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Linghan Xu, Jiaqi Zhang, Qiuhui Zhang, Xinxing Zhou, Shanshan Yu

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A peak carbon emission prediction method for enterprises based on IoT blockchain and grey neural network

Linghan Xu*, Jiaqi Zhang, Qiuhui Zhang,
Xinxing Zhou and Shanshan Yu

Guangzhou Power Supply Bureau of
Guangdong Power Grid Co., Ltd.,
Guangzhou, 510000, China
Email: xulinghan1995@163.com
Email: 18022322234@163.com
Email: 99774292@qq.com
Email: 331999673@qq.com
Email: 86706990@qq.com

*Corresponding author

Abstract: In order to solve the problems of low accuracy and poor carbon emission potential of traditional enterprise carbon emission peak prediction methods, this paper proposes an enterprise carbon emission peak prediction method based on a combination model of the internet of things (IoT), blockchain, and grey neural network. Firstly, use IoT technology to obtain carbon emission data of enterprises. Secondly, use the blockchain carbon trading model to analyse the factors affecting corporate carbon emissions. Then, with the help of a grey prediction model, the predicted carbon emissions of the enterprise are obtained through cumulative reduction. Finally, the grey neural network combination model is used to predict the peak carbon emissions of enterprises by taking cumulative emissions as input. The experimental results show that the accuracy of the carbon emission peak prediction method in this article can reach 99.9%, which can effectively improve the prediction effect of enterprise carbon emission peaks.

Keywords: carbon trading model; grey prediction model; internet of things blockchain; BP neural network; cumulative reduction.

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Biographical notes: Linghan Xu received her Master's degree in Computer Science from South China University of Technology. She is engaged in the research, construction and operation of marketing domain informatisation and digital technology of power supply enterprises. She is responsible for the formulation and implementation of marketing domain solutions, responsible for the digital support of modern power supply service systems, and have rich experience in carbon monitoring and carbon tracking, new energy-related digital landing and research.

Jiaqi Zhang received her Master of Computer Science from South China University of Technology. She has been engaged in the research, planning, construction and operation of informatisation and digital technology of power

supply enterprises for a long time. She participated in the construction, implementation and promotion of the fourth-generation management information system of Guangzhou Power Supply Bureau. She also participated in the formulation and pilot construction of the digital distribution network, and took the lead in the digitalisation of the whole technical landing support. She is responsible for the formulation and implementation of marketing domain solutions, focusing on the digital solution planning of new policies and innovative requirements.

Qihui Zhang is an undergraduate majoring in Electrical and Automation from Huazhong University of Science and Technology. She has been engaged in the research, planning, construction and operation of informatisation and digital technology of power supply enterprises for a long time. He participated in the construction, implementation and promotion of the fourth-generation management information system of Guangzhou Power Supply Bureau.

Xinxing Zhou received his Bachelor's degree in Network Engineering from Guangdong University of Technology. He has been engaged in the informatisation and digital construction of power supply enterprises for five years, and is responsible for the digital transformation of the marketing domain of Guangzhou Power Supply Bureau. He participated in the construction and promotion of the digital power grid 4321 in the Guangzhou Power Supply Bureau; participate in the development of the digital solution of the market domain of the Guangzhou Power Supply Bureau; and is responsible for the implementation, promotion and application of the plan.

Shanshan Yu received her Master's degree in Computer Science from South China University of Technology. She is engaged in the digital construction of the marketing domain of power supply enterprises. She participates in the construction and promotion of digital services of Guangzhou Bureau, and promotes the digital transformation of power supply enterprises.

1 Introduction

Many countries have established carbon emission control policies, and companies need to reduce carbon emissions in accordance with regulatory requirements. Predicting peak carbon emissions can help companies comply with relevant regulations (Liu et al., 2022; Zhang et al., 2023; Li and Dai, 2023). Based on the internet of things (IoT) technology, it is possible to monitor the carbon emission data generated by various activities of enterprises in real time, thereby providing support for detailed and targeted carbon emission management of enterprises. Blockchain technology bolsters the credibility of carbon emission data. By combining historical carbon emission data and other influencing factors, the grey neural network can accurately predict future carbon emission peaks and provide a scientific basis for enterprise decision-making (Zhang et al., 2022). In summary, research on enterprise carbon emission peak prediction based on the IoT, blockchain, and grey neural network can help enterprises improve environmental awareness, promote sustainable development, strengthen management and compliance, and also contribute to further exploration and development in the field of carbon emission prediction in the academic community (Li and Zhou, 2023).

