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The Carbon Emission Accounting and Prediction of the Power Generation Side based on LSTM in Jilin Province

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Abstract: In the context of global warming and the dramatic increase in greenhouse gas emissions, the power industry is the largest source of carbon emissions. Adjusting and optimizing the carbon dioxide emissions from the power industry will help China achieve its "dual carbon" goals and is of great significance for mitigating global carbon dioxide emissions. This paper takes six power plants in Jilin Province as the research objects, and firstly accounts for the carbon emission production data between January 2020 and December 2023 according to the "Accounting Methods and Reporting Guidelines for Greenhouse Gas Emissions from Enterprises - Power Generation Facilities". Then, LSTM was used to establish carbon emission prediction models for six different power plants in Jilin Province, and the analysis of each model showed that that the single-step prediction RMSEs are all less than one, with higher prediction accuracy, but only can used in short-term prediction, the multi-step prediction RMSEs are bigger than one, with lower prediction accuracy, but can used in long-term carbon emission trend prediction can be achieved. The carbon emission trend prediction of six power plants in Jilin province between January 2024 and August 2031 confirms that the carbon emissions of power plants will be affected by seasons and shown cyclical changes. Finally, reasonable policy recommendations are provided for the successful realisation of the "double carbon" target for electricity in Jilin Province.

Keywords: *carbon emission accounting, LSTM, carbon emission prediction, single-step prediction, multi-step prediction*

I. BACKGROUND AND SIGNIFICANCE

In the context of global warming and the dramatic increase in greenhouse gas emissions, to mitigate carbon dioxide emissions and alleviate the rapidly changing global environment, China has set corresponding carbon reduction targets, achieving carbon peak and carbon neutrality by 2030 and 2060 respectively. China's total carbon emissions are comprised of 90% carbon dioxide emissions from the energy sector, reducing the use of primary and secondary energy and gradually transitioning towards green energy is an effective means to achieve the "dual-carbon" target[1].In the energy sector, the transport sector is a key source of carbon dioxide emissions, and reducing carbon emissions in the transportation industry has a positive impact on the "dual carbon" goals. [2]. The carbon dioxide released by the power industry accounts for over 40% of China's carbon emissions, during from 2006 to the 2020, the electric power industry, in accordance with the requirements and deployment of the state, has implemented in-depth energy-saving and emission-reduction renovation, reduced the consumption of coal, and achieved a 36% reduction in electric power carbon dioxide emissions, which effectively slowed down the growth of total electric power carbon dioxide emissions. emission growth. At the same time, the power industry in Jilin Province in response to the "double carbon" target, also launched a number of policies [3], the power industry as China's largest source of carbon emissions, in the face of the current depth of emission reduction in the new situation, but also need to further improve the level of carbon reduction. Therefore, it is a profound impact to realise the accounting of carbon emissions and the prediction of carbon emission trends in the electric power industry in Jilin Province, in order to accelerate the realisation of the "double carbon" target.

Carbon dioxide emission related research mainly includes carbon emission influencing factors, carbon emission structure, carbon emission technology, and carbon emission prediction, among which carbon emission prediction has been a key direction of concern for scholars at home and abroad, they carried out related research from different industry backgrounds, such as electricity industry, transport industry [2], agriculture [5], construction industry [6], and industry [7]. Afzal H M. et al. in 2020 assessed the decomposition and decoupling elements affecting the

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relationship between energy carbon emissions and economic development through the Logarithmic Mean Dield's Index method with the Tapio (Carbon emission decoupling) decoupling model to predict the carbon emissions of electricity [8].Fan D C et al in 2021 proposed a method combining Particle Swarm Optimization (PSO) algorithm and BP (Back Propagation) neural network to achieve the trend prediction of the total carbon emissions on the supply side of the power system in 30 provinces, cmunicipalities and autonomous regions in China from 2020 to 2030 [9]. Long Short-Term Memory (LSTM) neural network is a method developed based on Recurrent Neural Network (RNN), and LSTM has better processing and prediction performance for important time intervals in time series, and has been successfully applied in image classification and other related fields of prediction [10].Shi X et al. in 2015 used the Convolutional LSTM Network (ConvLSTM) model for predicting rainfall intensity in localised areas over a relatively short period of time [11].Chen J et al. proposed Ensemble LSTM (EnsemLSTM), a new LSTM-based deep learning time series method for wind speed prediction in 2018 [12].Petersen C N et al. in 2019 proposed a deep network model with a self-coding decoding structure that enables multi-step prediction (MSP) for time series [13].By analysing the current status of carbon emission research in the power industry at home and abroad, the relevant studies on carbon emission forecasting have mainly focused on the analysis of factors affecting carbon emission forecasting and the measurement for the trend of the domestic total, while more research is needed to predict the carbon emission of the power industry.

