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Original Research

An Optimization Framework for Monitoring and Predicting Electricity Carbon Emissions Based on Sparrow Search Algorithm and Improved BPNN Neural Network

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Abstract

In recent years, abnormal weather has occurred frequently, and effectively controlling and reducing carbon emissions has become one of the important challenges currently faced by society. With the acceleration of electricity grid construction, a large number of new energy projects are gradually connected to the grid, and the electricity grid system is developing toward a clean and low-carbon direction. The prediction of power carbon emissions has enabled quantitative research on power system carbon emissions, and understanding the changing trend of power carbon emissions is of great significance for promoting the decarbonization of power systems.

This study constructs a PE-PACF-SSA-BPNN combined prediction model for electricity carbon emissions. First, external factors affecting electricity carbon emissions are selected based on the Pearson coefficient (PE), and partial autocorrelation analysis (PACF) is conducted on the electricity carbon emission sequence. The internal influencing factors of electricity carbon emissions are selected based on partial autocorrelation coefficients, which reflect the changing trends and patterns of electricity carbon emissions. Second, a BPNN neural network is used to model the correlation between electricity carbon emissions and influencing factors, and the BPNN parameters are updated through an error-propagation mechanism. Carbon emission prediction is realized based on influencing factors and the BPNN neural network.

Simultaneously, the Sparrow Search Algorithm (SSA) is used to optimize the weights between the input layer and the hidden layer of the BPNN to improve model robustness. The prediction errors of this model in four scenarios – China, Guangdong, Shandong, and Jiangsu – are 0.628%, 2.924%, 1.852%, and 1.321%, respectively. This research constructs a novel tool and method for carbon emission

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prediction in the power industry, which is helpful for the tracking and prediction of the carbon footprint of the power industry and provides a reference for its clean development.

Keywords: carbon emission prediction, carbon emission factors, electricity consumption, BP neural network, sparrow algorithm

Introduction

Electricity production is an important component of the industrial system. Due to the consumption of large amounts of fossil fuels in electricity production and greenhouse gases such as sulfur hexafluoride in transmission and transformation equipment, the impact of electricity carbon emissions on climate change and the electricity industry cannot be ignored. With the acceleration of the carbon reduction process, China is establishing a new type of power system that incorporates new energy. Power production is shifting from traditional dynamic power generation to clean and low-carbon power generation, and controlling carbon emissions from electricity has become a consensus worldwide. Electricity, as an important industrial production sector, has carbon emissions in various aspects, such as electricity production, transmission, distribution, and sales. Measuring the carbon emissions of electricity is not only a way to track the carbon footprint of the electricity sector, but also provides a foundation for reducing electricity emissions and promoting clean, low-carbon development. Based on the electricity carbon emission factors released by China, this study calculates the carbon emissions of China and major provinces, providing a basis for predicting electricity carbon emissions [1-3].

In recent years, China's electricity industry has been developing toward a clean and low-carbon direction. Conducting predictive research on power carbon emissions is not only an analysis and study of the future carbon development trend in the power industry, but also an analysis of the impact mechanisms and principles of power carbon emissions. Aiming to achieve the prediction of electricity carbon emissions, this study calculated and predicted the electricity carbon emissions in China, Guangdong, Shandong, and Jiangsu. Based on electricity consumption and emission factors, the electricity carbon emissions were calculated, and a PE-PACF-SSA-BPNN model was constructed to carry out the electricity carbon emissions prediction. The prediction results met the prediction goals and the prediction accuracy requirements.

Many scholars have conducted relevant research on the calculation of electricity carbon emissions. Wu et al. proposed the carbon emission flow theory for complex power grid structures, which calculates electricity carbon emissions distributed across multiple terminals using distributed computing methods [4]. Whittington believes that new energy generation is the most promising way to reduce carbon emissions from electricity and has studied the impact of renewable energy development on carbon emissions in the power system [5]. Lopez et al. believe that global decarbonization of electricity requires the elimination of thermal power plants and the development of new energy sources [6]. The research results indicate that electricity trading can reduce investment in renewable energy and improve the utilization efficiency of new energy installed capacity. Gordic et al. investigated residential electricity carbon emissions in 31 European countries, and the results showed that the average annual electricity carbon emissions per household were 1.36 tons of CO_2 equivalent [7]. Alajmi et al. found that improving energy efficiency can reduce the impact of electricity generation on the local environment by decomposing the factors contributing to the growth of carbon emissions in Saudi Arabia [8]. Ang and Su defined the total carbon intensity index of electricity, which is the energy-related carbon emissions divided by the amount of electricity generated [9]. Research shows that the carbon reduction potential of the power sector is enormous, and regions with high total carbon intensity in electricity often have a larger share of electricity production. Quaresma et al. optimized energy usage through a carbon source map and planned energy use in the Brazilian power sector, aiming to control the carbon emissions level of the power sector [10]. Steenhof and Hill studied the carbon emission scenarios of the future Russian power sector and considered scenarios such as Russia selling natural gas to Europe and Asia [11]. By improving energy efficiency and other measures, Russia's future carbon emissions will be reduced. Olsen et al. studied the impact of emission tax collection on electricity carbon emissions, and the results showed that adjusting the emission tax rate can reduce carbon emissions from electricity to within regulatory requirements [12]. Zhou and Huang found that the Regional Greenhouse Gas Initiative (RGGI) only reduces carbon emissions within the regulatory area through carbon emission transfer [13]. Except for the 14% reduction in carbon emissions resulting from the replacement of coal with natural gas, most carbon emissions have been transferred from regulated areas to non-regulated areas; in fact, these emissions have not truly disappeared. Gonela identified carbon emissions as one of the objectives for optimizing the power supply chain, considering factors such as carbon trading and carbon taxes, and determined the optimal power supply chain solution [14]. Vaissalo et al. studied the relationship between returns and volatility between the European carbon market and the electricity market [15].

Based on the research results on the formation mechanisms of electricity carbon emissions mentioned above, scholars have further studied the electricity carbon emissions prediction. Javadi et al. calculated indirect carbon emissions from electricity by tracking the source of electricity and constructed a radial basis model [16]. Su et al. constructed a machine learning-based carbon emission prediction model based on the power load data of green buildings in Dalian and monitored environmental temperature data [17]. Wu et al. conducted a full life-cycle assessment of electric vehicle batteries and estimated the carbon reduction potential of electric vehicle battery recycling, thereby reducing carbon emissions from electric vehicles [18]. Zhang et al. used the Monte Carlo method to calculate the carbon emissions of electricity under multiple scenarios in Jiangsu Province, and the results showed that trade openness plays a positive role in reducing electricity carbon emissions [19]. Li et al. conducted grey prediction on carbon emissions in Beijing and verified the positive impact of energy consumption intensity on carbon emissions [20]. Liu et al. studied the spatial heterogeneity of energy-related carbon emissions and predicted that improving public transportation and conserving electricity can effectively reduce carbon emissions [21]. Chen et al. designed a carbon emission decomposition framework and predicted the changes in China's carbon emission intensity from 2021 to 2030. The results showed that changes in energy structure can promote the process of carbon reduction [22]. Liu et al. used deep learning models to predict the carbon emissions brought about by the development of electric vehicles in China [23]. Li et al. studied the carbon emissions generated by wave energy generation throughout its entire lifecycle [24]. Ding et al. designed a model that combines a grey exponential model and correlation analysis to accurately predict China's energy-related carbon emissions [25]. Chen et al. further reduced the carbon emissions of the energy system by combining wind prediction and hydrogen low-carbon economic dispatch strategies [26]. Wang et al. found that the main source of carbon emissions in the aluminum industry comes from indirect carbon emissions from electricity production, and based on this, established a grey model to predict the emission reduction efficiency and potential of China's aluminum industry [27].