Ji et al. (2022) and others proposed a peak carbon emission prediction method for enterprises based on 4E balance, collecting historical carbon emission data of enterprises and combining economic indicators such as production scale, sales revenue, and profit. Analyse the correlation between carbon emissions and corporate economic indicators, establish an economic model to predict future carbon emission trends, use environmental monitoring data, climate change and other information, and consider the impact of external environmental factors on carbon emissions. Research the impact of social factors such as employee welfare, social responsibility, and employee training on carbon emissions in enterprises. But this method has poor prediction accuracy. Lv et al. (2023) proposed a scenario analysis based method for predicting the peak carbon emissions of enterprises, which formulates multiple different scenarios, such as high carbon emissions, low carbon emissions, business expansion, etc., to reflect possible future development paths. Collect historical carbon emission data of enterprises, as well as historical data on relevant situational factors. Clean and process data to ensure accuracy and availability. Based on the collected data, establish a statistical model for carbon emissions and predict future peak carbon emissions. However, this method has a lower prediction root mean square error. Cheng et al. (2023) proposed a peak carbon emission prediction method for enterprises based on Lasso GA-SVR, collecting historical carbon emission data of enterprises and relevant influencing factor data, such as production indicators, energy consumption, etc. Clean and normalise the data to ensure its quality and availability. Use Lasso regression algorithm for feature selection, penalise the objective function, and select variables that have a significant impact on carbon emissions. Use principal component analysis dimensionality reduction techniques to reduce the number of variables. Use genetic algorithm (GA) to optimise the parameters of support vector regression (SVR) and determine the optimal kernel function, penalty parameters, etc. Design appropriate fitness functions and operational strategies such as crossover and mutation based on problem requirements and algorithm effectiveness. Use the optimised SVR model to predict the peak carbon emissions of enterprises based on historical data and selected feature variables. Train and validate the model using both training and validation sets to evaluate its fit and generalisation ability. Based on the established model, predict future peak carbon emissions, but the predicted average absolute percentage error (MAPE) decreased.

In response to the above issues, this article proposes a method for predicting the peak carbon emissions of enterprises based on the IoT blockchain and grey neural network. The detailed research plan for this method is as follows:

- 1 Based on official data such as the China Energy Statistical Yearbook from 2000 to 2019, a unified price benchmark and specific methods are used to process corporate carbon emissions data. Real time monitoring and abnormal analysis of corporate carbon emissions data are achieved through IoT technology.
- 2 Based on the collected enterprise IoT data, a carbon trading model was designed using the Hyperledger Fabric platform to analyse the influencing factors of enterprise carbon emissions.
- 3 Build a combination model based on grey theory and neural network to predict the peak carbon emissions of enterprises. This model utilises grey theory to process incomplete data, while neural networks enhance their ability to fit and learn complex carbon emission data. Through this combination, the model can improve the

accuracy and reliability of predictions, assist enterprise managers in formulating effective emission reduction strategies, promote sustainable development and environmental protection.

2 Construction of carbon trading model based on IoT blockchain

2.1 Collection and processing of enterprise carbon emission data

Based on the availability of data and the consistency of statistical measures, this article selects data from 2000 to 2019, all of which are from the China Energy Statistical Yearbook, China Industrial Economic Statistical Yearbook, China Industrial Statistical Yearbook, and China Statistical Yearbook. The data related to prices are converted to comparable prices in 2000, and the industry gross domestic product and per capita gross domestic product are calculated using the industry factory price index. It should be noted that the industrial output value from 2000 to 2007 was obtained from the China Industrial Statistical Yearbook, and the data from 2008 to 2019 was calculated using the year-on-year growth rate of industrial added value published by the National Bureau of Statistics. The employment figures in the industry were measured by the average number of employees in large and medium-sized industrial enterprises from 2000 to 2013, and by the average number of workers in large and medium-sized industrial enterprises from 2014 to 2019. The consumption of coal needs to be converted into standard coal using the conversion coefficient. Partial missing values are filled in using the median of the previous and subsequent years (Dai et al., 2023). The variable description and source are shown in Table 1.

