warning and safety values.

The accession location was updated to:

$$x_{ij}^{t+i} = \begin{cases} Q * exp(\dfrac{x_{wj}^t - x_{ij}^t}{i^2}), i > NP/2 \\ x_{pj}^{t+1} + |x_{ij}^t - x_{pj}^{t+1}|A^+L, others \end{cases}$$

where x_{ij}^t denotes the best position of the discoverer at the t + 1th iteration; NP denotes the population size.

The location of the scourer is updated to:

$$x_{ij}^{t+i} = \begin{cases} x_{ij}^t + \beta|x_{ij}^t - x_{bj}^t|, f_i \neq f_g \\ x_{ij}^t + K\dfrac{|x_{ij}^t - x_{wj}^t|}{(f_i - f_w) + \varepsilon}, f_i = f_g \end{cases}$$

where, x_{bj}^t denotes the most accurate position at the iteration; β as the step control parameter; K is a random number on (-1,1); f_i,f_j,$f_w$denotes the current sparrow's fitness, global best and worst fitness, respectively. In summary, the sparrow search algorithm can effectively improve the adaptiveness of the LSTM prediction model, and can effectively avoid the influence of manually adjusting the LSTM parameters on the prediction results of each component.

C. *Combination Strategy of CNN and LSTM*

The combined model of CNN and LSTM has a more powerful ability to extract features from data. Among them, CNN does not require domain expertise to manually extract features and can directly learn the internal representation of time series data, while LSTM has stronger temporal feature extraction capability and can more accurately capture the information implied in time series trends. Combining CNN and LSTM can make full use of the advantages of these two neural networks to fully exploit the potential qualities of the data and provide support for prediction, and fully exploit the potential qualities of the data.

In this paper, we analyze various strategies of CNN-LSTM models based on related researches, and classify the combined CNN-LSTM strategies into parallel and serial strategies.

The serial strategy refers to the data sequence through the CNN network structure and the LSTM network structure, as shown in the following figure, the CNN network structure can be composed of one or more CNN networks, in order to extract different features, generally CNN networks use different convolutional kernels, after the CNN network extracts the features, multiple CNN networks are fused through the pooling layer or the fully connected layer; then, the fusion results are passed through the LSTM for Then, the fusion result is learned by LSTM; Finally, the final result is obtained by the fully connected layer.

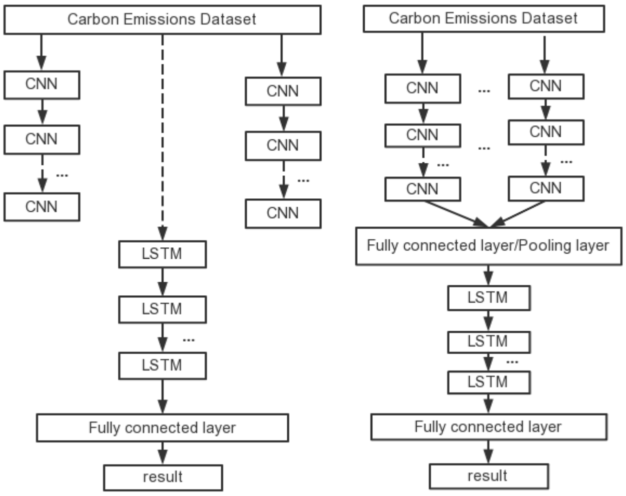

Fig. 3. Parallel and serial.

D. *Experimental Accuracy Test*

On the basis of the existing data, the speculation of the future change trend according to certain methods and laws can be used as the basis of carbon emission prediction. If the degree of the prediction effect is judged, it is necessary to introduce a special error evaluation system to indicate the error situation between the predicted value and the real value. If the error between the predicted value and the true value is smaller, it means that the prediction result is better and the prediction model is more effective, otherwise it means that the prediction model is less effective. In the course of our study, the conventional error evaluation indexes used in the experiment are mainly absolute percentage error (MAPE) and root mean square error (RMSE), where RMSE denotes the average error level between the actual observed value in each period and the predicted value in each period, and the expressions of each indicator are as follows.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - y_i\right)^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - y_i\right)^2}$$

$$MAE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|y_i - y_i\right|}$$

where y_i is the actual CO_2 emissions in year i, $\breve{y}_i$ is the projected CO_2 emissions in year i, and N represents the projection order.

IV. Model Construction

A. *Data source*

To fit and test the validity of the proposed CNN-LSTM model, we used data from China Energy Statistical Yearbook 2009-2019, including GDP, population, energy structure and urbanization rate.

B. *Parameter Setting*

The first 50% of the data volume for 10 years from 2009 to 2019 is set as the training set and the second 50% is the test set. Since the samples are small, the LSTM model parameters are designed with the standard 4 neural network units, the number of layers is 3, the number of neurons in each hidden layer is 2, the learning rate is set to the default learning rate, and the epoch parameter for convergence is 50, considering the fitting effect of the model and the required training time.

TABLE I. Carbon emission related data for 2009-2019.