Although some progress has been made in existing research, several limitations remain. Current research on electricity-related carbon emissions mainly focuses on specific power plants and power users, without conducting systematic studies on power carbon emissions at the regional level. At present, research primarily focuses on predicting energy-related carbon emissions, with less attention paid to the prediction of electricity-related carbon emissions. The prediction factors do not fully consider both internal and external influencing factors, which results in low prediction accuracy. Moreover, existing prediction models lack multi-scenario prediction capability and, in differentiated prediction scenarios, do not have the ability to autonomously adjust and optimize their parameters. This leads to reduced accuracy in predicting electricity-related carbon emissions in certain scenarios, making it difficult to meet the requirements of carbon emission prediction and mitigation.

Electricity-related carbon emissions are an important component of energy carbon emissions, accounting for over 80% of the total carbon emissions. With the construction of new power systems, the decarbonization process of electricity is gradually advancing, and the electricity system is gradually developing from high-carbon to low-carbon, with the proportion of clean energy gradually increasing. Forecasting electricity-related carbon emissions is of great significance for tracking the level of carbon emissions in the electricity system, promoting the gradual decarbonization of the electricity system, and controlling greenhouse gas emissions in the electricity system. Based on this, we calculated China's electricity carbon emissions over the past 20 years and proposed a PE-PACF-SSA-BPNN electricity carbon emission prediction model. The main innovations and contributions are as follows:

(1) A joint factor-screening model for electricity-related carbon emissions based on the Pearson coefficient and PACF analysis is established. First, the Pearson coefficient between external variables and electricity-related carbon emissions is calculated. Then, the partial autocorrelation coefficients of the electricity carbon emission sequence are computed, and internal influencing factors are selected based on these coefficients.

(2) A modeling framework for changes in carbon emission magnitude is constructed based on a BPNN neural network structure, with influencing factors as input-layer nodes and electricity-related carbon emissions as output-layer nodes. A neural network model linking influencing factors and electricity-related carbon emissions is established and optimized through the error-propagation mechanism of the BP neural network.

(3) To address the difficulty in selecting parameters for the input and hidden layers of the BPNN neural network, the Sparrow Search Algorithm (SSA) is employed to efficiently obtain the connection weights between layers. The optimization capability of the SSA-BPNN combined model is significantly enhanced, improving the adaptability and stability of the model and enabling more accurate prediction of electricity-related carbon emissions.

(4) A PE-PACF-SSA-BPNN combined prediction model for electricity-related carbon emissions is proposed to improve prediction accuracy. Prediction results for four scenarios (China, Guangdong, Shandong, and Jiangsu) indicate that the model demonstrates high accuracy, strong stability, and robustness. The proposed model provides a feasible solution for predicting carbon emissions in the electricity industry and supports the decarbonization and clean-energy transformation of the electricity system.

Materials and Methods

Determination of Influencing Factors by Combining the Pearson Coefficient and Partial Autocorrelation Analysis

Using the Pearson coefficient to calculate the correlation between external influencing variables and electricity-related carbon emissions, several variables with high correlations were selected as external influencing factors. Partial autocorrelation analysis (PACF) was used to measure the autocorrelation of the electricity-related carbon emission sequence, and several historical electricity-related carbon emission variables with high correlation were selected as internal influencing factors. The external and internal influencing factors together constitute the indicator system for the influencing factors of electricity-related carbon emissions. This method comprehensively considers the changing patterns and impact indicators of the electricity-related carbon emission sequence and represents an improvement and optimization over a single correlation measurement method.

The Pearson coefficient can be used to measure the degree of closeness between two variables, with a range of [-1,1]. For variables X and Y, the correlation coefficient R can be expressed as:

$$\mathrm{R} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

Among them, n is the sample size, and $\bar{X}$ and $\bar{Y}$ represent the mean values of variable X and variable Y, respectively. When R is greater than 0, two variables have a positive correlation; when R is less than 0, the two variables have a negative correlation, and when R = 0, the two variables are uncorrelated. The larger the absolute value of R, the stronger the correlation between variables.

The calculation steps of PACF are as follows:

(1) For a time series X_t, where t = 1, 2, ..., m, k represents the lag order. The autocorrelation coefficient is as follows:

$$\rho_k = \frac{Cov(X_t, X_{t-k})}{\sqrt{Var(X_t) \cdot Var(X_{t-k})}}$$

(2) When k = 1 is initialized, the partial autocorrelation coefficient $\psi_{11} = \rho_1$;

(3) For k>1, calculate the value of the partial autocorrelation coefficient ψ_k:

$$\psi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1}\psi_{k-1,j}\rho_{k-j}}{1 - \sum_{j=1}^{k-1}\psi_{k-1,j}\rho_j}$$

Sparrow Search Algorithm

The Sparrow Search Algorithm (SSA) simulates the hunting and anti-hunting processes of sparrows, dividing the sparrow population into discoverers, joiners, and scouts. The discoverer is responsible for indicating the direction of hunting for the group. After discovering a predator, the joiner begins to move toward the direction of the food. Scouts are responsible for observing potential dangers in their surroundings and guiding the sparrow population to engage in anti-predatory behavior. The specific process is as follows [28]:

(1) For a population consisting of n sparrows, the position of each sparrow is represented by x = $(x_1, x_2, ..., x_d)$. The corresponding objective function values are f = f$(x_1, x_2, ..., x_d)$.

(2) Individuals with higher objective function values are used as discoverers to search for food. In order to find food as quickly as possible, the search range of discoverers should be larger than that of joiners. Each iteration follows the formula:

$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^{t} \bullet \exp\left(\frac{-i}{\alpha t_{max}}\right), R_2 < ST \\ x_{i,j}^{t} + QL, R_2 \geq ST \end{cases}$$

Among them, $x_{i,j}^t$ is the coordinate of the i-th sparrow in the j-th dimensional space at the t-th iteration, α is a random number from 0 to 1, t_{max} is the maximum number of iterations, Q is a normal distribution function, L is a 1 × d matrix, and each element is 1. R_2 is the warning value with a range of [0,1], while ST is the safe value with a range of [0.5,1].

The joiner judges based on the objective function value and location of the food. When the joiner believes that the current food is of higher quality, they will move toward the location of the food and join the food competition. The successful joiner can replace the discoverer's location. The update of the joiner's location is as follows:

$$x_{i,j}^{t+1} = \begin{cases} Q \bullet \exp\left(\frac{x_{worst}^{t} - x_{i,j}^{t}}{i^2}\right), i > \frac{2}{n} \\ x_p^{t+1} + \left|x_{i,j}^{t} - x_p^{t+1}\right| A^{+} L, \quad others \end{cases}$$

Among them, x_{worst}^t is the global worst position in the t-th iteration. x_p^{t+1} is the optimal position occupied by the discoverer in the t+1 iteration. A is a 1 × d matrix, and each element is randomly assigned a value of 1 or -1; A^+ is the generalized inverse matrix of.

When i > 2/n, it indicates that the sparrow has a low objective function value, lacks competitiveness in food competition, and has not found an ideal position. It should fly to other places to continue foraging.

Select 10% of individuals in the sparrow population as scouts. When the scouts detect danger, they will promptly send out signals and the sparrows will continue to search for food in a new location.

$$x_{i,j}^{t+1} = \begin{cases} x_{best}^{t} + \beta \bullet \left|x_{i,j}^{t} - x_{best}^{t}\right|, & f \neq f_g \\ x_{i,j}^{t} + K \bullet \dfrac{\left|x_{i,j}^{t} - x_{worst}^{t}\right|}{(f - f_w) + \xi}, & f = f_g \end{cases}$$

Among them, x^{t}_{best} is the global optimal position at the t-th iteration, β is the step-size control parameter and follows a normal distribution. K is a random number within the range of [-1,1], f_g is the globally optimal objective function value, f_w is the globally worst objective function value, and ξ is a constant.