Table 1 Variable description and source

<i>Variable</i>	<i>Describe</i>	<i>Data sources</i>
Carbon emissions (CE)	Carbon emissions from various industries	China Energy Statistical Yearbook
Industry employment (EMP)	End of year employment in various industries	China Energy Statistical Yearbook
Urbanisation (URB)	National urbanisation rate	China Statistical Yearbook
Industry scale (ind)	Industry year-end gross domestic product	China Industrial Statistical Yearbook
Per capita gross domestic product (PGDP)	The gross domestic product of an industry divided by the number of employees in that industry at the end of the year	China Industrial Statistical Yearbook
Energy consumption (EC)	Total consumption of various energy sources in various industries	China Energy Statistical Yearbook
Energy intensity (EI)	Total energy consumption by industry divided by industry GDP	China Energy Statistical Yearbook
Coal proportion (ES)	Coal consumption by industry divided by industry energy consumption	China Energy Statistical Yearbook

The steps to process the collected carbon emission data of enterprises through IoT technology are as follows:

- 1 Deploy sensors within the enterprise to monitor the operational status of devices.
- 2 Transfer the data collected by sensors to the data centre through wireless or wired networks.
- 3 Establish a data processing system in the data centre to analyse real-time carbon emission data, monitor whether the data exceeds the normal range through preset thresholds or models, and identify potential abnormal situations.

2.2 Functional design of carbon trading model based on blockchain

The advantage of designing carbon trading models based on blockchain lies in its decentralised nature, allowing enterprises to directly engage in transactions, reducing intermediary costs and time delays. The invariance of blockchain ensures the immutability of transaction records, enhances the credibility of data and the reliability of auditing, and helps to ensure the compliance and transparency of carbon trading. The transparency of blockchain makes all transactions publicly accessible, facilitating supervision by regulatory agencies, enterprises, and the public, promoting the fairness of the carbon market, and encouraging enterprises to manage carbon emissions responsibly. The automatic execution function of smart contracts reduces the risk of human error and fraud, and improves transaction efficiency. These characteristics work together, making blockchain technology very advantageous in analysing factors that affect corporate carbon emissions. Invariance ensures the authenticity of historical data, facilitates the identification of trends and anomalies, transparency promotes data sharing and comparative analysis, and helps enterprises and regulatory agencies develop more effective emission reduction strategies and policies.

This article is based on the Hyperledger Fabric platform to design a carbon trading model. The data storage in Fabric consists of four databases, namely IdStore, stateDB, historyDB, and blockIndex (Teng et al., 2022; Zhen et al., 2022; Wu et al., 2023). According to the design of the model, data storage mainly involves stateDB and historyDB. StateDB represents the latest state of data storage, also known as the ‘world state’. HistoryDB represents the storage version changes caused by each transaction, recording the changes involved after each transaction is written into the blockchain. The storage of data adopts a key value database, which is stored in the form of an array, with each key corresponding to a set of values. The specific properties and functions in the array are shown in Table 2.

Blockchain is a decentralised trading model without exchanges acting as intermediaries. Each trading enterprise is directly connected to each other, as well as to each financial institution, and transactions can be conducted directly through smart contracts. Direct transactions between emission emitting enterprises and carbon finance loan transactions between enterprises and financial institutions. This can reduce the coordination and operational costs brought by transaction intermediaries. The functions of the model are shown in the following section.

Table 2 Data structure table

<i>Attribute</i>	<i>Definition of variables</i>
<i>Properties related to carbon trading</i>	
Carbon asset number	Carbon asset number
Enterprise ID	The primary key of the enterprise□
Enterprise type	Emission enterprises or financial institutions□
Quotation	Present the price at the time of the transaction
Transaction quantity	Set the quantity of a single transaction to 100 tons
Acceptable price range 1	The threshold for satisfaction=0
Acceptable price range 2	A threshold of satisfaction=1
transaction type	Purchase or sell carbon credits
Does the buyer take out a loan	Apply for loan or not apply for loan
Loan duration	The length of time from application to repayment
Actual payer	Buyer's enterprise or financial institution
<i>Information</i>	
Enterprise size	Enterprise size
Income cost ratio of financial institutions	Revenue/Total Operating Costs
Proportion of fixed assets of enterprises	Sum of assets, plant and equipment/total assets
Loan ceiling	The upper limit of loan applications based on mortgaged carbon quota information
Payable quantity	The amount that financial institutions should pay on behalf of enterprises
Total debt of the enterprise	The number of outstanding loans in previous loan transactions by the enterprise

2.2.1 Carbon quota allocation

The relevant government departments allocate the annual carbon quota to enterprises at the beginning of each year. As they allocate quotas to each enterprise, smart contracts automatically monitor whether the enterprise owes any loans to financial institutions. If there is no outstanding debt, the relevant department will allocate the intended amount to the enterprise (Liu et al., 2023). If there is a debt, the relevant department will allocate the carbon quota equivalent to the principal and interest of the debt to the corresponding financial institution, and then allocate the remaining carbon quota to the enterprise.

