



Assessment of carbon emission reduction contribution of Chinese power grid enterprises based on MCS-GA-ELM method

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Abstract

To achieve China's "double carbon" goal, it is necessary to make quantitative evaluation of the power grid enterprises' contribution to carbon emission reduction. This paper analyzes the contribution of power grid enterprises to carbon emission reduction from three points: power generation side, power grid side, and user side. Then, PLS-VIP method is used to screen the key influencing factors of carbon emission reduction contribution of power grid enterprises from three aspects: consumption of clean energy emission reduction, reduction of line loss emission reduction, and substitution of electric energy. Based on GA-ELM combined machine learning algorithm, we establish an intelligent evaluation model of power grid enterprises' carbon emission reduction contribution. Furthermore, according to the distribution law of key influencing factors, this paper uses Monte Carlo simulation method to calculate the contribution of power grid enterprises to carbon emission reduction by scenario, so as to evaluate the contribution of power grid enterprises to carbon emission reduction. Finally, combined with the relevant data of power grid enterprises from 2003 to 2019, this paper makes an empirical study on the completion of carbon emission reduction contribution and the promotion path.

Keywords Monte Carlo simulation · GA-ELM method · Power grid enterprises · Carbon emission reduction contribution · Assessment

Introduction

Background and motivation

In September 22, 2020, general secretary Xi Jinping announced in the general debate of the seventy-fifth UN General Assembly that we should strive to achieve the peak of carbon dioxide emissions by 2030 and strive to achieve carbon neutralization before 2060, that is, the goal of "double carbon" (Xi 2020). Therefore, low-carbon emission

reduction has become the development direction of all walks of life in China. It is estimated that in 2020, the total carbon emission of Chinese power industry will be about 3.6 billion tons, accounting for over one-third of the total national emission (about 9.9 billion tons) (BP 2020). As the industry with the largest proportion of carbon emission in China, the effect of power emission reduction will directly affect the successful completion of the "double carbon goal." Among them, power grid enterprises play an important role in connecting the preceding and the following in the power industry and are one of the key links to achieve the carbon emission reduction goal of the power industry (Meng 2021).

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Related work

Many studies have been carried out on carbon emission reduction, and different studies are committed to different links of carbon emission reduction. This paper reviews the relevant literature from three aspects: the analysis of the influencing factors of carbon emission reduction, the prediction model of carbon emission reduction, and the random uncertainty of carbon emission reduction.

The analysis of the influencing factors of carbon emission reduction has great significance for the subsequent data calculation of carbon emission reduction, which is directly related to the scientificity and effectiveness of the calculation results. Scholars at home and abroad have conducted a lot of research in this regard. In order to test the common benefits of carbon emission reduction and air pollution control, Jiang et al. analyzed the emission reduction and emission reduction factors of Jiangsu, Zhejiang, Yunnan, and Shanghai power industries, as well as the synergistic factors of technical and structural emission reduction measures (Jiang and Alimujiang 2020). Zhu et al. used the generalized partition index model to decompose the changes of carbon emissions of China's power industry from 2000 to 2015, and fully considered the impact of economy, population, and energy consumption on carbon emissions (Zhu et al. 2018). Liao et al. derived seven different drivers of carbon emissions in the power industry based on the log average factor index (LMDI) decomposition model. The positive or negative contribution of each driving force to the growth rate of carbon emission as well as the change of contribution rate and emission dynamics of each province is analyzed (Liao and Wang 2019). Some scholars have constructed the evaluation index system from five aspects affecting the regional carbon emission reduction capacity and established a comprehensive evaluation model based on entropy method (Pu and Li 2016). Cosimo magazzino, Marco Mele, and Nicolas Schneider studied the causal relationship between solar and wind energy production, coal consumption, economic growth, and carbon emissions in China, India, and the USA (Cosimo magazzino et al. 2021). Xia et al. combined multiple regression analysis, input–output analysis, and structural decomposition analysis to analyze the impact of input–output and structural decomposition on future carbon emissions (Xia et al. 2019). From the perspective of carbon emission efficiency, Sun et al. applied stochastic frontier analysis to screen the factors affecting carbon emission intensity (Sun et al. 2022). Other scholars use the extended STIRPAT model and ridge regression model to screen the influencing factors of carbon emission (Liu et al. 2018a, b).

The data of carbon emission reduction of power grid enterprises have the characteristics of continuity, fluctuation, and long time series. Therefore, it is suitable to use the relevant models in the field of machine learning to predict carbon emission reduction. Chinese carbon emission prediction research has been carried out for a long time. From similar studies in other carbon emission fields, we can find inspiration for the carbon emission reduction research of power grid enterprises. Gao et al. proposed a new fractional grey Riccati model. A fractional cumulative grey Gompertz model is designed to predict the trend of industrial carbon emission in the USA (Gao et al. 2021, 2022). Ren et al. constructed a fast learning network (FLN) prediction algorithm

based on chicken swarm optimization (CSO) to predict the carbon emissions of Guangdong Province from 2020 to 2060 (Ren and Long 2021). Dong et al. took 12 major industrial carbon emission industries in Henan Province of China as the research object, combined with LMDI method and Tapio decoupling model, built a decoupling effort model to analyze the impact of each effect on the decoupling relationship (Dong et al. 2021). In order to predict and analyze China's carbon emission trend, Zhou et al. proposed a new grey rolling mechanism based on the principle of information priority (Zhou et al. 2021). Other studies have constructed the carbon emission intensity prediction model based on factor analysis and limit learning machine and the BP neural network prediction model of carbon emission (Sun et al. 2022; Liu et al. 2018a, b; Sun and Huang 2022).

Analyzing the historical data of carbon emission reduction and predicting the future change trend cannot ignore the random uncertainty research of carbon emission reduction. In order to ensure the optimal development of complex power management system, Xie et al. established an interval fuzzy programming risk measurement model considering carbon capture technology and carbon emission reduction targets (Xie et al. 2019). Jin et al. proposed a stochastic dynamic economic scheduling model considering wind power uncertainty and carbon emission rights (Jin et al. 2019). Under the constraints of carbon emission intensity, Zhao et al. allocated carbon emissions to 41 industry departments in China to achieve the emission reduction target in 2030. A comprehensive allocation method based on input–output analysis and entropy weight is proposed (Zhao et al. 2017). Setting multiple scenarios is an effective method to study the uncertainty of carbon emission reduction. Meng et al. calculated the carbon emission reduction caused by three-phase load management imbalance on the basis of analyzing the relationship between current imbalance and network loss and iso14064-2:2006. At the same time, Monte Carlo method was used for the first time to predict the carbon emission of power industry in 2017–2030 under three different scenarios (Meng et al. 2018). Liu et al. constructed a low-carbon path analysis model of China's power industry based on era model and made a comparative analysis of carbon emissions under reference scenario, low-carbon scenario, and enhanced low-carbon scenario (Liu et al. 2018a, b).