BPNN Neural Network

The BPNN neural network is a neural network structure that backpropagates errors to correct parameters and achieve model optimization. The BP neural network consists of three layers: input layer, hidden layer, and output layer, with each layer containing several neurons [29]. When propagating forward, input data enters the model from the input layer, passes through the hidden layer and the activation function, and the information is conveyed to the output layer [30]. By calculating the error between the actual output value and the expected value, the weights and thresholds of the nodes are adjusted sequentially along the output layer, hidden layer, and input layer to achieve model training and optimization. The input neuron node is x_d, the hidden layer neuron node is z_j, the output neuron node is y_l, the connection weight between the input node and the hidden node is v_{jd}, the connection weight between the hidden node and the output node is w_{lj}, the threshold for the hidden node is b_j, the threshold for the output node is b_l, the activation function is f, and the expected output value of the output layer is t_b. The specific process is as follows:

(1) When the input layer data x_d passes through the hidden layer, the output value of the hidden layer is obtained by activating the function:

$$z_j = f(\sum v_{jd}\, x_d - b_j)$$

(2) The output value of the hidden layer further reaches the output layer, and the output result of the output layer is obtained through the activation function:

$$y_l = f(\sum w_{lj} z_j - b_l)$$

(3) The error obtained from the BP neural network is:

$$\mathrm{E} = \frac{1}{2}(\sum_{k=1}^{l} y_i - t_e)^2$$

(4) Use gradient descent to update weights and thresholds. First, take the derivative of the connection weights between the hidden layer and the output layer: δ

$$\frac{dE}{dw_{lj}} = (t_e - y_l) \times f'(net_l) \times z_j = \delta_l z_j$$

$$\delta_l = (t_e - y_l) \times f'(net_l)$$

(5) Similarly, taking the derivative of the connection weights between the hidden layer and the input layer:

$$\frac{dE}{dv_{jd}} = -\sum_{k=1}^{l} \delta_l\, w_{lj} f'\left(net_j\right) \times x_d = -\delta_j x_d$$

$$\delta_j = \sum_{k=1}^{l} \delta_l\, w_{lj} f'\left(net_j\right)$$

(6) The weight changes of the hidden layer and output layer, as well as the weight changes of the hidden layer and input layer, are as follows:

$$\mathrm{d}w_{lj} = -\eta \frac{dE}{dw_{lj}} = -\eta \delta_l z_j$$

$$\mathrm{d}v_{jd} = -\eta \frac{dE}{dv_{jd}} = \eta \delta_j x_d$$

Among them, η is the learning rate.

Similarly, the changes in the output layer threshold and the hidden layer threshold are:

$$\mathrm{d}b_l = -\eta \frac{dE}{db_l} = -\eta \delta_l$$

$$\mathrm{d}b_j = -\eta \frac{dE}{db_j} = -\eta \delta_j$$

The BPNN neural network optimizes the model through forward propagation of information and backpropagation of errors, with weights and thresholds adjusted. Training stops when the expected output accuracy is achieved.

PE-PACF-SSA-BP Combined Electricity Carbon Emission Prediction Model

In Fig. 1, using the Pearson coefficient to calculate the correlation between electricity carbon emissions and external influencing variables, and conducting PACF analysis on the electricity carbon emission sequence to select internal influencing factors, this joint factor-selection method (PE-PACF) considers both the intrinsic characteristics of electricity carbon emissions and external influences, and can effectively select the influencing factor indicators of electricity carbon emissions. An error backpropagation algorithm based on a BP neural network is proposed, and SSA is used to optimize the connection weights between the input layer and the hidden layer of the BP neural network, aiming to improve the convergence speed of the BP neural network and enhance the stability of the model. The PE-PACF-SSA-BPNN combination prediction model comprehensively measures the impact of external and internal factors on electricity carbon emissions based on the characteristics of electricity carbon emissions. The efficiency and prediction accuracy of the BP neural

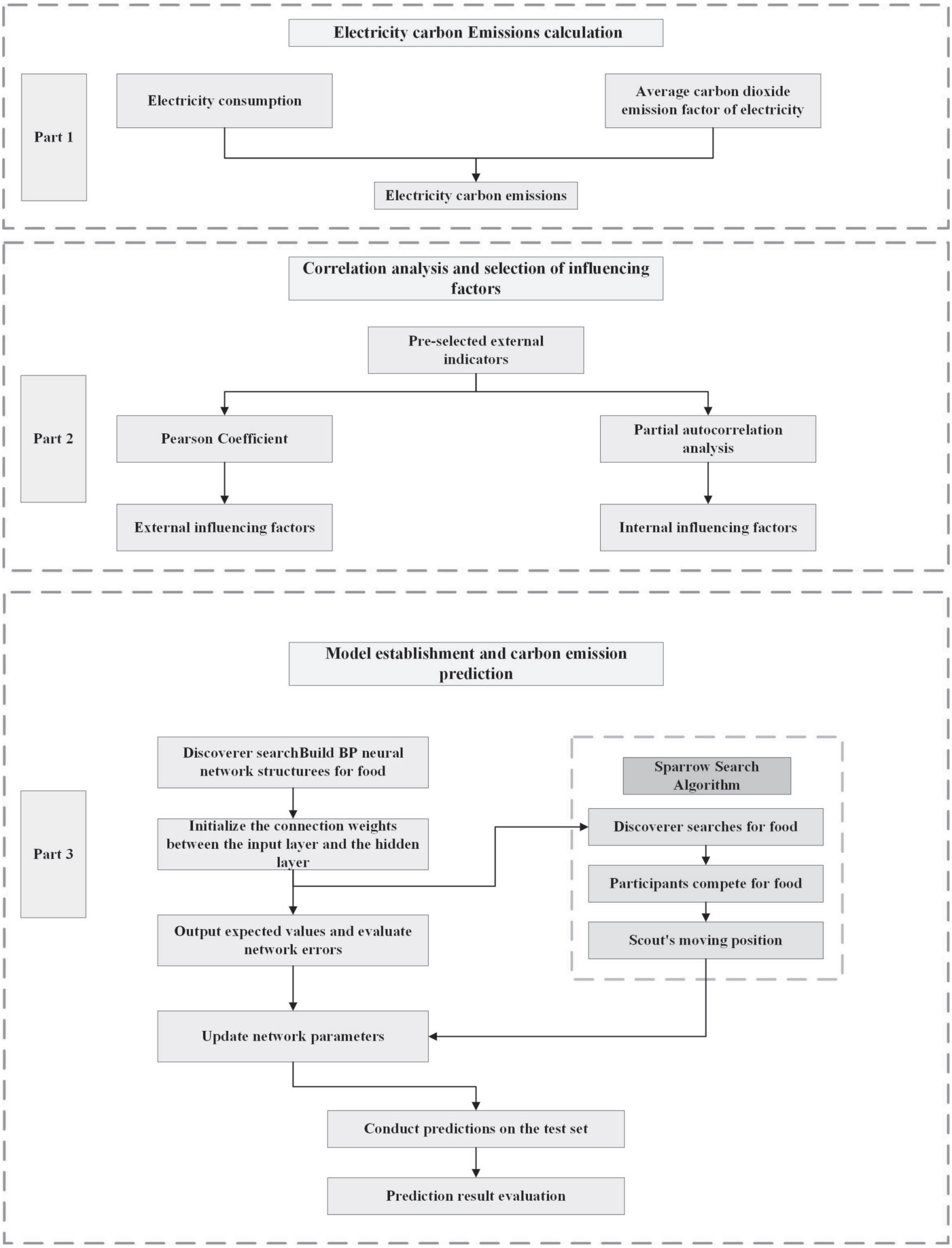

Fig. 1. PE-PACF-SSA-BPNN combined forecasting model.

network optimized by SSA have been improved, and the PE-PACF-SSA-BPNN combination model can effectively predict electricity carbon emissions.