Year	GDP (100 million yuan)	Population (10,000 yuan)	Energy structure (coal accounts for%)	Urbanization rate (%)	EC (10,000 tons)
2009	125275	133450	71.0	48.30	155263
2010	138554	134091	69.2	49.90	162490
2011	151856	134735	70.2	51.27	171992
2012	163852	135404	68.5	52.57	217698
2013	176633	136072	67.4	53.73	223449
2014	189704	136782	65.8	54.77	218176
2015	202983	137462	63.8	56.10	217321
2016	216786	138271	62.3	57.35	212111
2017	231744	139008	60.6	58.50	206021
2018	247271	139538	59.0	59.60	201407
2019	262355	140005	57.7	60.60	192992

V. Experimental Results and Analysis

The comparative results of MSE, RMSE and MAE of several models in the fall are compared as shown in the table below. It shows that CNN-LSTM has the best performance in all comparative metrics compared to the other models, with the RMSE value of only 25.9 and the lowest MAE value of 22.1. In the single model, the overall performance is lower than that of the hybrid model, while LSTM is slightly better than CNN in all metrics.

TABLE II. Performance comparison of different models

Model	MSE	RMSE	MAE
CNN	810.0	32.8	27.6
LSTM	668.6	27.7	24.9
CNN-LSTM	417.8	25.9	22.1

A line graph of the fit of the true and predicted values of carbon emissions using different models based on the data set selected for the years 2015-2019 in Figure 4. The hybrid model CNN-LSTM fits the true value curve more closely and has stronger predictive power than the single LSTM.

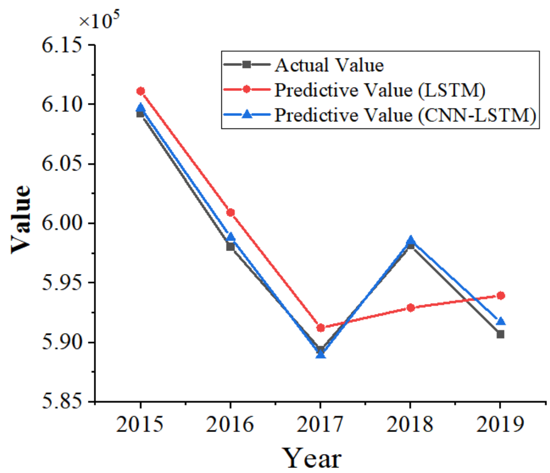

Fig. 4. True and predicted values.

Based on the above carbon emission prediction results, we can further calculate and analyze the carbon emission intensity and per capita carbon emission, and then predict the carbon emission in China in the next ten years, as shown in the following table.

TABLE III. Carbon emission intensity and per capita emission projections for the next decade.

Years	Carbon emission intensity (Ton of carbon / million yuan)			Carbon emissions per capita (Tonnes of carbon/person)		
	High Carbon	Baseline	Low Carbon	High Carbon	Baseline	Low Carbon
2023	1.933	1.812	1.786	4.256	4.174	4.170
2024	1.872	1.756	1.716	4.353	4.247	4.241
2025	1.816	1.690	1.649	4.389	4.280	4.267
2026	1.764	1.647	1.599	4.451	4.401	4.391
2027	1.709	1.589	1.546	4.462	4.414	4.350
2028	1.648	1.534	1.489	4.539	4.459	4.423
2029	1.578	1.481	1.427	4.571	4.501	4.461
2030	1.517	1.402	1.368	4.612	4.579	4.516
2031	1.483	1.369	1.310	4.697	4.612	4.601
2032	1.427	1.318	1.289	4.718	4.687	4.634
2033	1.397	1.279	1.213	4.779	4.723	4.712

For 2023-2033, under the high-carbon, baseline and geologically low-carbon scenarios, the carbon intensity of China's energy consumption in 2023 will reach 1.933 tC/MW, 1.812 tC/MW and 1,786 tC/MW, respectively, a decrease of 21%, 30% and 32% respectively compared to 2010, and this reduction target under the high-carbon scenario is not This reduction target was not achieved under the high carbon scenario. In contrast, the low carbon scenario accomplishes the carbon emission reduction target called for by the country and has a relative degree of accomplishment.

VI. CONCLUSION

Based on the CNN-LSTM neural network model, this paper predicts the total carbon emissions and the carbon emissions of the population in China, and can derive the carbon emission intensity and per capita carbon emissions under certain economic growth expectation. This paper proposes the following policy recommendations: (1) Stabilize the carbon emission intensity expectation and promote the "carbon peak" work steadily. Low-carbon policies should have a long-term vision, take into account the overall situation, and grasp the strength of policy implementation to avoid being too hasty or not strong enough.(2) Deal with the relationship between pollution reduction and carbon reduction, energy security, industrial chain supply security and food security, and the normal life of the public. In the process of cognition, citizens should enhance their awareness of low carbon and environmental protection, strengthen their sense of social responsibility, and encourage more potential green low carbon consumers to become green
low carbon practitioners.

ACKNOWLEDGMENT

We thank the anonymous reviewers and editors for their very constructive comments. The work is supported by key teaching research project of graduate school of Anhui University of Finance and Economics under grant No. cxjhjyzda 1803, Teaching Research Project of Anhui Provincial Education Department under grant No. 2020jyxm0037, No. 2020zyrc020, Undergraduate teaching quality and teaching reform project of Anhui University of Finance and Economics under Grant No. acszjyyb2021035, and Anhui University of Finance and Economics Undergraduate Scientific Research Innovation Fund Project under grant No. XSKY22027ZD.

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