The research and achievements of other scholars are shown in the Table 1.

Since the end of 2019, COVID-19 has swept the world, and the world situation has become more complex, which has profoundly affected and changed global and regional energy consumption and carbon emissions. Wang et al. analyzed the various impacts of COVID-19 on China's environmental development, and discussed Chinese future economic development and its impact on the world economy

Table 1 Summary of literature

Ref	Research object	Research method	Conclusion
Köne and Büke (2019)	Historical and projected carbon emissions from fossil fuel combustion in Turkey	IPCC	All impacts on CO ₂ emissions have been positive in historical assessments
Sun et al. (2022)	Middle East and North Africa carbon emissions	Continuously updated fully modified and bias-corrected methods	Rapid urbanization and economic growth have led to higher carbon emissions
Nakhli et al. (2022)	US economic policy in the context of carbon neutrality	Bootstrap rolling approach Granger causality test	Take clean energy and green energy as the goal of all and sustainable cleaner production
Rahman et al. (2022)	The world's 25 largest emerging economies	ARDL, PMG	Energy intensity and industrialization will increase carbon intensity, while renewable energy use and urbanization will reduce carbon intensity
Wang and Li (2019)	China's power industry and non-fossil-fuels	GS2SLS	The increase in the share of non-fossil-fuel power generation has reduced carbon dioxide emissions from the power sector
Li et al. (2020)	Carbon emission reduction benefits of wind power projects	Life cycle assessment theory	Compared with ordinary coal-fired power plants, this power project has great emission reduction potential
Jin et al. (2022)	Low carbon power dispatching and carbon emission reduction	Distributed robust optimization model	Further promote the best combination of thermal power and wind power to establish the synergy of carbon emission reduction
Shi (2022)	China's carbon emissions under the background of carbon neutrality	LASSO, PCA, DE-GWO	DE-GWO optimized SVR has higher prediction accuracy than other algorithms
Zhao and Yang (2022)	Carbon emission reduction in China	DMD	The testing results validate the accuracy and application value of the DMD short-run forecast
Pan et al. (2020)	Carbon dioxide emissions from China's industrial sector	Multi-sector intertemporal optimization model	Forecast the CO ₂ emission trends of 14 industrial departments in 31 provinces of China from 2012 to 2050

by scenarios (Wang and Su 2020; Wang et al. 2021, 2022; Whang and Zhang 2021). It also needs to explore the development mode of carbon emission reduction of power grid enterprises to adapt to the new international environment.

Contribution and organization

Generally speaking, there are few studies on carbon emission reduction of power grid enterprises, and there are few studies on the evaluation method of carbon emission reduction contribution of power grid enterprises. In addition, the research on carbon emission reduction mostly focuses on one of the above aspects, and there is a lack of research that integrates the three aspects. Therefore, under the background of the national evaluation of carbon reduction contribution of energy industry (Su 2021), this research has important theoretical and practical significance.

This paper combines the influencing factors of carbon emission reduction, data prediction model, and uncertainty analysis. Collect and sort out the relevant data of carbon emission reduction and influencing factors of power grid companies, screen out the main influencing factors of carbon emission reduction contribution of power grid enterprises by using the combination with qualitative and quantitative analysis methods, replace the training sample set constructed by the main influencing factors and carbon emission reduction contribution value of power grid enterprises over the years into GA-ELM model for training and learning, and design the carbon emission reduction differentiation scene of power grid enterprises, The Monte Carlo simulation method is used to randomly generate influencing factors' value of carbon emission reduction, which is substituted into the trained GA-ELM model for the prediction and analysis of carbon emission reduction contribution value. Finally, according to the statistical index analysis of carbon emission reduction contribution prediction value, the evaluation of carbon emission reduction contribution of power grid enterprises is completed, so as to provide decision-making basis for power grid enterprises to carry out optimal management of carbon emission reduction.

Influencing factors

Current situation of carbon emission reduction contribution of power grid enterprises

As a link and platform connecting the upstream and downstream of the power industry, power grid enterprises will play an important strategic supporting role in realizing China's carbon peak and carbon neutralization strategic objectives. Through the in-depth implementation of the new energy security strategy of "four revolutions and one cooperation,"

take measures to support clean energy consumption, realize fine line loss management, and improve the proportion of energy consumption and power efficiency of power terminals, so as to contribute to the goal of carbon peak and carbon neutralization.

State Grid Corporation of China (SGCC) vigorously promotes clean energy substitution, changes energy consumption mode, focuses on "new electrification," comprehensively builds a modern power grid, drives the upstream and downstream of the industrial chain and value chain, and speeds up the construction of a clean, low-carbon, safe, and efficient energy system. At the same time, adhere to green development and serve the goal of "carbon peak and carbon neutralization." By the end of 2020, the State Grid Corporation of China had completed the task of "replacing coal with electricity" in this year, accounting for 26.8% of renewable energy power generation, recovered 220.6 tons of sulfur hexafluoride gas, and completed 193.8 billion kWh of electricity substitution (China State Grid Corporation 2020).

In accordance with the carbon emission reduction plan, China Southern Power Grid has strengthened the allocation of clean energy and helped the five southern provinces build a low-carbon and clean energy structure. The installed capacity and electricity of non-fossil energy in the whole network have accounted for more than 50% for 5 consecutive years; continuously optimize the power grid structure, control the line loss rate at 5.59%, and save 3.66 billion kWh and 1.07 million kW of power on the demand side (China Southern Power Grid 2020).

The contribution of carbon emission reduction proposed in this paper can be understood as a new concept, which is divided into five parts according to various channels of energy conservation and emission reduction. By calculating the saved electricity consumption or clean energy power generation of each part, assuming that these electricity are generated by thermal power generation, the converted carbon emission reduction can be calculated through the coal electricity conversion coefficient, and the final carbon emission reduction contribution of power grid enterprises can be obtained by accumulating all parts. Based on the carbon emission reduction work currently carried out by China's two major power grid enterprises, this paper designs the calculation formula of carbon emission reduction contribution, as follows:

$$CTB_c = \Delta C_{P\%} + \Delta C_R + \Delta C_S + \Delta C_{IES} + \Delta C_E \quad (1)$$