Calculation of China's Electricity Carbon Emissions

Selection of Carbon Emission Data

This study selects annual data on China's electricity carbon emissions as the research sample, considering that China has a large power system and high electricity consumption, and is promoting the low-carbon transformation and development of the power system. Guangdong, Shandong, and Jiangsu are the provinces with the highest electricity demand and electricity carbon emissions in China. Therefore, electricity carbon emission data from Guangdong, Shandong, and Jiangsu are selected as provincial samples.

Carbon Emission Factor of the Electricity Grid

The carbon emission factor of the electricity grid is used to measure the greenhouse gas emissions generated by the use of one kilowatt-hour of electricity in a given region. In 2024, the Chinese Ministry of Ecology and Environment and the National Bureau of Statistics released the "2021 Electricity Carbon Dioxide Emission Factors". The average carbon dioxide emission factor of China's electricity was 0.5568 $kgCO_2$/kWh, while the average electricity carbon dioxide emission factors of Guangdong, Shandong, and Jiangsu were 0.4715 $kgCO_2$/kWh, 0.6838 $kgCO_2$/kWh, and 0.6451 $kgCO_2$/kWh, respectively. The differences in emission factors among provinces are caused by differences in electricity production structures. Guangdong's power production is mainly based on clean energy sources such as nuclear power and gas-fired power generation, and its carbon emission level is lower than the national average. Shandong's power production is mainly based on traditional thermal power, resulting in a relatively high carbon emission factor. Table 1 shows the electricity consumption of the samples.

Based on the average carbon dioxide emission factor of electricity, the calculated electricity carbon emissions are shown in Table 2 and Fig. 2. From 2004 to 2023, China's electricity carbon emissions showed an increasing trend. In 2023, China's electricity carbon emissions were 5.136 billion tons of CO_2 equivalent, while the electricity carbon emissions of Guangdong, Shandong, and Jiangsu were 0.4009, 0.5447, and 0.5053 billion tons of CO_2 equivalent, respectively.

Table 1. Electricity consumption in China and major provinces (unit: 100 million kWh).

Year	China	Guangdong	Shandong	Jiangsu
2004	21971.37	2387.14	1693.71	1820.08
2005	24940.32	2674	1912	2193
2006	28587.97	3004.03	2272.07	2569.75
2007	32711.81	3394.05	2596.05	2952.02
2008	34541.35	3504.82	2726.97	3118.32
2009	37032.14	3609.64	2941.07	3313.99
2010	41934.49	4060	3298	3864
2011	47000.88	4399.02	3635.26	4281.62
2012	49762.64	4619.4	3794.6	4580.9
2013	54203.41	4830.1	4083.1	4956.6
2014	57829.69	5235.23	4223.49	5012.54
2015	58019.98	5310.69	5117.05	5114.7
2016	61205.09	5610.13	5390.75	5458.95
2017	65913.97	5958.97	5430.16	5807.89
2018	71508.2	6323.35	6083.87	6128.27
2019	74866.12	6696	6219	6264
2020	77620.17	6926	6940	6374
2021	85200.1	7867	7383	7101
2022	88357.62	7870	7559	7400
2023	92241	8502	7966	7833

Table 2. Electricity carbon emissions in China and major provinces (unit: 100 million tons CO_2).

Year	China	Guangdong	Shandong	Jiangsu
2004	12.234	1.126	1.158	1.174
2005	13.887	1.261	1.307	1.415
2006	15.918	1.416	1.554	1.658
2007	18.214	1.600	1.775	1.904
2008	19.233	1.653	1.865	2.012
2009	20.619	1.702	2.011	2.138
2010	23.349	1.914	2.255	2.493
2011	26.170	2.074	2.486	2.762
2012	27.708	2.178	2.595	2.955
2013	30.180	2.277	2.792	3.198
2014	32.200	2.468	2.888	3.234
2015	32.306	2.504	3.499	3.299
2016	34.079	2.645	3.686	3.522
2017	36.701	2.810	3.713	3.747
2018	39.816	2.981	4.160	3.953
2019	41.685	3.157	4.253	4.041
2020	43.219	3.266	4.746	4.112
2021	47.439	3.709	5.048	4.581
2022	49.198	3.711	5.169	4.774
2023	51.360	4.009	5.447	5.053

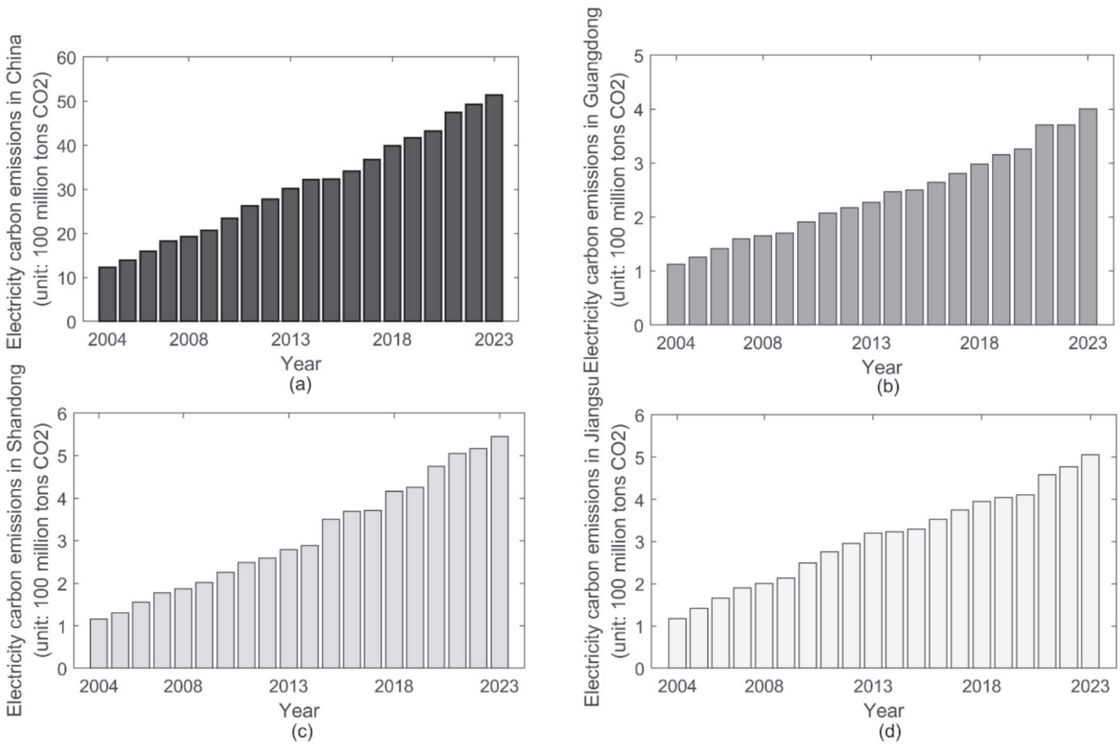

Fig. 2. Sample electricity carbon emissions.

Empirical Prediction Research

Research on the Correlation between Electricity Carbon Emissions and External Factors

In Table 3, the correlation between external influencing factors such as GDP (100 million yuan), population (10000 people), employment rate (%), fiscal expenditure (100 million yuan), consumer price index, railway passenger volume (10000 people), total retail sales of consumer goods (100 million yuan), and electricity carbon emissions was calculated. The correlation between the consumer price index and electricity carbon emissions varies greatly (0.991 in China, -0.302 in Guangdong, -0.489 in Shandong, -0.412 in Jiangsu), and the correlation is low on provincial samples. Therefore, it is considered to exclude this indicator. In addition, the correlation between the employment rate (%) indicator and electricity carbon emissions is also low, except for 0.901 in the Jiangsu sample; the correlation in the other three samples is lower than 0.63. It is considered to exclude the employment rate (%) indicator as well.

After calculating the Pearson correlation coefficient, five indicators - namely GDP (100 million yuan), population (10000 people), fiscal expenditure (100 million yuan), railway passenger volume (10000 people), and total retail sales of consumer goods (100 million yuan) - were selected as the final external influencing factors and input variables for the electricity carbon emission prediction model.