Through the research on the current status of research at home and abroad as well as the actual needs of Jilin Province for the realisation of the "dual-carbon" target, this paper takes a certain six power plants as the research object, and the main research content includes: ①Completed the accounting of data of six power plants in Jilin Province. ②Completion of carbon emission trend prediction and analysis of Six Power Plants in Jilin Province Using LSTM Neural Networks.③Analyse the carbon emission situation and put forward effective suggestions on the electric power system in Jilin Province.

II. RESEARCH METHODS

A. Accounting methods

In order to enable forecasting the carbon emission trends in power industry, firstly, the historical carbon emission data needed to be accurately accounted [14].Accounting methods are classified as the actual measurement method, factor decomposition method, mass balance method and IPCC(Intergovernmental Panel on Climate Change) list method [15].The “IPCC Guidelines for National Greenhouse Gas Inventory”, issued by the United Nations Intergovernmental Panel on Climate Change, are the most up-to-date methodology and rules for the establishment of national greenhouse gas inventories and for emission reduction compliance in countries around the world, which have the advantages of being comprehensive, systematic, standardised and authoritative, as well as being simple in its calculation methods, therefore, this paper adopts the IPCC Inventory Methodology and Reporting Guidelines for Enterprise Greenhouse Gas Emission Accounting and Reporting - Power Generation Facilities to realise carbon emission accounting for six power plants in Jilin Province.

1) Accounting boundaries and emission sources

According to the guidelines, the boundary of this accounting mainly includes the power generation facilities of six power plants in Jilin Province, which mainly include combustion units, steam and water units, electrical units, control units and desulphurisation and denitrification units.The range of GHG emissions accounting and reporting for power generation facilities includes CO2 emissions from fossil fuel combustion and CO2 emissions from purchased electricity use.

2) Accounting methods

The accounting formula for CO2 emissions can be represented as follows:

$$\mathrm{E} = \mathrm{E}_{\mathrm{burn}} + \mathrm{E}_{\mathrm{electric}} \quad (1)$$

In equation(1), $\mathrm{E}_{\mathrm{burn}}$ represents emissions from fossil fuel combustion, $\mathrm{E}_{\mathrm{electric}}$ represents emissions from purchased use of electricity, where $\mathrm{E}_{\mathrm{burn}}$ and$\mathrm{E}_{\mathrm{electric}}$ are expressed as shown in equations(2)and(3), respectively:

$$E_{\text{burn}} = \sum_{i=1}^{n} (AD_i \times EF_i) \tag{2}$$

In equation(2),ADi denotes activity data for the type i fossil fuel,EF_i represents the CO2 emission factor for the type i fossil fuel.

$$E_{electric} = AD_{electric} \times EF_{electric} \tag{3}$$

In equation(3), AD_{electric} denotes purchased electricity consumption, EF_{electric} denotes the grid emission factor,emissions per unit of MWh of electricity consumed.

$$EF_i = CC_i \times OF_i \times \frac{44}{12} \tag{4}$$

In equation(4),CC_i denoting the carbon content per unit calorific value of the type i fossil fuel,OF_i denotes the carbon oxidation rate of fossil fuel type i,44/12 represents the ratio of the relative molecular mass of carbon dioxide to carbon

B. Accounting methods

LSTM is a special kind of RNN, increased the number of forgetting and memory neurons on the basis of the traditional RNN, the structure is shown in Fig. 1. In time series prediction, LSTM can explore the nonlinear relationship between variables and deal with longer time series [16], and its unique gated neural unit can learn and analyse the time series [17], so as to improve the prediction accuracy. When performing time series forecasting, the methods can be divided into single-step prediction (SSP) and MSP.SSP involves utilizing historical data to predict the value of the subsequent time step in time series analysis. The complete dataset is partitioned into training and testing subsets in a certain proportion when making predictions and then the historical data is used for modelling to achieve the prediction.MSP also known as long-term forecasting, it is the use of historical time series $[y_1, \cdots, y_n]$ to forecasting t-step time series $[y_{m+1}, \cdots, y_{m+t}]$,where n denotes the number of observed data, $m \geq n$, t denotes the prediction range. Since MSP is a prediction of several future time steps, MSP models are more practical compared to SSP, as the time step length increases, the accuracy tends to diminish in MSP models [18].

This paper introduces LSTM to construct a model for predicting carbon emissions, and single-step and multi-step forecasts are used to predict and compare the time series of carbon emissions from six power plants in Jilin Province.

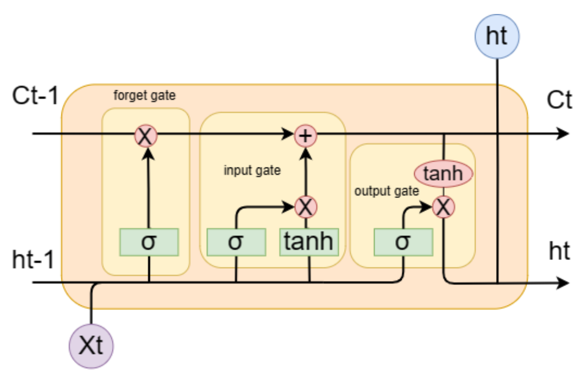


Fig. 1 LSTM cell structure diagram

The steps of the CO2 emission prediction model based on LSTM on the power generation side in Jilin Province are as follows:

1 Calculate the carbon emission accounting data of six power plants in Jilin Province in order to train the models.

2 To preprocess the carbon emission accounting data from the power generation side of six power plants in Jilin Province, which includes operations such as removing outliers, processing missing values, normalising, etc., in order to achieve the prediction.