$$\Delta C_{P\%} = \Delta E_{P\%} \times \eta_{P\%} \quad (2)$$

$$\Delta C_R = \Delta E_R \times \eta_R \quad (3)$$

$$\Delta C_S = \Delta E_S \times \eta_S \quad (4)$$

$$\Delta C_{IES} = \Delta E_{IES} \times \eta_{IES} \quad (5)$$

$$\Delta C_E = \Delta E_E \times \eta_E \quad (6)$$

CTB_c refers to the contribution of carbon emission reduction, $\Delta C_{P\%}$ refers to the reduction of line loss, ΔC_R refers to the consumption of clean energy, ΔC_S refers to the substitution of electric energy, ΔC_{IES} refers to the reduction of comprehensive energy services, and ΔC_E refers to the reduction of energy supply and energy efficiency services, with the unit of 10^4 t. $\Delta E_{P\%}$ refers to reducing line loss and saving electricity, ΔE_R refers to clean energy generation, ΔE_S refers to electricity substitution, ΔE_{IES} refers to comprehensive energy service saving, ΔE_E refers to optimized energy supply and energy efficiency service saving, with the unit of 108 kWh. $\eta_{P\%}$ refers to the carbon emission reduction conversion coefficient of line loss electricity, η_R refers to the carbon emission reduction conversion coefficient of clean energy electricity, η_S refers to the carbon emission reduction conversion coefficient of electricity substitution electricity, η_{IES} refers to the emission reduction conversion coefficient of comprehensive energy services, and η_E refers to the emission reduction conversion coefficient of energy supply and energy efficiency services, in kg/kWh.

Due to the difficulty of data collection of comprehensive energy service emission reduction, energy supply, and energy efficiency service emission reduction, this example only considers three parts: reducing line loss emission reduction, consuming clean energy emission reduction, and electric energy substitution emission reduction.

Analysis on influencing factors of carbon emission reduction contribution

Selection of screening methods for influencing factors

In order to systematically analyze the influencing factors of the contribution of power grid enterprises to carbon emission reduction (Lin and Qi 2018), starting from the three sub indicators constituting the contribution of power grid enterprises to carbon emission reduction, based on artificial experience and literature review, 26 influencing factors on the three sub-indicators of carbon emission reduction contribution are collected. The details are shown in Fig. 1 (note: the length of high-voltage transmission line refers to the length of ≥ 220 kV AC transmission line, and the availability factor of high-voltage transformer refers to the availability factor of transformer ≥ 110 kV and above).

This paper studies a variety of influencing factor screening methods and compares the traditional principal

component analysis method, grey correlation degree method, and PLS-VIP method. Compared with PLS-VIP method, the influencing factors screened by principal component analysis method and grey correlation degree method have a higher repetition rate of influencing factors among sub-indexes and poor performance in the preliminary trial calculation learning accuracy. Therefore, PLS-VIP method is determined to be used as the influencing factor screening method in this paper.

Influencing factors screening by PLS-VIP method

Based on the preliminary collection of influencing factors, this paper uses PLS-VIP screening method (Liu and Jiang 2017; Liu 2016) and considers the VIP value of influencing factors and the actual correlation. Thirteen main influencing factors are screened from three aspects: consumption of clean energy emission reduction, reduction of line loss emission reduction, and electric energy substitution emission reduction. The details are shown in Figs. 2 and 3 (note: the 13 influencing factors obtained by screening are shown in bold text in the figure).

In order to highlight the impact of the three sub-indicators of carbon emission reduction contribution on the contribution of carbon emission reduction, according to the selected influencing factors and combined with the reality, this paper sets up four scenarios: control type, strengthening the reduction of line loss type, strengthening the consumption of clean energy type, and strengthening the power substitution type. The four scenarios correspond to the change range combination of different influencing factors. The subsequent contribution analysis of carbon emission reduction in this paper is based on these four scenarios (Tian et al. 2021).

Methodology

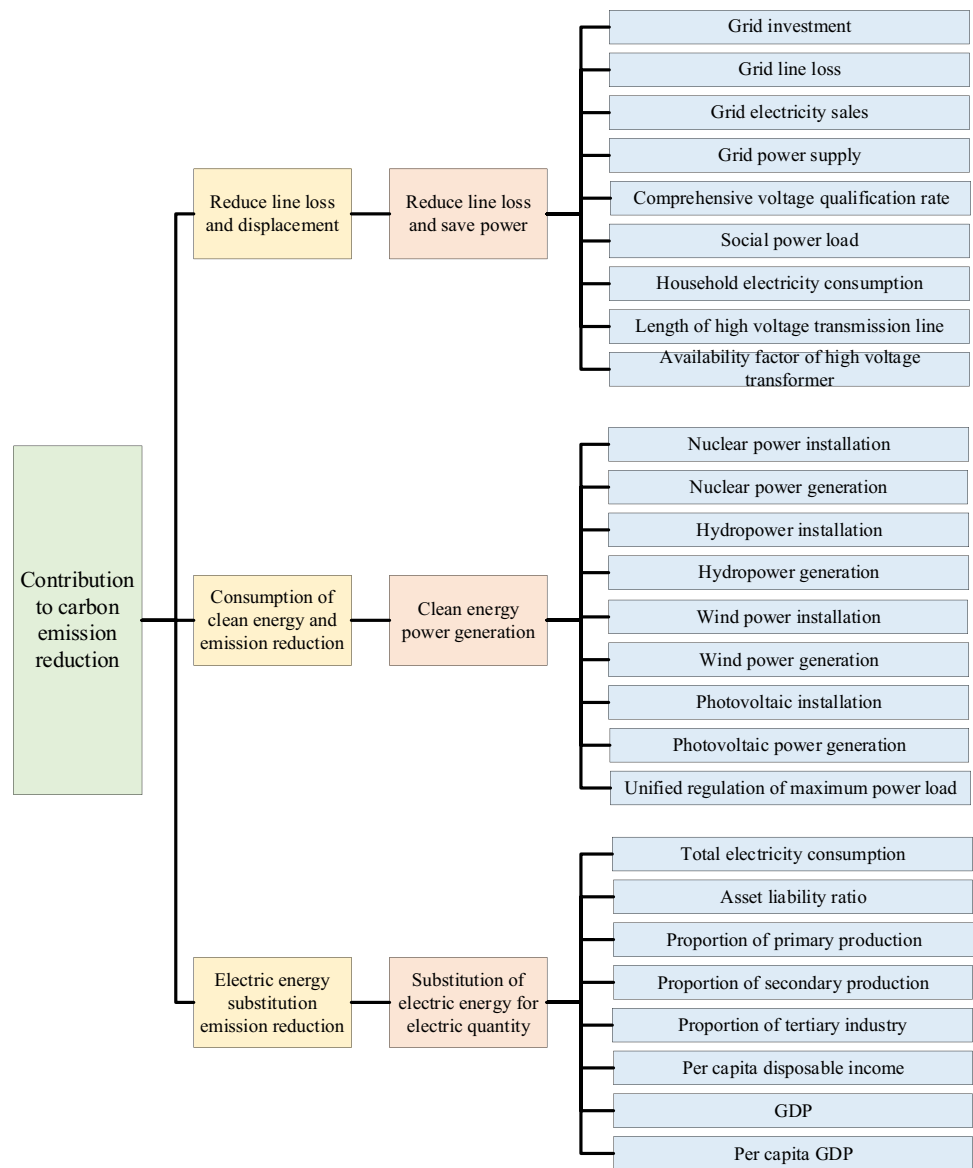
In this paper, the machine learning combination algorithm and Monte Carlo simulation method are combined to construct the carbon emission reduction contribution evaluation model of power grid enterprises. The specific process of the model is shown in Fig. 4.