Research on Autocorrelation of Carbon Emission Sequences

First, autocorrelation analysis of electricity carbon emissions was conducted. As shown in Fig. 3, recent carbon emission data are highly correlated with current carbon emissions, while more distant carbon emission data have a relatively small impact on current carbon emissions. However, the results of the correlation analysis do not eliminate the mutual influence between

Table 3. Pearson coefficient calculation of external factors.

Area	GDP (100 million yuan)	Population (10000 people)	Employment rate (%)	Fiscal expenditure (100 million yuan)	Consumer Price Index	Railway passenger volume (10000 people)	Total retail sales of consumer goods (100 million yuan)
China	0.998	0.971	0.539	0.991	0.991	0.779	0.992
Guangdong	0.996	0.965	0.567	0.973	-0.302	0.814	0.984
Shandong	0.995	0.968	0.627	0.989	-0.489	0.835	0.972
Jiangsu	0.991	0.971	0.901	0.991	-0.412	0.862	0.987

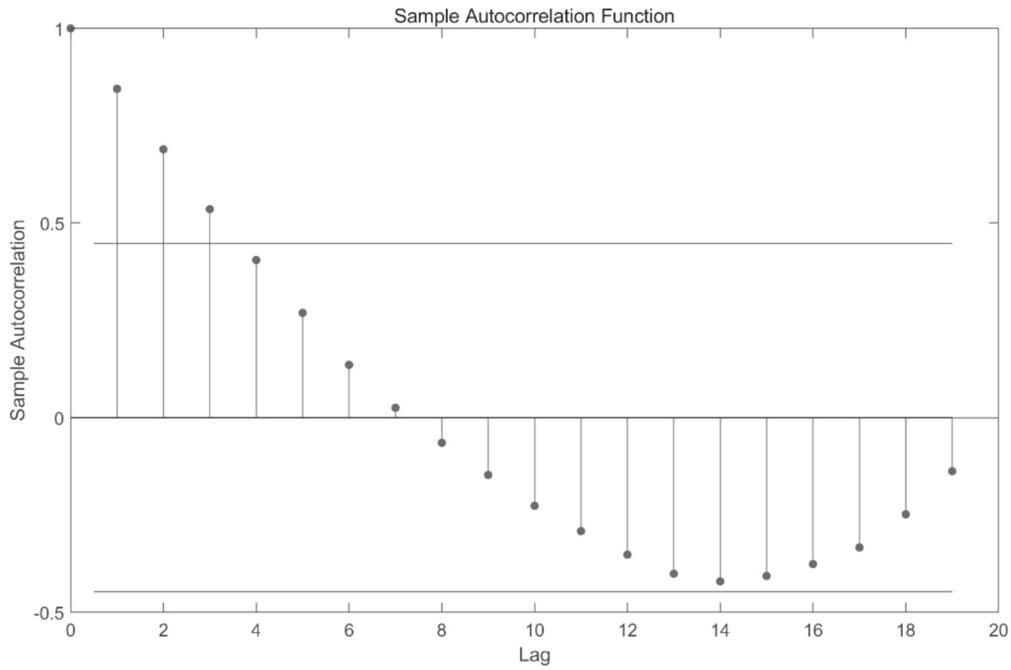

Fig. 3. Autocorrelation analysis of carbon emission sequences.

factors; therefore, further partial autocorrelation analysis is required.

In Fig. 4, in the sample of carbon emissions from China's electricity industry, the carbon emission data from 1 day ago, 7 days ago, 8 days ago, 9 days ago, and 10 days ago have the greatest impact on current electricity carbon emissions. In the carbon emission samples of Guangdong's electricity sector, the carbon emission data from 1 day ago, 9 days ago, 10 days ago, 14 days ago, and 16 days ago have the greatest impact on current electricity carbon emissions. In the carbon emission samples of Shandong's electricity sector, the carbon emission data from 1 day ago, 5 days ago, and 9 days ago have the greatest impact on current electricity carbon emissions. In the carbon emission samples of Jiangsu's electricity sector, the carbon emission data from 1 day ago, 10 days ago, 11 days ago, 12 days ago, and 13 days ago have the greatest impact on current electricity carbon emissions.

According to the PACF analysis results, the historical data with high influence are used as input variables for the electricity carbon emissions prediction model, which enables the model to effectively simulate the trend of carbon emission changes, improve the stability and fitting accuracy of the model, and establish a foundation for efficient electricity carbon emission prediction.

Model Establishment and Parameter Setting

In Table 4, the main parameters of the PE-PACF-SSA-BP model constructed by combining the Pearson coefficient and PACF analysis are as follows: the maximum lag order of PACF is set to 20, and the number of discoverers, joiners, and scouts in the SSA algorithm is 15, 75, and 10, respectively. The safety value ST is set to 0.85 in order for the discoverer to find the target faster and guide the group to move quickly toward the target direction, thereby improving the efficiency of the SSA algorithm. The maximum number of iterations is set to 80 to avoid the algorithm over-optimizing and consuming excessive resources, thereby missing the most suitable model parameters.

The activation function of BPNN selects a commonly used and high-performance sig function, with 5+x input neurons. 5 represents the GDP (100 million yuan), population (10000 people), fiscal expense (100 million yuan), railway passenger volume (10000 people),

Table 4. Main parameter table.

Model	Parameters	Value
PACF	Maximum lag order	20
SSA	Number of discoverers	15
	Number of joiners	75
	Number of scouts	10
	ST	0.85
	Maximum Number of Iterations	80
BPNN	activation function	sig
	Input neurons number	5+x
	hidden neurons number	12
	Output neurons number	1

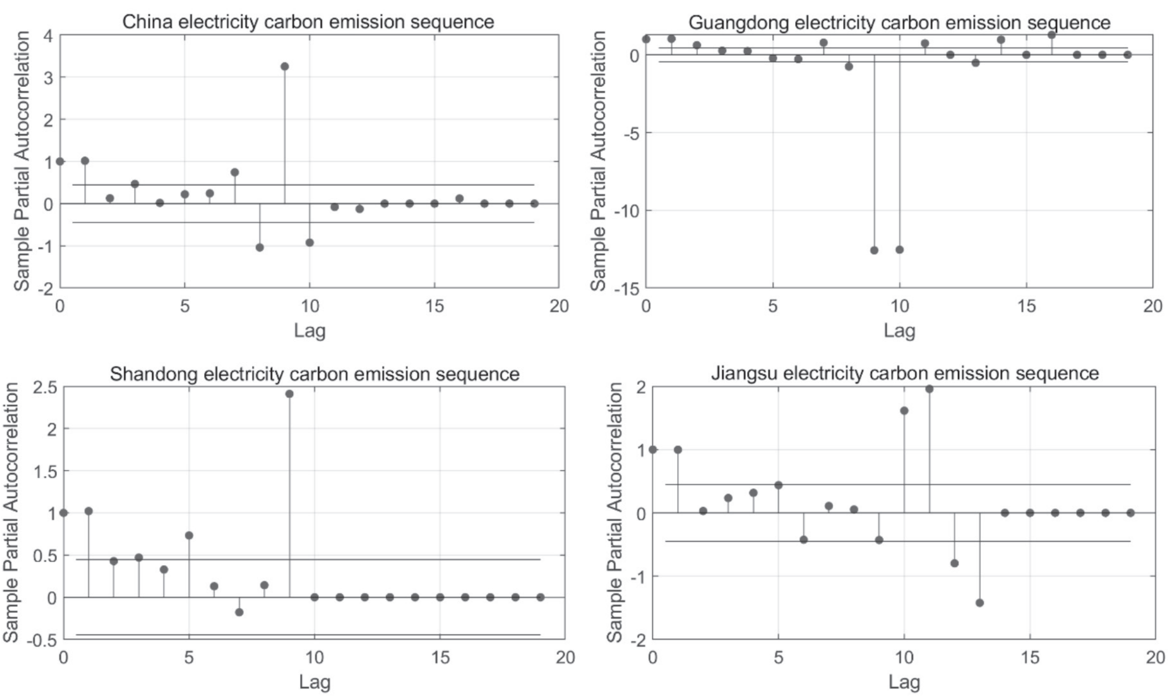

Fig. 4. Partial autocorrelation analysis of carbon emission sequences (China, Guangdong, Shandong, and Jiangsu).

and total retail sales of consumer goods (100 million yuan) selected based on the Pearson coefficient. The x represents the internal impact variable obtained from PACF analysis. The number of hidden layer neurons is set to 12, and previous studies have shown that 12 neurons are beneficial for improving model stability and learning ability (Bai et al., 2024). There is only one output neuron, and the output result is the predicted value of electricity carbon emissions for the current year.