3 Divide the dataset into training sets and testing sets with time series to ensure that the LSTM model has good generalisation ability when performing data prediction.

4 Using LSTM neural network to construct the prediction model. The divided training sets is input into the LSTM model for training, and the parameters are adjusted to minimize the error between the predicted and actual values.

5 Evaluating the performance of the model on unknown data using the test set to verify the applicability and accuracy of the model.

6 Optimise the model based on the test results.

Through the above steps, the prediction can be accomplished.

III. RESULTS AND ANALYSES

A. Selection of data

The data source of this paper shown in Table 1 is the production data related to carbon emissions from six power plants in Jilin Province between January 2020 and December 2023, with the sampling interval of 1 month, and a total of 48 sets of experimental data. The first 70% of the data is used as the training set, with the remaining data reserved for the test set.

B. Carbon accounting results

Because of the large amount of data involved, only the 2020 production data of one of the six power plants within Jilin Province is shown as an example.

Table. 1 Production data of a power plant in Jilin Province in 2020

Time	Types of coal-fired fuels	Fuel consumption(t)	Low level calorific value of coal fuels(GJ/t)	Carbon content per unit calorific value of coal-fired fuels(tC/GJ)	Elemental carbon content of coal combustion(tC/t)
2020.01	Lignite	110550	12.738	0.02748	0.35
2020.02	Lignite	0	0	0	0
2020.03	Lignite	0	0	0	0
2020.04	Lignite	175430	13.033	0.02659	0.3466
2020.05	Lignite	184626	13.485	0.02791	0.3764
2020.06	Lignite	208601	12.883	0.02781	0.3583
2020.07	Lignite	249403	12.36	0.02922	0.3611
2020.08	Lignite	233180	12.943	0.02645	0.3424
2020.09	Lignite	150345	12.916	0.02858	0.3692
2020.10	Lignite	220710	12.822	0.02876	0.3687
2020.11	Lignite	125848	14.051	0.02618	0.3678
2020.12	Lignite	138600	13.948	0.02687	0.3748
2020 total	Lignite	1797293	13.045	0.02767	0.361

Analysing the results of the accounting of the six power plants, the power plants Fig. 2(a)-(f) all reach the point of maximum carbon emissions near January 2020-2023, respectively. and t The reason for this report is that during the period from December to February each year, the Jilin Province area is in the middle of the winter heating period, and since coal is still the main heat source for heating in the northern part of China, the carbon emissions will show an upward and downward trend during the period from December to February each year, the carbon emissions of other months over time have a significant decrease compared to December-February. Through the above analysis, seasonal factors have a significant impact on carbon emissions in Jilin Province, and the results show a periodic pattern with seasonal changes.