GA-ELM model

Genetic algorithm

Genetic algorithm (GA) is a heuristic intelligent search algorithm with good robustness and strong global search ability (Holland 1975). Its implementation path is shown in Fig. 5.

Fig. 1 Influencing factors of carbon emission reduction contribution



Reduce line loss and displacement			Consumption of clean energy and emission reduction			Electric energy substitution emission reduction		
S/N	Influencing factor	M1 VIP	S / N	Influencing factor	M1 VIP	S / N	Influencing factor	M1 VIP
8	High voltage transmission line length	1.55989	11	Wnd power installed capacity	1.06718	25	Asset liability ratio	1.66989
9	Availability factor of high voltage transformer:	1.45041	13	Wind power generation	1.06224	22	The proportion of secondary production	1.16577
2	Line loss of power grid	1.12215	14	The maximum power load for unified regulation	1.05546	23	The proportion of tertiary industry	1.05467
5	The qualified rate of comprehensive voltage	0.76414	12	Hydropower generating capacity	1.0532	19	Power consumption of the whole society	0.90842
1	Power grid investment	0.75626	18	Nuclear power generation	1.04795	26	Per capita GDP	0.72717
4	Grid power supply	0.71906	16	Nuclear power installed capacity	1.0439	20	GDP	0.70524
6	Social power load	0.71632	10	Hydropower installed capacity	1.03599	21	The proportion of primary production is	0.67075
7	Household electricity consumption	0.71565	15	PV installed capacity	0.75584	24	Per capita disposable income	0.66245
3	Electricity sales of power grid:	0.71112	17	Photovoltaic power generation	0.74282			

Fig. 2 PLS-VIP screening results of influencing factors of carbon emission reduction contribution

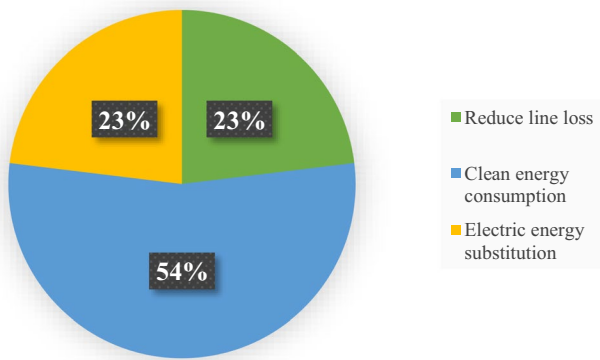
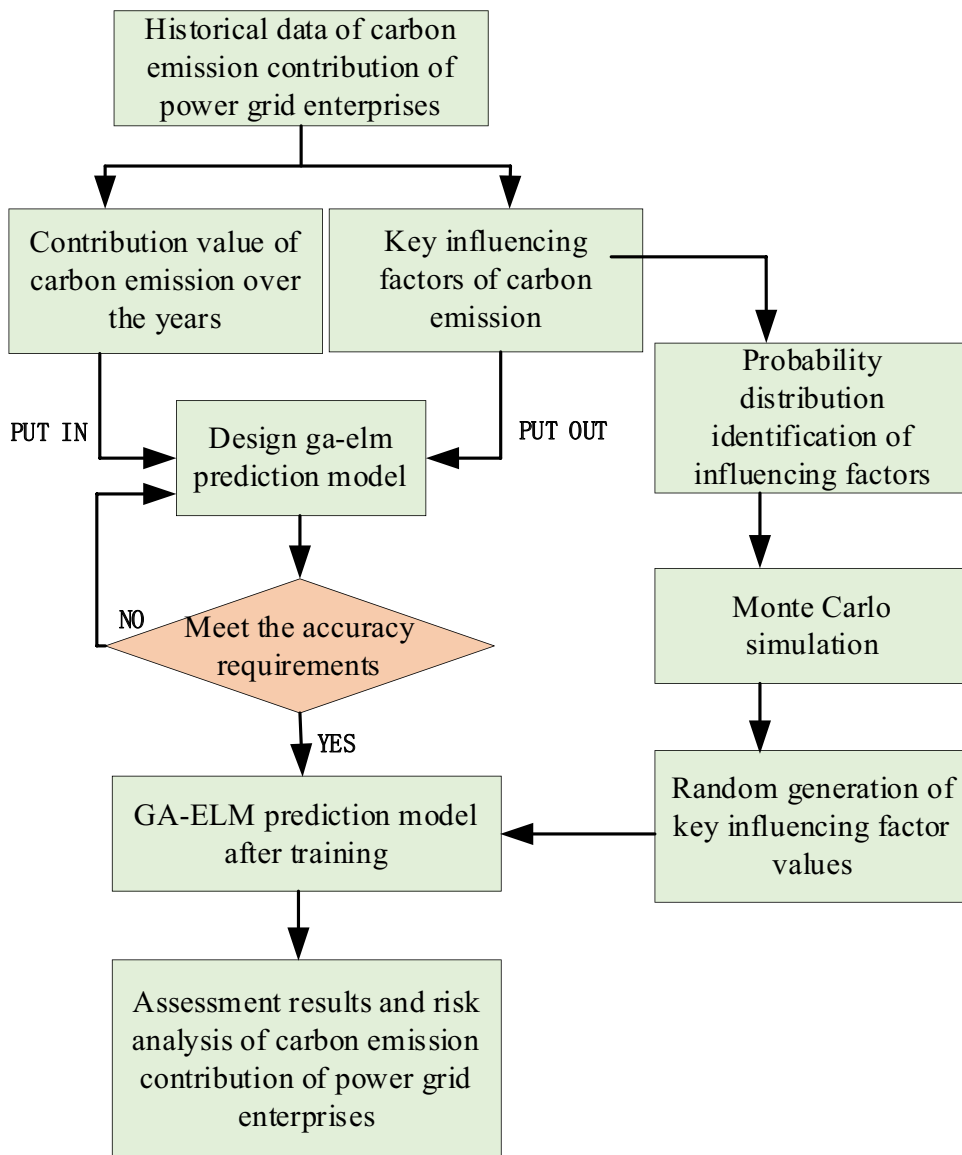


Fig. 3 Proportion of influencing factors

Extreme learning machine

Limit learning machine (ELM) is a single hidden layer feed-forward neural network learning algorithm (Huang et al. 2006). Before training, the algorithm needs to randomly set the input layer weight matrix and threshold, and keep the matrix and threshold unchanged during the training process. The prediction accuracy is improved by optimizing the number of hidden layer neuron nodes. It has the advantages of simple structure, few calculation parameters, fast training speed, and good generalization performance (Xu et al. 2019). Compared with the traditional neural networks, especially the single hidden layer feedforward neural networks (SLFNS), the limit learning machine is faster than the traditional learning algorithm on the premise of ensuring the learning accuracy.