2.2.2 Carbon trading

Each enterprise proposes a demand for purchase or sale, and the smart contract executes a transaction matching algorithm for the enterprise. Firstly, with the goal of maximising the matching quantity, high-quality bidding buyers and sellers are matched. Then, with the goal of maximising the total satisfaction, match other buyers and sellers to increase the number of matching pairs and increase the number of transactions (Li et al., 2023).

2.2.3 *Carbon finance*

Carbon finance solves the problem of loan difficulties for buyer enterprises. The buyer enterprise chooses whether to apply for financing loans when proposing a purchase demand. The financing loan method is to apply for a loan with the company's carbon futures as collateral. If applying for a loan, you also need to provide the minimum loan duration and maximum loan interest rate. Perform carbon finance loan matching through smart contracts, aiming to maximise overall satisfaction by matching buyer enterprises with financial institutions. When matching, the smart contract first needs to determine whether the interest rate and loan duration proposed by the financial institution meet the requirements, and then check whether the enterprise has sufficient loan limits. If the conditions are met, matching will be performed.

2.2.4 *Repay the loan*

When the repayment date of the enterprise loan expires, the smart contract is executed to transfer the principal and interest owed by the borrower's enterprise to the financial institution. If the borrower's enterprise lacks funds, the smart contract will record the amount of debt owed by the enterprise and transfer the collateral to the financial institution that provided the loan.

2.3 *Construction of carbon trading model*

There are three types of members in the blockchain based carbon trading model, namely seller enterprises, buyer enterprises, financial institutions, and relevant government departments. Buyer and seller enterprises refer to carbon emitting enterprises in various industries (Hu et al., 2022). In the model, each emission enterprise is directly connected to each other, as shown in the dashed box, and peer-to-peer transactions can be directly executed by smart contracts. Financial institutions include banks and other enterprises that can provide loan services to enterprises. Each financial institution is directly connected to each emission enterprise, and each financial institution can conduct carbon trading and carbon finance loan transactions with each emission enterprise. The relevant government departments refer to the national agencies responsible for the operation of carbon trading in China, which are directly connected to emission enterprises and financial institutions. The trading system is open, and every enterprise can easily and freely join the blockchain carbon trading system, as shown in Figure 1.

According to the chronological order, the action sequence of each member in the model is as follows:

- 1 Enterprise registration. Enterprises input their true information into the blockchain system, with specific attributes including: enterprise size and profitability. Most of this information is applicable to enterprises applying for financing loans.
- 2 The relevant government departments allocate carbon quotas to enterprises. Determine the carbon quota for the current year based on the emission situation of the enterprise in previous years. Before allocation, check whether the enterprise has matured carbon futures assets that have been mortgaged to financial institutions. If so, allocate the carbon quota with the same value as the principal and interest of the

debt to the corresponding financial institution. If not, allocate all the carbon quotas to the enterprise.

- 3 Enterprises apply for transactions. Enterprises determine whether they are sellers or buyers based on their own needs, and then submit transaction applications. If it is the seller, the enterprise uploads information such as the selling quantity, bid price, and acceptable transaction price range. If it is the buyer, in addition to the same information as the seller, the buyer also needs to determine whether the transaction needs to apply for a loan and have the financial institution make the payment on their behalf. If applying for a loan, the enterprise also needs to provide relevant information such as the loan duration.
- 4 At the end of the loan term, the smart contract automatically transfers the principal and interest of the buyer's funds to the financial institution in arrears. If there is not enough funds in the buyer's account, the amount of debt will be recorded in the blockchain. When the government allocates carbon credits in the year of futures maturity, the carbon credits will be transferred in spot to financial institutions as collateral.

In addition to the above behaviours, each member in the model can also perform queries and other behaviours, such as using blockchain traceability to query the ownership change route of carbon assets, querying the number of carbon assets held by a certain enterprise, and querying the transaction information of a certain transaction. The specific behaviours of the members are summarised in Table 3.