Error Evaluation

Aiming to evaluate the prediction error of electricity carbon emissions, the following three error indicators are constructed:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\%$$

Among them, n represents the number of predicted points, $\hat{y}_i$ represents the predicted value, and y_i represents the actual value.

Model Training

In Fig. 5, the training error of China's electricity carbon emission samples decreased to the lowest level at the 38th time, and the training process error decreased rapidly. In recent years, China's electricity carbon emissions have been mainly affected by the growth in electricity demand and the increase in the proportion of new energy installed capacity. The training errors of carbon emission samples from Guangdong, Shandong, and Jiangsu provinces all reached their lowest point later, which is related to the high volatility of provincial electricity carbon emission data. Based on the above results, there are significant differences in the training process of electricity carbon emission prediction models in different regions, which is related to the formation process and variation patterns of local electricity carbon emissions.

Model Comparison

To further validate the effectiveness of the PE-PACF-SSA-BP model, a model comparison framework shown in Fig. 6 was proposed. By comparing with other prediction models, the study evaluates the selection of influencing factors, model construction, and model optimization, and tests the predictive performance of the model on the test set data for China, Guangdong, Shandong, and Jiangsu. By comparing and analyzing the predictive performance of multiple samples and models, it is possible to objectively and comprehensively evaluate the advantages and disadvantages of the constructed model, which is essential for establishing a robust electricity carbon emission prediction model.

After optimization by the SSA algorithm, the performance of the BPNN model is improved, making it easier to escape local optima and identify better model parameters. By testing the SSA-BPNN model, the optimization effect of the SSA algorithm, as well as the necessity of using SSA optimization, can be more effectively evaluated.

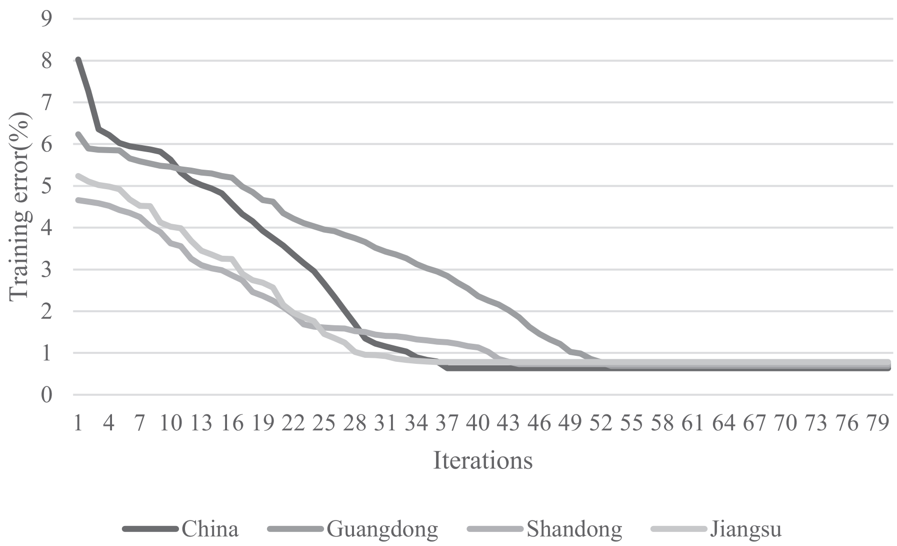

Fig. 5. Model training process.

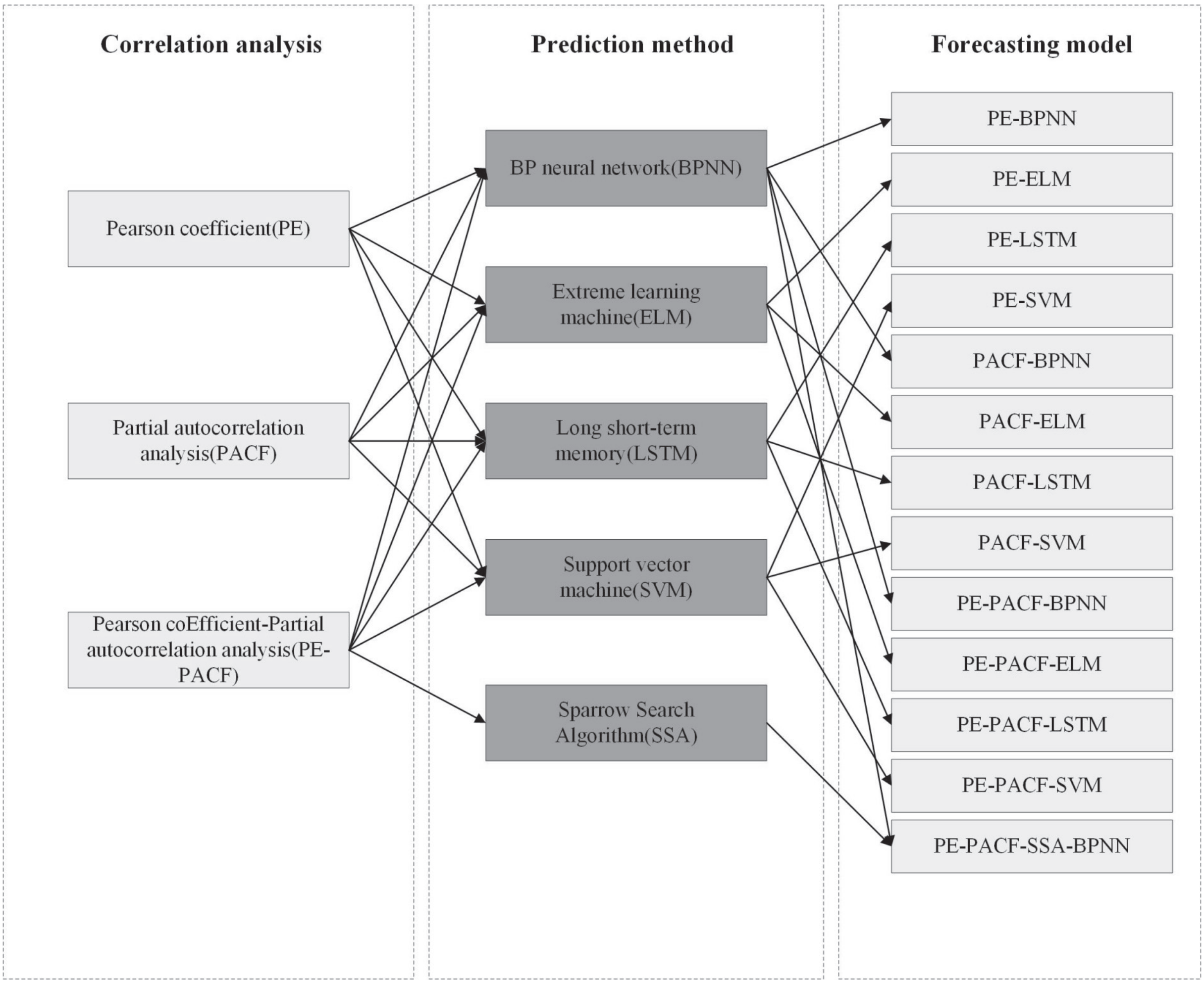

Fig. 6. Comparison of carbon emission models.