Fig. 4 Road map of carbon emission reduction assessment model



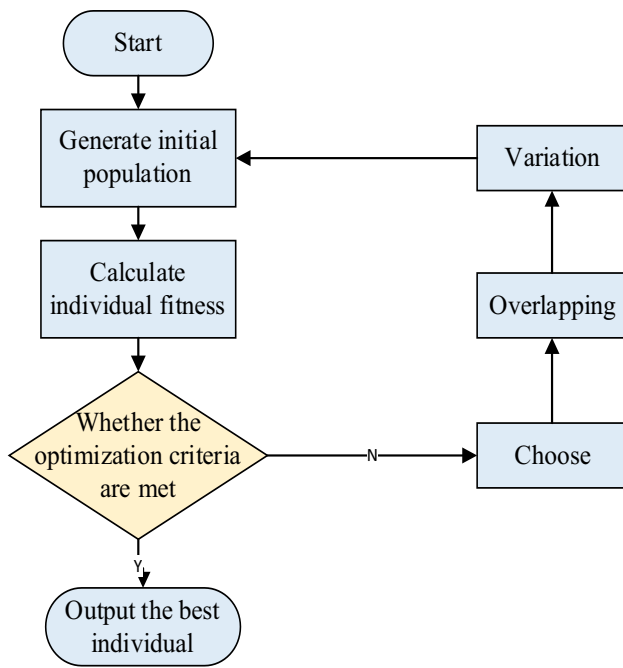


Fig. 5 Basic flow chart of genetic algorithm

Suppose there are N training samples (x_i, y_i) , input data $x_i = [x_{i1}, x_{i2} \dots x_{im}]^T$, and the expected output is $y_i = [y_{i1}, y_{i2} \dots y_{im}]$, that is, there are m neuron nodes in the input layer and n neuron nodes in the output layer. Let the hidden layer have l nodes, ω_{ij} represents the weight of the input layer node i and the output layer node j , and b_l represents the threshold of the hidden layer node l , both of which are randomly generated. If β_{ij} is taken as the connection weight between the hidden layer i and the output layer j , $g(\bullet)$ is the activation function, and the two are adjustable objects, the actual output y' can be expressed as

$$y'_j = \sum_{i=1}^l \beta_i \cdot g(\omega_i \cdot x_i + b_i), j = 1, 2, \dots, n \tag{7}$$

The model can be expressed as

$$H \cdot \beta = T \tag{8}$$

H is the output of the hidden layer node, β is the output weight, and T is the expected output.

Among

$$H = \begin{pmatrix} g(\omega_1 x_1 b_1) & \dots & g(\omega_1 x_1 b_1) \\ \vdots & \ddots & \vdots \\ g(\omega_1 x_N b_1) & \dots & g(\omega_1 x_N b_1) \end{pmatrix} \tag{9}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix}, T = \begin{bmatrix} y_1^T \\ \vdots \\ y_N^T \end{bmatrix} \tag{10}$$

The output weight β can be determined accordingly

$$\beta^* = H^+ \cdot T \tag{11}$$

H^+ is the Moore Penrose generalized inverse of the matrix. It can be proved that the norm is the smallest and unique.

Implementation process of GA-ELM algorithm

- (1) Setting of genetic algorithm parameters: the initial parameters of genetic algorithm include population number, crossover probability, mutation probability, chromosome length, selection rules, maximum iteration times, etc., different parameter combinations will have a great impact on the optimization results. For example, the number of populations will affect the calculation rate and the potential to produce better solutions, and the crossover probability and mutation probability will affect the transmission of excellent genes.
- (2) Population initialization: determine the neural network topology of ELM, including the number of input and output nodes of the prediction model, and set the number of hidden layer nodes; the weight matrix and threshold of ELM neural network are randomly generated and binary coded to form the chromosome of the initial population.
- (3) Individual fitness calculation: for each individual of each generation of population, ELM algorithm is used to obtain the output matrix, and the second norm of the difference between the calculated result and the expected matrix is used as the individual fitness.

The formula is

$$E = \sqrt{\sum_{i=1}^n (y'_i - y_i)^2} \tag{12}$$

n is the number of samples, y'_i is the predicted value obtained from ELM training, and y_i is the sample data. The smaller the objective function is, the regression fitting error will be smaller, and the fitness will be higher.

- (4) Population iteration: the roulette method is used to select the cross population. All individuals in each generation will have a certain probability of variation and genotype change, which is conducive to a better solution. The optimal solution of each generation is recorded in the population iteration process. When the

maximum number of iterations is reached, the optimal value in the optimal solution of each generation is the final prediction result.

- (5) Advantages of GA-ELM model: the neural network input parameters of elm are optimized through the process of genetic algorithm, including structural parameter optimization and weight threshold parameter optimization. On the basis of genetic algorithm, it can improve the accuracy of elm output prediction value, so as to achieve better prediction effect, and provide a basis for the subsequent assessment of carbon emission reduction contribution by scenario.

Monte Carlo simulation

Monte Carlo method, also known as random simulation method, key is to generate random numbers that obey a certain distribution. The basic principle is as follows.

Let the cumulative frequency function of the random variable be X , and the latter $F_X(x)$ is the random variable defined on $(0,1)$, which is recorded as U , and its cumulative frequency function is

$$F_U(\alpha) = P\{U \leq \alpha\} = P\{X \leq F^{-1}(\alpha)\} = F_X F_x^{-1}(\alpha) = \alpha \tag{13}$$

where F_x^{-1} is the inverse function of F_x because

$$F_U(\alpha) = \alpha \tag{14}$$

The description U is subject to uniform $(0,1)$ distribution. As long as a random number α evenly distributed on $(0,1)$ is generated, a value of the random variable X can be obtained

$$X = F_x^{-1}(\alpha) \tag{15}$$

On the basis of the above principle, a hypothetical function $Y = f(x_1, x_2, \dots, x_n)$ is set, in which the probability distribution of variables is x_1, x_2, \dots, x_n . A set of random variable values $x_{1i}, x_{2i}, \dots, x_{ni}$ are obtained by generating random numbers, and the value y_i of the function Y is obtained from the corresponding relationship.

$$y_i = f(x_{1i}, x_{2i}, \dots, x_{ni}) \tag{16}$$

A set of function Y values y_1, y_2, \dots, y_n can be obtained by repeating multiple independent sampling. When the simulation times are enough, the probability distribution of the function Y can be obtained approximately. Therefore, paying attention to the selection of probability distribution of random variables is the key to Monte Carlo simulation.