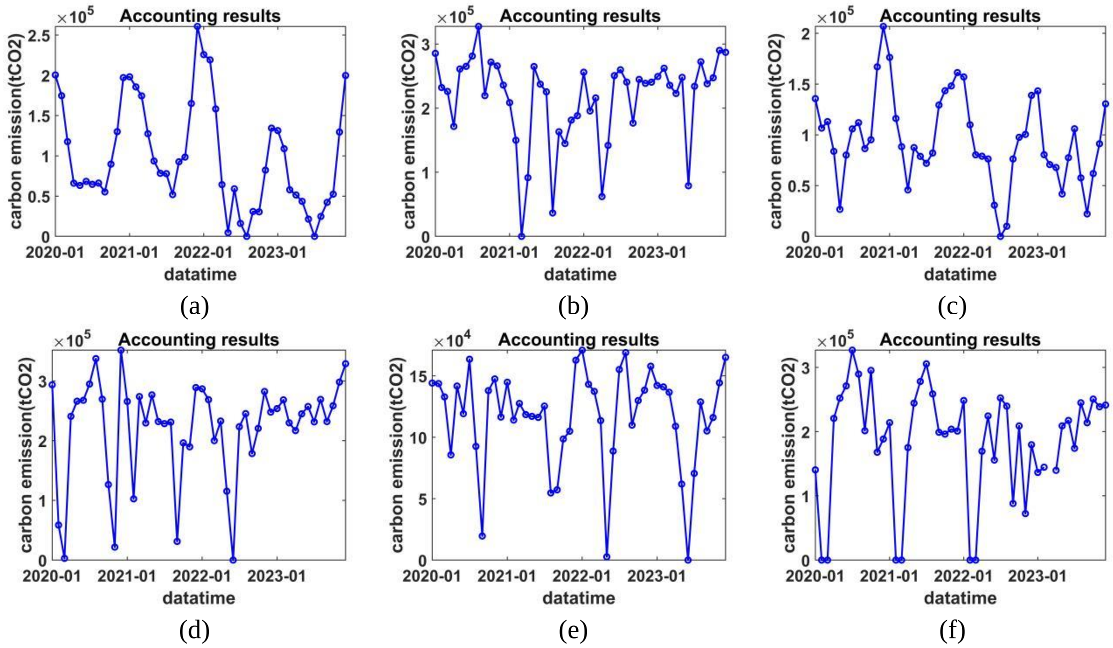


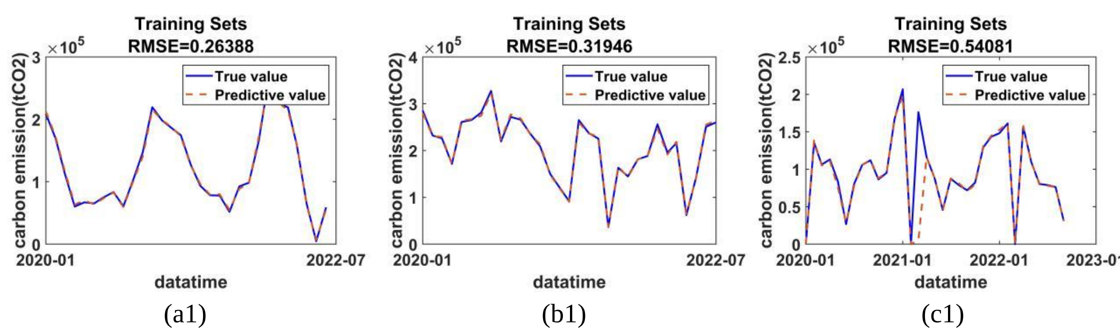
Fig. 2 Accounting results for six power plants in Jilin province

C. Carbon emission projection results

In this paper, the carbon emissions of six power plants in Jilin Province are forecasted using LSTM, encompassing both single-step and MSP methodologies.

1) SSP

In this paper, firstly the production data of a six power plants in Jilin province from January 2020 to December 2023 are used for SSP, and the data are preprocessed and then the carbon emission production data are divided into 70% training set and 30% test set. The training set data consisted of data between January 2020 and July 2022, and the test set data consisted of data between August 2022 and December 2023, then the LSTM SSP model was built with the number of hidden layers as 1, the fully connected layer as 1, the maximum number of iterations as 1500, and the learning rate factor as 0.04.Fig. 3 (a1) to Fig. 3 (f1) shown the comparison between the actual and predicted values of carbon emissions from January 2020 and July 2022 for the training set under the SSP of the LSTM model for six power plants in Jilin province, respectively. Fig. 3(a2) to Fig. 3(f2) shown the actual values of carbon emissions for the test set August 2022 and December 2023 compared to the predicted values based on the SSP model. The RMSEs of the six prediction models are all less than 1, which is a good prediction and can achieve a more accurate prediction.