Figure 1 Blockchain-based carbon trading model diagram

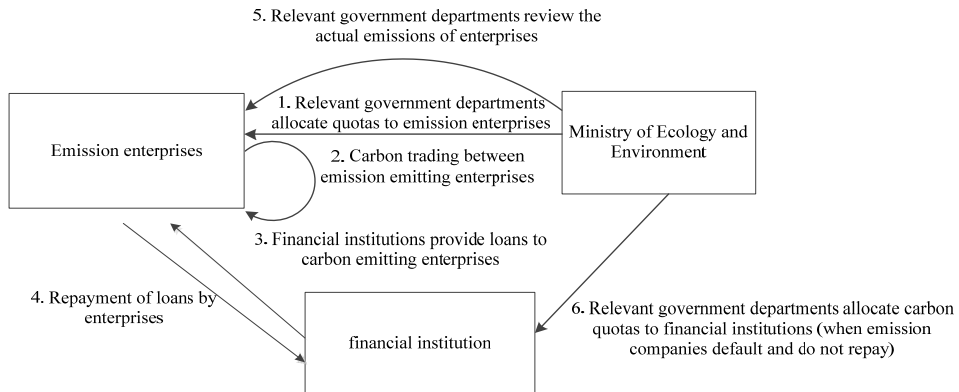


Table 3 Summary of member behaviours

Member		Behaviour
buyer	1	Present your own quotation and acceptable range of transaction prices during trading
	2	Query carbon asset information
seller	3	Inquire about the carbon information held by a certain enterprise
	4	Accept or reject transaction matching results
	5	Submitting or not submitting a loan application (buyer)

Table 3 Summary of member behaviours (continued)

<i>Member</i>		<i>Behaviour</i>
financial institution	1	Provide financial services to enterprises
	2	It is possible to sell the carbon credits held in the market, with specific actions following the seller's instructions.
Relevant government departments	1	Allocate carbon credits to enterprises
	2	Review the company's emissions at the end of each period

3 Prediction method for peak carbon emissions of enterprises based on the IoT and grey neural network

3.1 BP neural network

Due to the booming development of data, deep learning has been widely applied in various fields. Deep learning was conceived in the 1980s and has dominated in the past decade. The application of cloud computing has reduced training time for deep learning. In fields such as industrial automation, aerospace and national defence, medical research, autonomous driving, and electronic consumption, deep learning has more advantages than traditional machine learning. Deep learning is a multi-level representation method that primarily utilises artificial neural networks to achieve hierarchical structures.

Multi layer feedforward (BP) neural networks have excellent nonlinear classification and prediction capabilities. This model mimics the structure, function, and information processing of human brain activity, with many processing units connected together in different forms. Neural networks can process data on a large scale in parallel and are widely used in nonlinear problems. Usually, BP neural network models are combined with other optimisation algorithms to predict carbon emission trends.

Most grey prediction models are combined with scenario analysis methods to compare the carbon emission trends predicted by different technological scenarios. However, due to low prediction accuracy and long training time, it is easy to fall into local extremes. Therefore, this article improves the grey model through BP neural network to optimise the prediction results of enterprise carbon emissions peak. Using this method to predict the future trend of carbon peak in China's eight major industrial sectors is more accurate and expands the relevant research on carbon peak prediction.

3.1.1 Number of hidden layer nodes

Too few hidden layer nodes can lead to an increase in training times. The excessive number of hidden layer nodes leads to a decrease in training times, which makes it difficult for the neural network to learn well and affects training accuracy. The reference formula for selecting the optimal number of hidden layer nodes is as follows (1)–(3):

$$l < n - 1 \quad (1)$$

$$l < \sqrt{(m+n)} + \alpha \quad (2)$$

$$l = \log_2 n \quad (3)$$

Among them, n , l and m represent input layer nodes, hidden layer nodes, and output layer nodes, respectively. α is a constant between 0 and 10. The selection of hidden layer nodes is usually first determined by the above three formulas to roughly determine the range of node numbers. Then, using the trial and error method, the sizes of R_2 and MRSE are compared (R_2 is closer to ± 1 , better, RMSE is closer to 0, better), and finally the optimal number of nodes is determined.

3.1.2 Neural network algorithm process

The specific process of neural networks is as follows:

- Step 1 Network initialisation. Determine the input dimension based on the input sample, set the input layer and excitation function to $g(x)$, $g(x)$ as the Sigmoid function, and the expression (4):

$$g(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

- Step 2 Output of hidden layer and output layer

BP neural networks generally consist of three layers, namely input layer, output layer, and output layer. The number of nodes in the input layer, hidden layer, and output layer is set to Step 2: Output of hidden layer and output layer

BP neural networks generally consist of three layers, namely input layer, output layer, and output layer. The number of nodes in the input layer, hidden layer, and output layer is set to m , n , and s .