The implementation process of Monte Carlo simulation is as follows.

- (1) Identify the probability distribution of key influencing factors from 2003 to 2019 as the basis of Monte Carlo simulation.
- (2) Set the interval value of each influencing factor according to the planning value of influencing factors and the change law of historical data.
- (3) Set the scenario according to the interval value combination of different influencing factors.
- (4) According to the scenario, the values of influencing factors are substituted into the GA-ELM model for calculation, and the corresponding prediction value interval is obtained.
- (5) Carry out carbon emission reduction contribution assessment according to scenarios according to the predicted value range.

Validation

GA-ELM model training

Combined with the relevant data of carbon emission reduction contribution of State Grid Corporation of China from 2003 to 2019, this paper is divided into 17 samples per year. Because the number of data samples is less than 20, the leave one out cross validation method is used to divide the original samples into training set and test set, and replace them into GA-ELM model for training. One sample is selected as the test set and other samples as the training set for 17 times. Calculate the model prediction and evaluation indexes RMSE, MAPE, and Mae after each division. Of which,

RMSE is root mean square error

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \tag{17}$$

MAPE is mean absolute error

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right| \tag{18}$$

MAE is mean absolute error

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \tag{19}$$

The range of evaluation indexes is $[0, +\infty)$, which is equal to 0 when the predicted value is completely consistent with the real value; the greater the error, the greater the evaluation index value.

The calculation results of model training prediction and evaluation indicators are shown in Table 2.

Table 2 Calculation of prediction and evaluation indexes

Test set S/N	RMSE	MAPE	MAE
1	2.317193	0.357813	2.315615
2	1.295339	0.313542	1.159566
3	3.782085	0.03289	3.782001
4	3.113254	0.008745	2.825851
5	3.040492	0.017905	2.635209
6	6.095427	0.021399	6.069361
7	2.981327	0.008311	2.742712
8	1.895883	0.01402	1.773419
9	6.684465	0.192899	6.045269
10	1.376654	0.013619	1.104589
11	9.296619	0.172793	8.799222
12	32.58407	0.0993	29.19733
13	27.2893	0.082711	21.80134
14	18.84218	0.185172	13.27881
15	19.16411	0.10642	15.35119
16	114.4797	0.057287	83.28221
17	79.3367	0.045019	66.28528
Average	19.62205	0.101756	15.79112

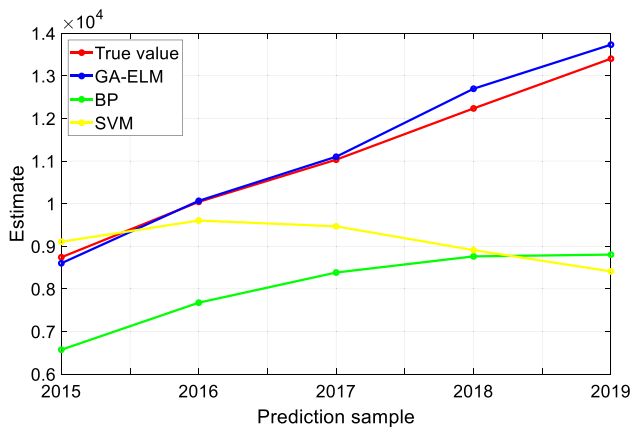


Fig. 6 Comparison of learning accuracy of three prediction models

It can be seen from Table 1 that the average values of RMSE and Mae after training with the leave one cross validation method are less than 20, and the average value of MAPE is less than 1, which can meet the error standard. The current model can be used to predict the contribution value of carbon emission reduction of power grid enterprises in the future.

In order to highlight the prediction accuracy of the model, this paper compares the prediction accuracy of the model with the prediction results of traditional BP neural network,

support vector machine model, and limit learning machine model. The results are shown in Fig. 6.

The fitting accuracies R^2 of three models are 0.9973, 0.8796, and 0.4724.

Therefore, the GA-ELM model has higher accuracy and reliability. The current model can be used to predict the contribution value of carbon emission reduction of power grid enterprises.

Carbon emission reduction contribution assessment

This paper uses the crystal ball plug-in to identify the probability distribution of the historical data of 13 key influencing factors in Excel as the basis of Monte Carlo simulation.

According to the planning value of influencing factors and the change law of historical data, four scenarios are set: control type, enhanced line loss reduction type, enhanced consumption of clean energy type, and enhanced electric energy substitution type.

Scenario 1 is a control type, which is a normal development trend without intervention of other policy factors in the future obtained by analyzing the historical data of influencing factors, and is used to form a control with the latter three scenarios.

Scenarios 2, 3, and 4 are to strengthen the three sub-indicators of carbon emission reduction contribution, respectively, adjust the interval value of key influencing factors of the sub-indicators, keep the other influencing factors unchanged, and generate the enhanced interval value combination of influencing factors. Taking scenario 2 as an example, based on the interval value of control influencing factors, the value interval of power grid line loss is reduced according to the lower confidence limit of crystal ball plug-in predictor by 5%, and the value interval of high-voltage transmission line length and high-voltage transformer availability factor is increased according to the upper confidence limit of predictor by 5%, so as to obtain the interval value combination of enhanced line loss influencing factors.

The interval values of each influencing factor are set as shown in Table 3.

Carbon emission contribution prediction and assessment analysis

Four groups of random numbers of influencing factors in 2000 are generated from the change interval of influencing factors in four scenarios as the input value of GA-ELM model. The trained GA-ELM model is used to predict the contribution of carbon emission reduction and sort out the output results. The predicted value ranges corresponding to the change ranges of different influencing factors under the four scenarios are shown in Table 4.