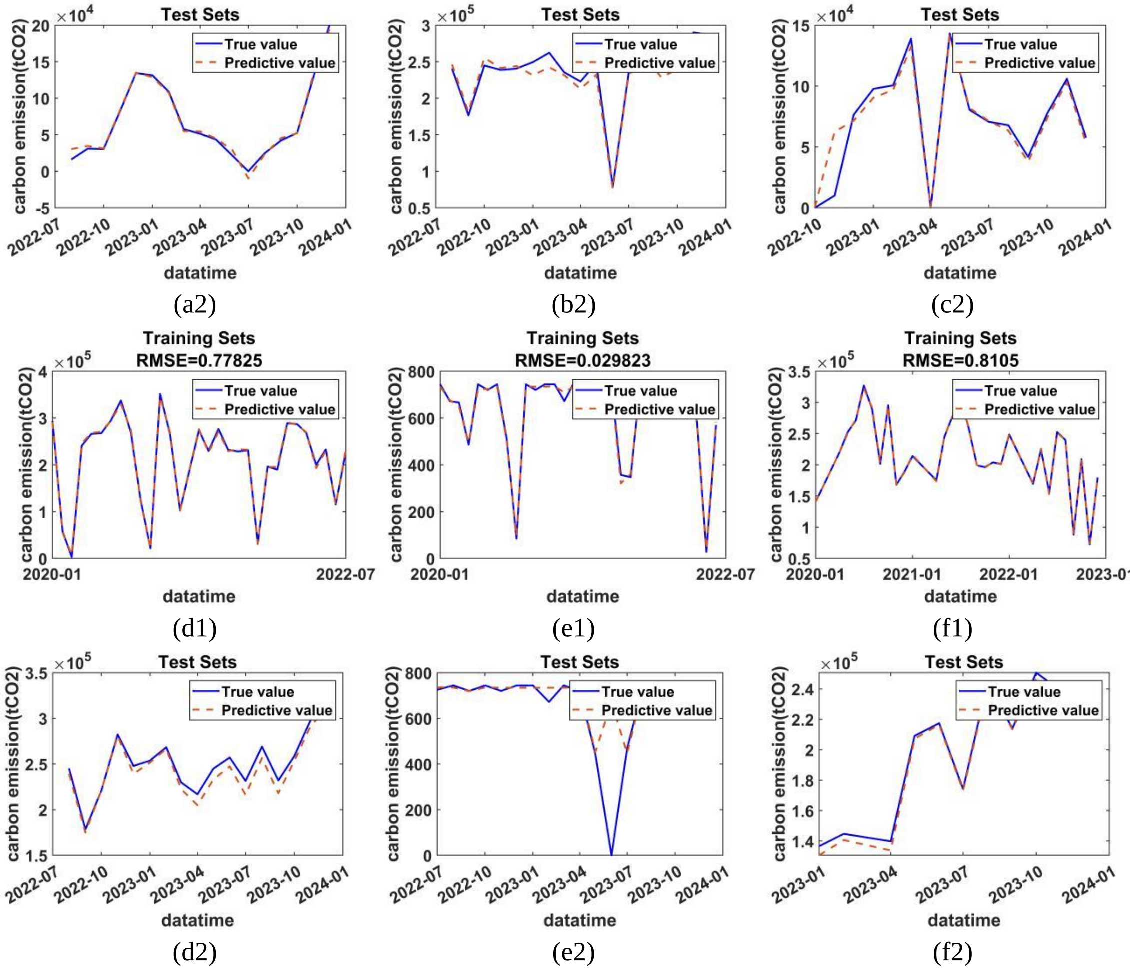
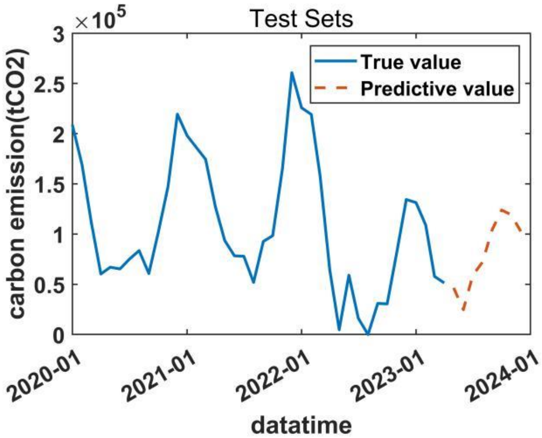


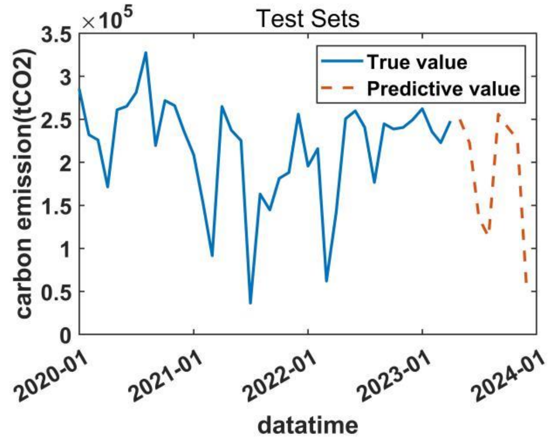
Fig. 3 Results of LSTM SSP for six power plants in Jilin province

2) MSP

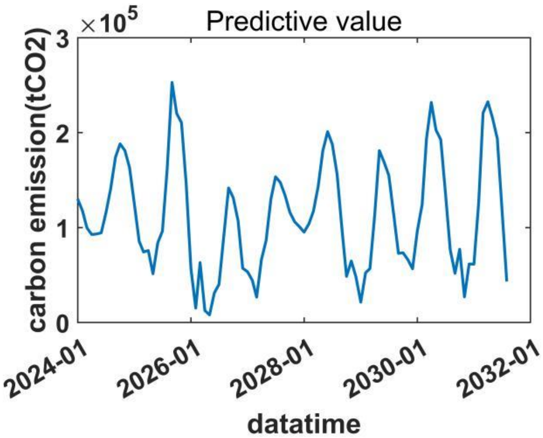
The actual data of six power plants in Jilin Province from January 2020 to December 2023 were used for MSP, and after preprocessing the data, the data were partitioned into training and testing sets, with the training set consisting of the data between January 2020 and April 2023, and the test set data consisting of the data between May 2023 and December 2023, to forecast carbon emissions during the specified time frame of January 2024 to 2031 August .An LSTM MSP model is built for prediction with an activation function of Adam, number of hidden layers of 1, fully connected layers of 1, maximum number of iterations of 1000, and a learning rate factor of 0.4.Fig. 4(a1) to Fig. 4(f1) shown the comparative carbon emission prediction results for the six power plants across both the training and testing datasets. Fig. 4(a2) to Fig. 4(f2) respectively shown the projected carbon emission trends for six power plants in Jilin Province from January 2024 to August 2031.MSP achieves the prediction of longer-term trends in carbon emissions, but the prediction accuracy is not as good as that of SSP due to the longer prediction period and the RMSE of the six prediction models are bigger than 1.