The output formula of the hidden layer is shown in equation (5):

$$H_k = f\left(\sum_{i=1}^m x_i \cdot w_{ik} - a_k\right) \quad (5)$$

Among them, $i = 1, 2, \dots, m$, $k = 1, 2, \dots, n$, and w_{ik} is the connection weight coefficient from the input layer to the hidden layer, and a_k is the bias.

The output formula of the output layer is shown in equation (6):

$$O_j = \sum_{k=1}^n (H_k \cdot w_{kj}) - b_j \quad (6)$$

Among them, $j = 1, 2, \dots, s$. w_{kj} is the connection weight coefficient from the hidden layer to the output layer, and b_j is its bias.

- Step 3 Calculate the error

Error refers to the difference between the output of the input layer and the expected output, as shown in formula (7):

$$e_j = O'_j - O_j \quad (7)$$

Among them, O'_j represents the expected output value, and O_j is the true value.

Step 4 Update weights

The weight update formula from the input layer to the hidden layer is shown in equation (8):

$$w_{ik} = w_{ik} + \theta H_k (1 - H_k) \cdot x_i \sum_{j=1}^s (w_{kj} \cdot e_j) \quad (8)$$

The threshold update formula from the hidden layer to the output layer is shown in equation (9):

$$w_{kj} = w_{kj} + \theta H_k \cdot e_j \quad (9)$$

Step 5 Update threshold

The threshold update formula from input layer to hidden layer is shown in equation (10):

$$a_k = a_k + \theta H_k (1 - H_k) \sum_{j=1}^s (w_{kj} \cdot e_j) \quad (10)$$

The threshold update formula from the hidden layer to the output layer is shown in equation (11):

$$b_j = b_j + e_j \quad (11)$$

Step 6 Determine the ending conditions.

If the error of e_j is within a reasonable range, the calculation will end.

Otherwise, the hidden layer and output layer will be recalculated, returning to step two.

3.2 Design of grey prediction model

The grey prediction model, also known as the GM model, can analyse small sample data through operations such as accumulation and subtraction, thereby mining the development laws of the predicted object and obtaining the predicted value of the predicted object. The GM (1, 1) model is the most commonly used model in grey systems.

Before using the grey prediction GM (1, 1) model to model corporate carbon emissions, the raw data is first subjected to a level comparison test. If the level comparison test fails, it indicates that the data sequence is not suitable for the grey prediction model. Grade ratio test is to observe whether the grade ratio of the original data is within the acceptable coverage range, and its calculation formula is as follows:

$$\lambda(i) = \frac{x^{(0)}(i-1)}{x^{(0)}(i)} \quad (12)$$

After testing, if all raw data levels are within the range of $(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}})$, it indicates that the original sequence can be modelled using a grey prediction model for carbon emissions. If one or more data level ratios do not fall within the interval $(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}})$, it

is necessary to perform data processing on the original cotton yield sequence. There are various methods for data processing, including root to power and constant transformation. The specific process of modelling carbon emissions GM (1, 1) is as follows.

3.2.1 Carbon emission data accumulation calculation

The input data for the GM (1, 1) model is $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$.

The cumulative sequence of $x^{(0)}$ is $x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)\}$, of which $x^{(1)}(K) = \sum_{i=1}^K x^{(0)}(i)$, $i = 1, 2, \dots, n$.

3.2.2 Establishing nearest neighbour sequences

$$Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)\} \quad (13)$$

$$Z^{(1)}(K) = \frac{[x^{(1)}(K) + x^{(1)}(K-1)]}{2}, k = 2, 3, \dots, n \quad (14)$$

3.2.3 Building predictive modelling

Due to the similarity of solutions between $3x^{(1)}(K)$ and first-order linear differential equations, a differential equation is constructed for $444x^{(1)}(K)$:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \quad (15)$$

Among them, a is the development coefficient, and b is the grey action quantity. For solving differential equations, it can be concluded that:

$$X^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a} = b \quad (16)$$

3.2.4 Model solving

If the parameter vector $\hat{a} = [a, b]^T$ is set, then solve for parameter a, b using the least squares method.