Results and Discussion

Prediction of China's Electricity Carbon Emissions

Carbon emission data from 2004 to 2013 were selected as the training set. In Fig. 7, the comparative model is able to predict the trend of changes in China's electricity carbon emissions well. In recent years, China's electricity carbon emissions have been on the rise, and the power system is running smoothly, which makes it relatively easy to predict the trend of China's electricity carbon emissions. This is similar to Alajmi (2022). However, based on the carbon emission predictions from various years, the PACF-SVM model has a significant prediction error in 2021 and 2022. This may be due to a lack of consideration for the impact of external factors on electricity carbon emissions, and the limited accuracy of a single time series model in predicting carbon emissions.

In Table 5, the prediction errors of the ELM model are generally large (the MAPE value of PE-ELM is 2.070%, the MAPE value of PACF-ELM is 2.097%, and the MAPE value of PE-PACF-ELM is 1.254%). The relatively simple structure and low reliability of the ELM model make it perform poorly in predicting carbon emissions in China's electricity industry. The robustness of the BPNN model is significantly higher than that of ELM, and the MAPE value of PE-PACF-BPNN is 1.458%, which is better than most of the comparison models. In addition, the MAPE value of the deep learning model PE-PACF-LSTM is 1.315%, the RMSE value is 0.562, and the MAE value is 0.533. This indicates that the reliability and accuracy of a single BPNN model are still low. By using the optimization algorithm SSA to select the weights of BPNN, the predictive performance of the model has been further improved. The MAPE value of PE-PACF-SSA-BPNN is 0.628%, the RMSE value is 0.315, and the MAE value is 0.266.

Prediction of Guangdong Electricity Carbon Emissions

In addition to China's electricity carbon emissions, we also conducted provincial-level electricity carbon emissions forecasts. Guangdong, as one of the provinces with rapid economic development in China, generates

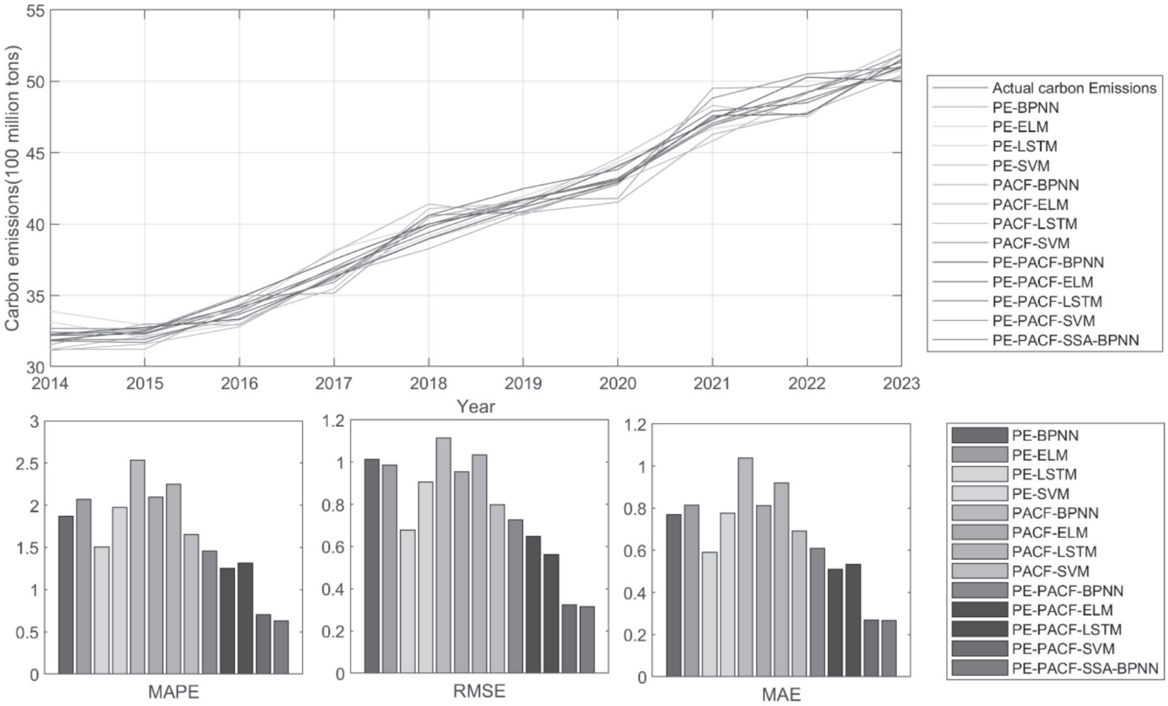

Fig. 7. Prediction of electricity carbon emissions in China.

a significant amount of carbon emissions from electricity every year. The predictive performance of the comparative model for the trend of electricity carbon emissions is relatively low, especially in the past three years, where the prediction error of carbon emissions is relatively large. On the one hand, in recent years, Guangdong's electricity carbon emissions have been on the rise. On the other hand, Guangdong Province has attempted to reduce the intensity of electricity carbon emissions by developing gas turbines, new energy, and other technologies, which has further increased the difficulty of predicting carbon emissions. This is consistent with Chen et al. (2022).

Unlike the carbon emission prediction results for China's power industry, the error in the carbon emission prediction for Guangdong's regional power industry is relatively large. On the one hand, due to the influence of various factors on regional electricity carbon emissions and the fact that Guangdong's electricity production relies on natural gas transported by sea routes, there are significant fluctuations in carbon emissions, making prediction difficult. In Table 5, compared with the PE-LSTM model, the PE-BPNN model shows lower errors (MAPE = 4.763%, RMSE = 0.188, MAE = 0.153). This indicates that deep learning may not be suitable for all prediction problems. For the prediction of electricity carbon emissions, the complex structure of the LSTM may lead to model overfitting, further increasing prediction error. The BPNN has high stability and adaptability, and its structure is simpler than that of the LSTM, making it an effective option for predicting electricity carbon emissions. The prediction error of the PE-PACF-SSA-BPNN model is MAPE = 2.924%, RMSE = 0.103, and MAE = 0.086. The PE-PACF method selects both internal and external influencing factors of electricity carbon emissions, ensuring comprehensive information input and improving the accuracy of model predictions.

Prediction of Shandong Electricity Carbon Emissions

Shandong is a major economic province in China, with a huge chemical industry and strong electricity demand. By predicting and testing Shandong's electricity carbon emissions, the effectiveness of the model is verified. The PE model (including PE-BPNN, PE-ELM, PE-LSTM, and PE-SVM) has a large error, and the error tends to be biased toward one side, which is unfavorable for predicting changes in electricity carbon emissions. For a period of time, the predicted value of carbon emissions from electricity may continue to be higher or lower than the actual value, which will affect the judgment of relevant departments on the actual level of carbon emissions from electricity. Considering the reasons for this, a single PE model does not take into account trend changes in carbon emission sequences and does not include historical data as input variables for the carbon emission prediction model. After combining PACF analysis, the predictive performance of the PE-PACF-BPNN model is significantly improved.

As shown in Table 5, the prediction accuracy of PE-PACF-ELM (MAPE = 2.726%, RMSE = 0.138, MAE = 0.116) is better than that of PE-PACF-LSTM (MAPE = 3.169%, RMSE = 0.152, MAE = 0.133), indicating that neural network models can outperform

Table 5. Prediction error of electricity carbon emissions in China, Guangdong, Shandong, and Jiangsu.