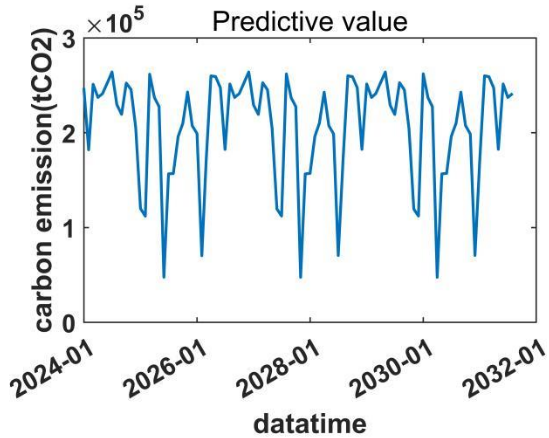
(a1)



(b1)



(a2)



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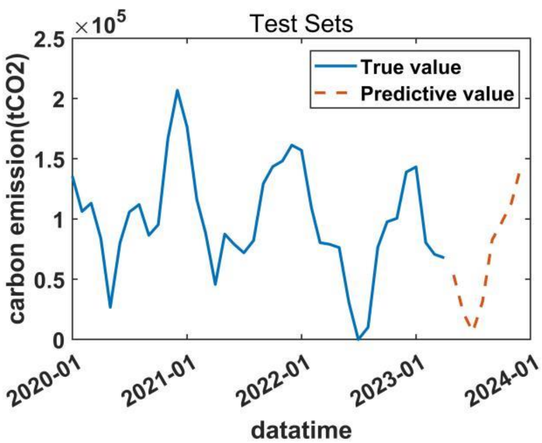
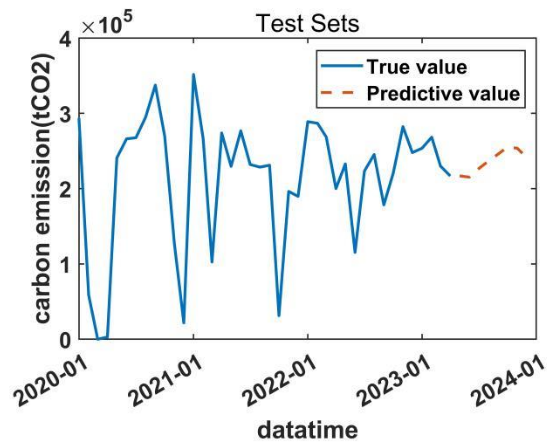
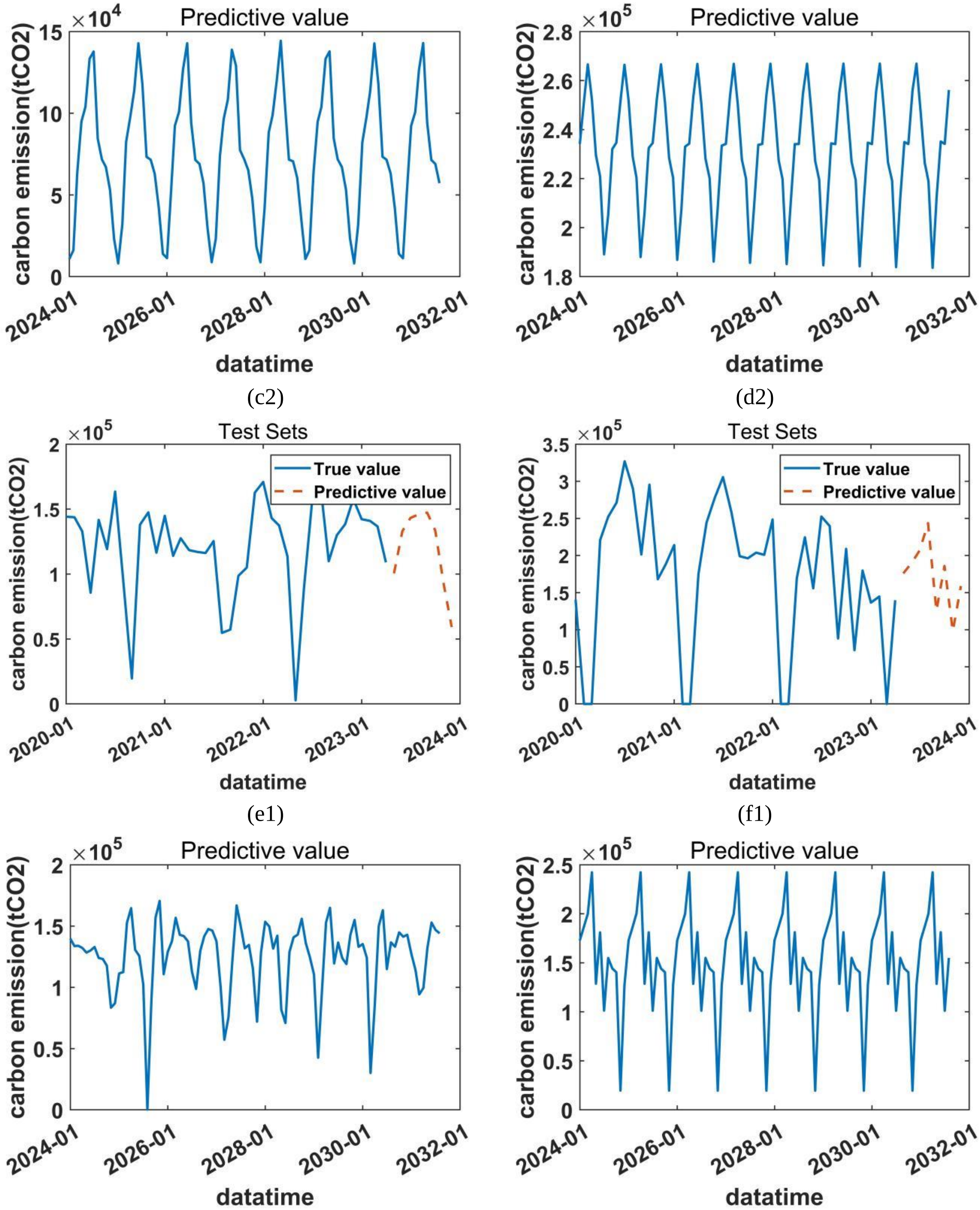