$$\hat{a} = (B^T B)^{-1} B^T Y_n \quad (17)$$

Among them, the construction form of $Y_n = \{x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)\}^T$, B is as follows:

$$B = \begin{bmatrix} -Z^{(0)}(2) & 1 \\ -Z^{(0)}(3) & 1 \\ \dots & \dots \\ -Z^{(0)}(n) & 1 \end{bmatrix} \quad (18)$$

3.2.5 Predicted restoration value

The above parameters are solved and fed into formula (4). The data is accumulated to obtain $X^{(1)}(k+1)$, and then the data is reduced to obtain the predicted value of the enterprise's carbon emissions.

$$\hat{X}^{(0)}(k+1) = \hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k) \quad (19)$$

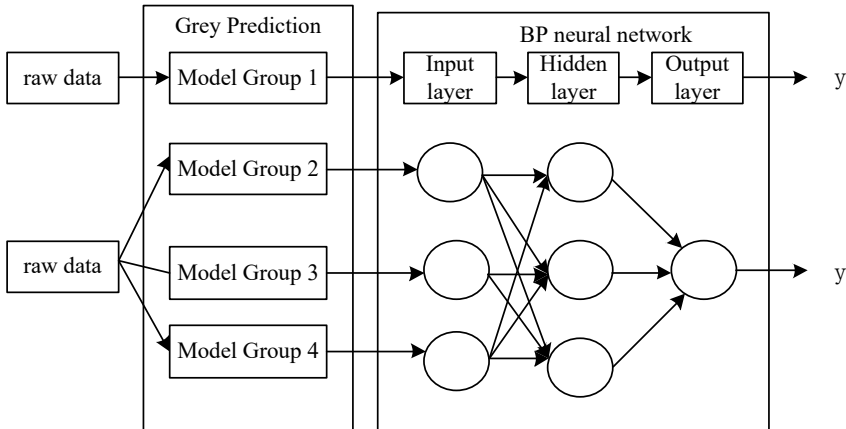
$$\hat{X}^{(0)}(k+1) = (1 - e^a) \left(X^{(0)}(1) - \frac{b}{a} \right) e^{-ak} \quad (20)$$

3.3 Grey neural network combination model for predicting the peak carbon emissions of enterprises

The grey neural network combination model combines the predictive ability of grey theory with the learning ability of neural networks to operate and learn cumulative emission data to predict carbon emission peaks. Grey theory processes incomplete data by constructing a grey model (GM (1, 1)), revealing the inherent development trends of the data, and capturing the rate of change of the data through first-order differential processing. Neural networks utilise their powerful machine learning capabilities to learn complex patterns and relationships from training data, adjust their weights to better fit the changing patterns of carbon emission data. The combination model takes the prediction results of the grey model as one of the inputs to the neural network, while also inputting cumulative emission data. The task of the neural network is to learn the relationship between the two and adjust its internal parameters based on the prediction results of the grey model and other relevant information to improve the accuracy of the prediction.

The specific model is shown in Figure 2.

Figure 2 Grey neural network combination model



As shown in Figure 2, the input of the model is cumulative carbon emissions. The output is peak carbon emissions of enterprises.

The accuracy of predicting the peak carbon emissions of enterprises using GM(1, 1) and BP neural network is A_1 and A_2 , respectively.

$$A_{it} = 1 - \left| \frac{y_{it} - \hat{y}_{it}}{y_{it}} \right| \quad (21)$$

Among them, y_{it} represents the actual peak value of corporate carbon emissions, $\hat{y}_{it}$ represents the predicted peak value of corporate carbon emissions, and A_{it} represents the prediction accuracy of A_1 or A_2 .

Let the mean and mean square deviation of A_1 and A_2 be E and δ , respectively.

$$E = \frac{1}{n} \sum_{i=1}^n A_{it} \quad (22)$$

$$\delta = \sqrt{\frac{1}{n} \sum_{i=1}^n (A_{it} - E)^2} \quad (23)$$

If the validity is set to S , the formula is expressed as follows:

$$S = E(1 - \delta) \quad (24)$$

In the concept of effectiveness, the higher the value of effectiveness, the better the performance of the enterprise's carbon emission peak prediction model. If the effectiveness of the grey prediction model is S_1 and the effectiveness of the neural network model is S_2 , then the weight coefficient of the enterprise carbon emission peak prediction model is:

$$k_i = \frac{S_i}{S_1 + S_2} \quad (25)$$

The calculation formula for the combination prediction model is:

$$y = k_1 y_1 + k_2 y_2 \quad (26)$$

To achieve peak prediction of enterprise carbon emissions based on IoT blockchain and grey neural network.