Table 3 Interval values of influencing factors in four scenarios

	Control type	Strengthen and reduce line loss type	Strengthen the consumption of clean energy	Enhanced electric energy substitution
Grid line loss/ 10^8 kWh	[3001.3,3079.9]	[2149.5,2834.6]	[3001.3,3079.9]	[3001.3,3079.9]
Length of high voltage transmission line/km	[577,389.5,679,833.9]	[584,772.6,693,605.8]	[577,389.5,679,833.9]	[577,389.5,679,833.9]
Availability factor of high voltage transformer/%	[99.82,99.84]	[99.92,99.99]	[99.82,99.84]	[99.82,99.84]
Unified regulation of maximum power load/ 10^4 kW	[95,079.6,114,331.8]	[95,079.6,114,331.8]	[98,053.8,117,693.4]	[95,079.6,114,331.8]
Hydropower installation/ 10^4 kW	[23,150.2,24,133.04]	[23,150.2,24,133.04]	[23,631.9,27,705.7]	[23,150.2,24,133.04]
Hydropower generation/ 10^8 kWh	[8364.2,9341.4]	[8364.2,9341.4]	[8842.1,10,765.2]	[8364.2,9341.4]
Wind power installation/ 10^4 kW	[19,253.9,28,356.8]	[19,253.9,28,356.8]	[20,131.6,35,046.1]	[19,253.9,28,356.8]
Wind power generation/ 10^8 kWh	[3467.6,4730.9]	[3467.6,4730.9]	[3630.1,5935.5]	[3467.6,4730.9]
Nuclear power installation/ 10^4 kW	[3264.8,4375.1]	[3264.8,4375.1]	[3542.6,5628.8]	[3264.8,4375.1]
Nuclear power generation/ 10^8 kWh	[2412.9,3621.9]	[2412.9,3621.9]	[2530.13,4342.97]	[2412.9,3621.9]
Proportion of secondary production/%	[63.04,67.32]	[63.04,67.32]	[63.04,67.32]	[67.42,68.19]
Proportion of tertiary industry/%	[16.76,20.86]	[16.76,20.86]	[16.76,20.86]	[17.30,24.02]
Asset liability ratio/%	[55.81,56.07]	[55.81,56.07]	[55.81,56.07]	[58.96,64.20]

Table 4 Prediction range of carbon emission reduction contribution

Scenario type	Prediction range of carbon emission reduction contribution/ 10^4 t
Control type	[16,629.24,24,491.95]
Strengthen and reduce line loss type	[16,142.30,24,711.69]
Strengthen the consumption of clean energy	[15,515.10,27,497.82]
Enhanced electric energy substitution	[16,850.51,27,424.04]

The fitting distribution of 2000 carbon emission reduction contribution predicted value output by each scenario with crystal ball plug-in is shown in Fig. 7 (the unit of all carbon emission reduction contributions in the figure is 10^4 t).

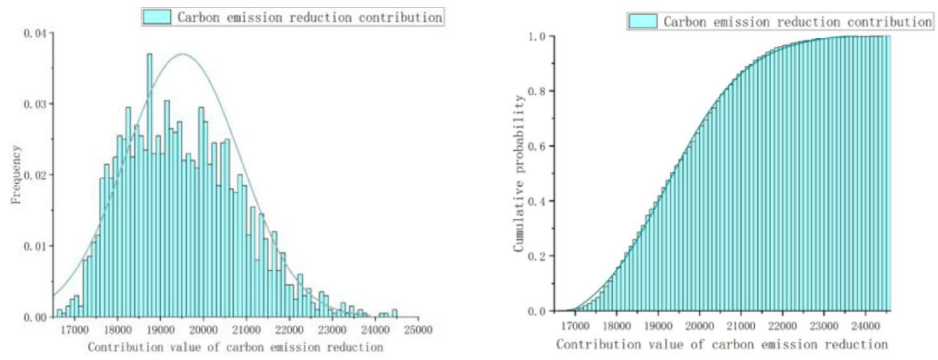
Due to the large deviation of the output results of a small number of predicted values, the predicted values with a cumulative probability of 10–90% are selected as the effective predicted values. The filtered predicted value range is shown in Table 5.

Comparing the predicted value of carbon emission reduction contribution of the four scenarios, it can be seen that since the consumption of clean energy currently accounts for a large part of the contribution to carbon emission reduction, the predicted value range reflects that the carbon emission reduction contribution of the development model of strengthening the consumption of clean energy is the highest. In addition, adopting the development mode of strengthening power substitution can also bring considerable contribution to carbon emission reduction. According to the future development trend, without considering the introduction of new policies and changes in the development mode of power grid companies, the control impact factor interval value and GA-Elm model are

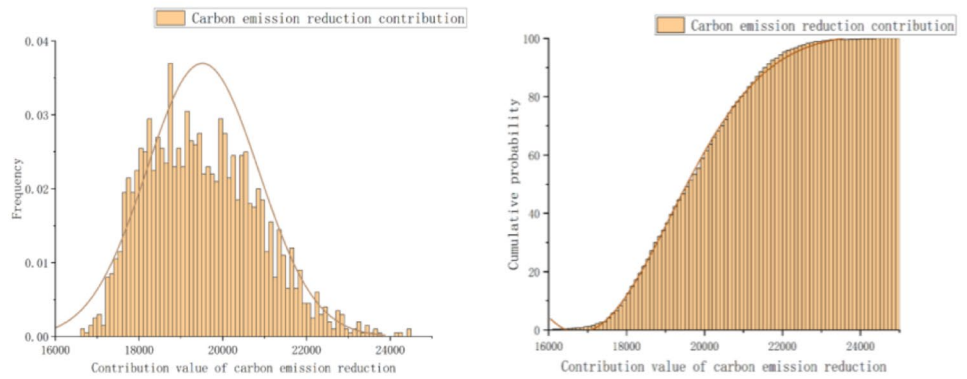
used to predict the carbon emission reduction contribution index in the next 5 years, and the predicted average value is 20101.4×10^4 t. As shown in Fig. 8, in each scenario, the cumulative probability of exceeding the predicted value is 32.6%, 38.3%, 69.8%, and 59.8%, respectively. It can also be concluded that the development model of strengthening the consumption of clean energy and strengthening the substitution of electric energy can better achieve the contribution index of carbon emission reduction in the future.

Adopting the development mode of strengthening clean energy consumption is the future development direction of power grid enterprises most advocated in the text. Under this mode, it can maximize the carbon emission reduction capacity of power grid enterprises, and be in an active and advantageous position in the future carbon emission reduction development planning goals. For power grid enterprises, in addition to pursuing the economic benefits of enterprise development, they also need to pay attention to the social and environmental benefits brought by the development process. Therefore, combined with MCS-GA-ELM power grid enterprise carbon emission reduction contribution assessment under various scenarios, it can provide

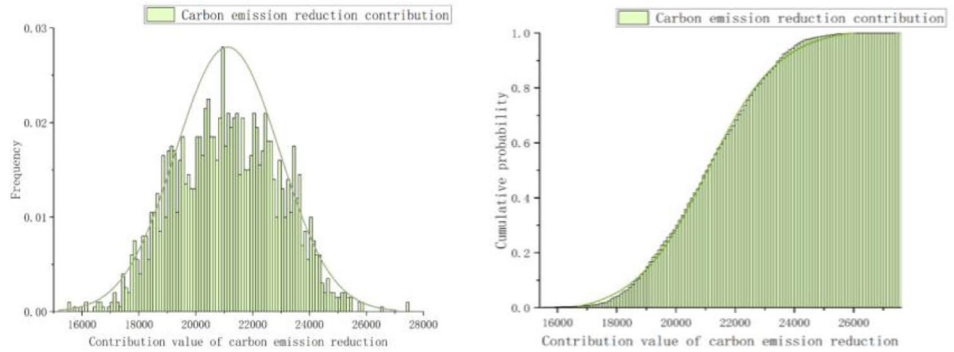
Fig. 7 Fitting distribution of predicted value of carbon emission reduction contribution