(c1)



(d1)



(c2) (d2)

(e1) (f1)

(e2) (f2)

Fig. 4 Results of LSTM MSP for six power plants in Jilin province

By analysing the results of the two predictions, where the model of the power plant (a), the RMSE is 0.26388 under SSP and 321.579 under MSP. Therefore, SSP accuracy is higher when making predictions. Since MSP is a method of achieving trend forecasts for large amounts of future data or long time series based on known data information; In contrast, for SSP, only test validation of the input data or short time series prediction is required. Therefore, MSP and SSP have their own advantages. Therefore, different forecasting have their own advantages; in SSP the RMSE of the forecasting model is smaller and the accuracy of the forecasting model is larger, in MSP as the time step increases, the accuracy of the MSP model decreases and the RMSE of the forecasting model is larger, but it is able to make predictions for the long time trend in the future. By analysing the carbon emission data of six power plants in Jilin Province from January 2024 to August 2031 achieved by LSTM MSP and based on the natural situation of Jilin Province, the data on carbon emissions from the electricity generation side of Jilin Province show a cyclical trend with seasonal changes, mainly due to the fact that a large amount of coal is used for heating in the winter in Jilin Province, during which the carbon emission values are the highest, carbon emissions in the remaining months will be less than carbon emissions in the winter months, thus analysing the carbon emissions on the generation side will vary according to the seasons during the year.

Based on the assessment of the carbon emission forecast data from Jilin Province's plants (a), due to the existence of a large number of coal-fired and gas-fired power plant enterprises in Jilin Province, in order to respond to the "dual-carbon" target, to achieve energy saving and emission reduction on the power generation side, and to accelerate the realization of carbon peaks, the relevant enterprises of the electric power industry in Jilin Province should take corresponding measures in respect of carbon emissions.

D. Suggestions on Carbon Emission Measures for the Electricity Sector in Jilin Province

In order to respond to the "dual-carbon" objective, carbon emissions from the power sector in Jilin Province also need to take corresponding measures, and the following recommendations are put forward:

1 For the enhancement of clean energy, advocate for the advancement of Jilin Province's power system towards clean energy, particularly by expanding the utilization of renewable energy sources. Offer incentives and assistance for clean energy production, fostering the progression of the power system towards a more sustainable trajectory.

2 Utilizing smart grid technology and integrating energy storage systems. Enhancing the intelligent development of the power infrastructure and implementing state-of-the-art monitoring, control, and scheduling systems to enhance the adaptability and efficacy of grid operations. Invest in green technology R&D and promote innovation in new energy and smart grid.

3 Energy co-operation and co-construction. Encourage the Jilin Electricity System to promote energy cooperation and co-construction projects at the community level. Establish a synergy mechanism for the Jilin power system to promote collaborative planning of energy and electricity demand, and to achieve energy sharing and collaborative management to reduce overall carbon emissions.