Region	China			Guangdong			Shandong			Jiangsu		
Models	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE
PE-BPNN	1.869	1.014	0.769	4.763	0.188	0.153	4.567	0.216	0.19	3.791	0.188	0.156
PE-ELM	2.07	0.985	0.815	5.69	0.19	0.169	5.783	0.262	0.232	5.875	0.276	0.242
PE-LSTM	1.505	0.677	0.59	5.089	0.187	0.163	4.657	0.235	0.203	3.431	0.172	0.138
PE-SVM	1.976	0.906	0.776	4.264	0.148	0.129	3.368	0.189	0.147	4.6	0.198	0.183
PACF-BPNN	2.534	1.114	1.038	3.922	0.149	0.117	3.394	0.189	0.147	3.457	0.159	0.143
PACF-ELM	2.097	0.953	0.812	5.29	0.19	0.167	3.795	0.183	0.145	3.983	0.19	0.163
PACF-LSTM	2.251	1.035	0.919	4.534	0.155	0.143	3.202	0.147	0.133	3.583	0.167	0.147
PACF-SVM	1.653	0.797	0.692	4.013	0.155	0.124	3.039	0.154	0.13	2.158	0.102	0.088
PE-PACF-BPNN	1.458	0.726	0.61	3.875	0.141	0.124	2.655	0.133	0.112	2.964	0.122	0.118
PE-PACF-ELM	1.254	0.649	0.51	4.445	0.16	0.142	2.726	0.138	0.116	1.775	0.082	0.071
PE-PACF-LSTM	1.315	0.562	0.533	3.471	0.119	0.104	3.169	0.152	0.133	2.67	0.124	0.107
PE-PACF-SVM	0.702	0.325	0.269	3.141	0.11	0.096	2.381	0.121	0.101	2.299	0.101	0.091
PE-PACF-SSA-SVM	0.628	0.315	0.266	2.924	0.103	0.086	1.852	0.084	0.075	1.321	0.064	0.053

deep learning models when sufficient input information is available. This finding is opposite to the results reported by Tian et al. (2022). Therefore, a PE-PACF-SSA-BPNN model was constructed, and the robustness of the optimized BPNN model was significantly enhanced. In the electricity carbon emission prediction experiment for Shandong electric power, the PE-PACF-SSA-BPNN model achieved the highest prediction accuracy, with error indicators of MAPE = 1.852%, RMSE = 0.084, and MAE = 0.075, outperforming the comparison models. As a major electricity-consuming province in China, Shandong generates a large amount of electricity carbon emissions every year. Conducting prediction experiments on Shandong's electricity carbon emissions, therefore, provides an effective test of the PE-PACF-SSA-BPNN model. The results demonstrate that the PE-PACF-SSA-BPNN model can accurately predict Shandong's electricity carbon emissions.

Prediction of Jiangsu Electricity Carbon Emissions

As a coastal province in China, Jiangsu has convenient waterways and transportation conditions and has developed industries such as electronics, metallurgy, and textiles. It consumes a large amount of electricity annually and has high electricity carbon emissions. Unlike Guangdong and Shandong, the PE-ELM and PE-LSTM models show unsatisfactory performance in predicting the trend of electricity carbon emissions in Jiangsu. Especially from 2017 to 2020, the predicted values deviated significantly from the actual values, which may be due to poor model stability and insufficient input variables to support the model's predictions.

As shown in Table 5, the models that only calculated the Pearson coefficient or only performed PACF analysis performed poorly. The model using the Pearson coefficient is highly sensitive to changes in external factors and cannot fit well with changes in the carbon emission curve. However, the model that underwent PACF analysis lacks the necessary input of external influencing factors. Such models rely solely on historical carbon emission values to generate predicted electricity carbon emissions at the current time point and do not account for the impact of external factors. Therefore, the PE-PACF-BPNN model combines both internal and external influencing factors; it can better provide accurate prediction results. The prediction error of the PE-PACF-BPNN model in the electricity carbon emission experiment for Jiangsu power is MAPE = 2.964%, RMSE = 0.122, and MAE = 0.118. Obviously, the predictive performance of the PE-PACF-ELM model outperforms that of the PE-PACF-BPNN model, indicating that the single BPNN model failed to obtain suitable model parameters for prediction. After optimizing the BPNN weights using the SSA algorithm, the prediction accuracy of the PE-PACF-SSA-BPNN model improved, with a prediction error of MAPE = 1.321%, RMSE = 0.064, and MAE = 0.053.

The prediction results across multiple regions indicate that the PE-PACF-SSA-BPNN model has high stability and can accurately predict electricity carbon emissions under various scenarios. The model demonstrates high accuracy and strong adaptability.

In addition, the model can be further extended to fields such as power load forecasting and photovoltaic output forecasting to verify its performance.

Table 6. Abbreviation table.

Abbreviation	Name
BPNN	Back propagation neural network
MAE	Mean absolute error
MAPE	Mean absolute percentage error
PACF	Partial autocorrelation analysis
PE	Pearson coefficient
RGGI	Regional Greenhouse Gas Initiative
RMSE	Root mean square error
SSA	Sparrow search algorithm

Conclusions

The current installed capacity of China's power industry has a high growth rate, and the rapid development of the power industry urgently requires the emergence of a corresponding carbon footprint monitoring technology. The model constructed in this article establishes a relatively stable and high-precision electricity carbon footprint prediction model. On the one hand, the power structure of the electricity system is becoming more diverse, and clean power generation is gradually developing into the main power generation method of the electricity system. On the other hand, through measures such as energy-saving renovation, demand-side management, and replacement of fluorine-free equipment, the carbon emission intensity of the electricity system has also been further reduced. The main reason for the current increase in carbon emissions from electricity is the rising electricity demand. This article constructs a novel PE-PACF-SSA-BPNN electricity carbon emission prediction model and conducts empirical research on China's electricity carbon emissions. The main conclusions are as follows:

(1) Based on electricity consumption and average electricity carbon emission factors, the electricity carbon emission levels in China and different provinces are calculated. The electricity carbon emission factors vary in different regions, representing different carbon emission intensities. This method effectively calculates the carbon emissions level of China's electricity in the past 20 years, and shows that China's electricity carbon emissions have shown an upward trend in the past 20 years. This trend reflects the continuous increase in China's electricity consumption and carbon emissions in recent years, and it is urgent to control electricity carbon emissions.

(2) The PE-PACF joint factor analysis method provides a solution for factor screening of carbon emissions in electricity. Firstly, the correlation between external variables and electricity carbon emissions is measured using the Pearson coefficient to determine external factors; Further analyze the internal influencing factors of electricity carbon emissions through PACF. The PE-PACF method provides sufficient input information for the power carbon emission prediction model and establishes a data foundation for the model construction.

(3) An electricity carbon emission prediction model based on a BPNN neural network framework was constructed, and the connection weights between the input layer and the hidden layer were obtained through the SSA algorithm. The connection weights and thresholds between the hidden layer and the output layer were obtained through the error propagation mechanism. This model combines the advantages of the SSA algorithm and the error correction principle of the BPNN neural network, greatly improving the prediction accuracy and stability of the electricity carbon emission prediction model.

(4) The research on predicting carbon emissions from electricity in China, Guangdong, Shandong, and Jiangsu shows that the PE-PACF-SSA-BPNN model has prediction errors of 0.628%, 2.924%, 1.852%, and 1.321% on the above four samples, respectively. The model can achieve high accuracy in predicting electricity carbon emissions in different regions. The input of multiple influencing factors and the optimization of the SSA algorithm make the model highly robust, enabling accurate prediction of electricity carbon emissions in different scenarios. This provides a reference for regulating the level of carbon emissions in electricity and implementing carbon reduction measures. The research results also provide a reference for China's power system to quickly achieve decarbonization goals in the future.

By using the model proposed in this article to predict carbon emissions in the power industry, we can accurately track the trend of carbon emissions changes and study the potential impact of rapid development on carbon emissions in the power industry. This is of great significance for promoting carbon neutrality in the power industry.

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Conflict of Interest

The authors declare no conflict of interest.

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