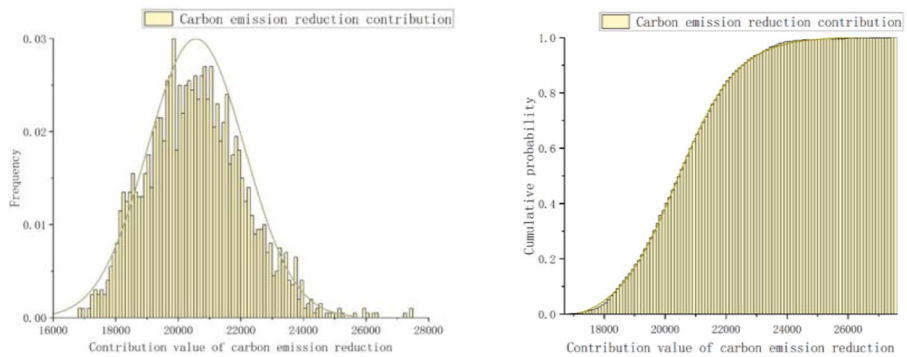
a) Distribution fitting diagram of control prediction results



b) Distribution fitting diagram of strengthen reduce line loss type prediction result



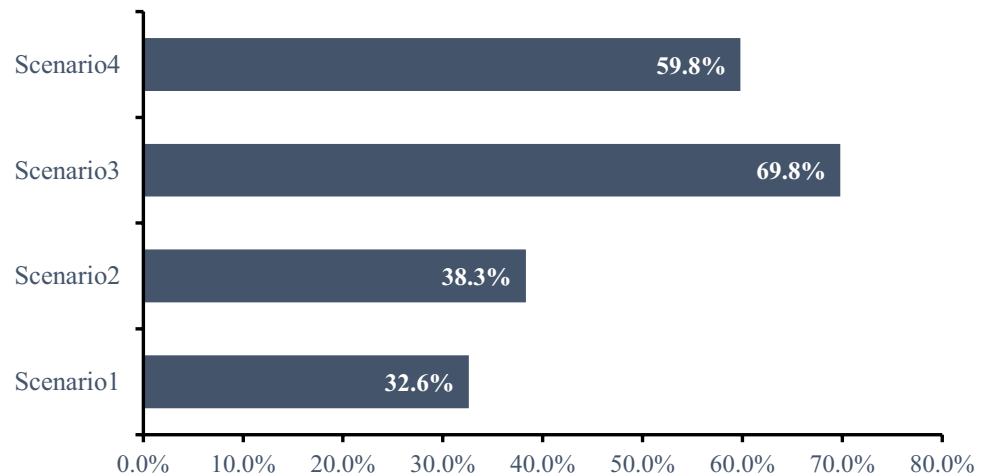
c) Distribution fitting diagram of prediction results of enhanced consumption of clean energy



d) Distribution fitting diagram of strengthen electric energy substitution prediction results

Table 5 Prediction range of carbon emission reduction contribution after screening

Scenario type	Prediction range of carbon emission reduction contribution/10 ⁴ t
Control type	[17,854.20,21,329.82]
Strengthen and reduce line loss type	[17,982.42,21,596.79]
Strengthen the consumption of clean energy	[18,738.90,23,527.22]
Enhanced electric energy substitution	[18,550.85,22,593.92]

Fig. 8 Probability of achieving carbon emission reduction contribution targets in four scenarios

new research ideas for the future comprehensive development and strategic layout of power grid enterprises.

Compared with previous studies on carbon emission reduction, the new concept of carbon emission reduction contribution proposed in this paper is used to study power grid enterprises to explore their future development path in response to the dual carbon goals proposed by the state, and opens up a new research direction from the perspective of power grid enterprises. It has great innovative value in theory and application prospects.

Conclusion

In this paper, GA-ELM model is used to predict the contribution value of carbon emission reduction under various scenario development modes in the future. The prediction error is reasonable, and different scenario development modes are evaluated according to the results.

This paper has the following suggestions for the development of power industry in the future:

- (1) In the future development of China's power industry, the scale of clean energy power generation will gradually expand. In the scenario of strengthening clean energy consumption, the corresponding power

grid enterprises contribute the most to carbon emission reduction in all scenarios. Therefore, we should first vigorously develop clean energy power generation, increase investment in clean energy power generation, and increase the proportion of clean energy power generation in the total power generation. For example, time of use tariff is adopted to improve the demand of users for clean energy power generation, vigorously develop energy storage technology, and enhance the consumption capacity of clean energy power generation.

- (2) Due to strengthening the reduction of line loss, the contribution of power grid enterprises to carbon emission reduction is not significantly higher than that of the control. It is suggested to maintain the current line loss rate level and ensure the power supply reliability of the current scale power generation level.
- (3) As the contribution of strengthening the electric energy substitution scenario to the carbon emission reduction of power grid enterprises is significantly higher than that of the control scenario, it is suggested to use the increased clean energy power generation as an alternative energy for some fossil fuel energy, such as vigorously developing coal to electricity, accelerating the construction of electric vehicle network, and striving to achieve a higher level of electric energy substitution and emission reduction.

The above suggestions have certain reference significance for the future investment direction, management mode, and production mode of China's power grid enterprises. In the future development and construction of power grid enterprises, it is an inevitable trend to carry out the updating and upgrading of power generation technology and implement the reform of power grid policies. On the basis of this paper, we can continue to carry out research on the field of strengthening clean energy consumption and carbon emission reduction of power grid enterprises, and we can also study new carbon emission reduction contribution management mode on the basis of new historical data changes.

In the future, with the introduction of further control measures taken by China on carbon emission reduction, the structure of multi-energy power generation will be further adjusted; combined with the impact of COVID-19 on the world's energy development, new development trends will appear on the basis of existing historical data. The model needs to predict the contribution value of carbon emission reduction more accurately according to the new data obtained in the future and provide more valuable development models and strategies. There are more development models for the contribution of carbon emission reduction. This paper only lists four, and there are other development models with better effects to be further explored.

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Data availability The data used in the current research can be obtained from the energy statistical yearbook and the social responsibility report of power grid enterprises.

Declarations

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