IV. Conclusion

Against the background of global warming and the dramatic increase in greenhouse gas emissions, and this study aims to achieve the "double carbon" goals, the carbon emissions of six power plants in Jilin Province are accounted for with the aim of predicting the trend in carbon emissions. Firstly, the carbon emission related data of six power plants in Jilin Province from January 2020 to December 2023 are accounted for, and secondly, SSP of the carbon emission is executed by LSTM, and the RMSE of the prediction model is less than 1. Meanwhile, MSP of carbon emission is executed for the period of January 2024 to August 2031 by LSTM, and the RMSE of the prediction model is greater than 1. Simultaneously, the prediction of carbon emissions from January 2024 to August 2031 was conducted using LSTM, and the RMSE of the prediction model exceeding 1. Finally, the outcomes of the two forecasting models are juxtaposed and scrutinized. Owing to the distinct winter heating season in Jilin Province, the carbon emissions from power plants are susceptible to seasonal variations, manifesting cyclical fluctuations. In order to achieve the goal of "double carbon", this paper proposes the following recommendations regarding the characteristics of carbon emissions in the power industry of Jilin Province: (1) advancing the adoption of clean energy, (2) expediting the implementation of smart grids and energy storage technology, and (3) fostering collaboration and joint development of energy resources. The research conducted in this paper holds practical significance in achieving the "dual carbon" objectives of the power industry in Jilin Province.

References

[1] H P Huang, Z X Li, D Huang, M Z Xie, and Z P Wang. Research on the measurement, analysis and prediction of agricultural carbon emissions in Jiangxi province under the “Dual Carbon” goals. Journal of Ecology and Rural Environment, vol. 40(02), pp: 179-190, 2024.

[2] D Yang, Y H Li, and C L Tian. Research on natural peak characteristics and peak forecast of carbon emissions in transportation industry. Journal of Transportation Systems Engineering and Information Technology, in press.

[3] The People's Government of Jilin Province. Jilin provincial people's government on the issuance of Jilin province "Fourteenth Five-Year Plan" energy conservation and emission reduction comprehensive implementation program notice. Gazette of the People's Government of Jilin Province, vol. 22, pp: 3-10, 2022.

[4] The People's Government of Jilin Province. Circular of the Jilin provincial people's government on the issuance of the implementation program of carbon peaking in Jilin province. Gazette of the People's Government of Jilin Province, vol. 21, pp: 3-14, 2022.

[5] W Q Guo, Q Y Tan, M Lei, and X Q Xu. The spatial and temporal evolution of carbon emission intensity in rural China and the influencing factors. Journal of Henan University of Science & Technology (Social Science Edition), in press.

[6] J G Niu, F R Wang, B X Xin, M Q Wang, and M R Rong. Space-time evolution and peak path analysis of carbon emission efficiency of construction industry in Hebei province. Journal of Hebei University of Geology, vol. 47(01), pp: 105-111, 2024, doi: 10.13937/j.cnki.hbdzdxxb.2024.01.015.

[7] H P Wang, K Liu. Tapio decoupling analysis and scenario prediction of carbon emission in paper industry in Fujian province. Transactions of China Pulp and Paper, in press.

[8] M A Afzal, S Chen, Decoupling of energy-related CO2 emissions from economic growth: a case study of Bangladesh. Environmental Science and Pollution Research International, vol. 27, pp: 20844-20860, 2020.

[9] D C Fan, X F Zhang. scenario prediction of China's carbon emissions based on PSO-BP neural network model and research on low carbon development path. SINO-GLOBAL ENERGY, vol. 26, pp: 11-19, 2021.

[10] Y L Zhou, F J Chang, L C Chang, I F Kao, and Y S Wang. Explore a deep learning multi-output neural network for regional multi-step-ahead air quality forecasts. Journal of Cleaner Production, vol. 209, pp: 134-145, 2019.

[11] X Shi, Z Chen, H Wang, D Y Yeung, W K Wong, and W C Woo. Convolutional LSTM network: a machine learning approach for precipitation nowcasting. advances in neural information processing systems, vol. 28, 2015.

[12] J Chen, G Zeng, W Zhou, W Du, and K D Lu. Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization. Energy Conversion and Management, vol, 165, pp: 681-695, 2018.

[13] N C Petersen, F Rodrigues, and F C Pereira. Multi-output bus travel time prediction with convolutional LSTM neural network, Expert Systems With Applications, vol. 120, pp: 426-435, 2018.

[14] J Xu, H L Xu, and Y Y Li. Study on accounting method of process carbon emissions in iron and steel enterprises and case analysis. ENERGY FOR METALLURGICAL INDUSTRY, vol. 42, pp: 9-14, 2023.

[15] Q T Hao, M X Huang, and G Bao. Study on carbon emission calculation methods overview and its comparison. Chinese Journal of Environmental Management, vol. 04, pp: 51-55, 2011.

[16] Z L Cheng, X Q Zhang, and Y Liang. Railway freight volume prediction based on LSTM network. Journal of the China Railway Society, vol. 42, pp: 15-21, 2020.

[17] T Z Lu, X C Qian, S He, Z Y Tan, and F Liu. A time series prediction method based on deep learning. Control and Decision, vol. 36, pp. 645-652, 2021.

[18] S B Taieb, G Bontempi, A F Atiya, and A Sorjamaa. A review and comparison of strategies for multi-step ahead time series forecasting based on the NN5 forecasting competition. Expert Systems With Applications, vol. 39, pp: 7067-7083, 2012.