4 Experiment

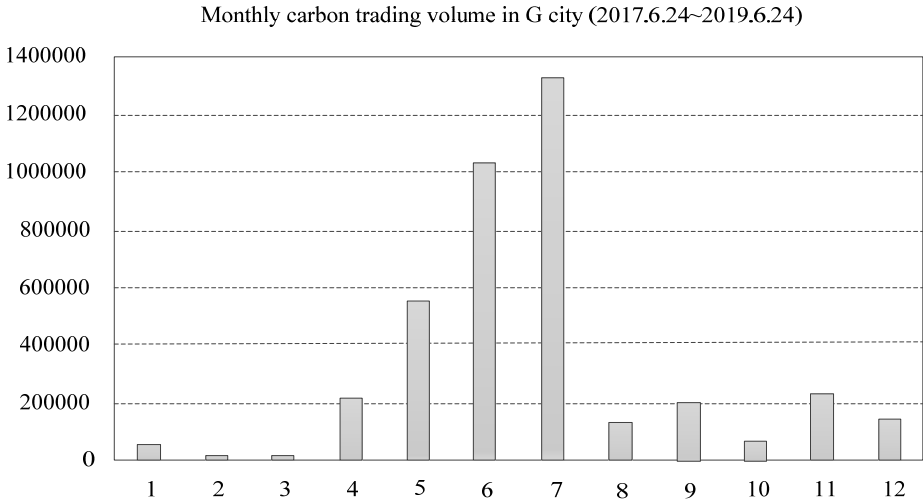
4.1 Experimental design

After sorting out the trading volume of the first two years, it was found that there are peaks and valleys in China's carbon market trading, with significant differences in trading volume, as shown in Figure 3. The main reason for the significant difference, apart from the long holiday periods in February and October, is that relevant departments will carry out quota liquidation on enterprises from May to July.

Due to the significant difference in transaction volume, consider the impact of different transaction volumes on transaction success rate and enterprise satisfaction in the two transaction modes. Referring to the actual trading situation, during the simulation, the peak period is set to propose an average trading volume of 22,000 tons/day for carbon trading in July, and the low period is set to propose a carbon trading volume of 2000 tons/day. When setting the number of enterprises, this article sets: each enterprise only

submits an application for a transaction of 100 tons. The number of sellers and buyers is equal, and the sum of buyers and sellers is not a constant. Each enterprise only applies for a transaction of 100 tons for convenience. If Company A applies multiple times, it can be named A1, A2, etc.

Figure 3 Statistical chart of monthly carbon trading volume in G city



4.2 Experimental result

4.2.1 Accuracy of enterprise carbon emission peak prediction

To verify the effectiveness of the method proposed in this article in predicting the peak carbon emissions of enterprises, the methods of Ji et al. (2022), Lv et al. (2023), and this article were used to predict the accuracy of the peak carbon emissions of enterprises. The results are shown in Table 4.

Table 4 Accuracy of peak carbon emission prediction for enterprises

Number of enterprises/piece	Carbon emission peak prediction accuracy/%		
	Ji et al. (2022) method	Lv et al. (2023) method	Proposed method
172	58.9	59.6	99.8
180	63.0	62.5	99.9
188	66.8	68.9	99.2
196	72.1	66.3	99.6
204	75.5	69.0	99.3
212	78.2	72.4	99.5

The prediction accuracy of this method is significantly higher than that of the methods in Ji et al. (2022) and Lv et al. (2023) for all listed companies. For example, when the number of enterprises is 180, the prediction accuracy of our method reaches 99.9%, while the methods in Ji et al. (2022) and Lv et al. (2023) are 63.0% and 62.5%, respectively.

With the increase in the number of enterprises, from 172 to 212, the prediction accuracy of the method in this article has always remained above 99%, demonstrating strong stability. This indicates that the method proposed in this article is not affected by changes in sample size and can adapt to datasets of different sizes.

4.2.2 Analysis of carbon reduction potential in the industrial sector of enterprises

The peaking of industrial sub sectors is a prerequisite for the overall peaking of industry. Therefore, it is necessary to further analyse the relationship between the peaking of industrial sub sectors, and it is even more necessary to analyse the emission increase risks and emission reduction potential of each department. Table 5 reports the peak and peak time of the industrial sector of enterprises under three scenarios.

Table 5 Peak time and peak of industrial sector in enterprises

Industry	Low carbon scenario		Benchmark scenario		High energy consumption scenario	
	Peak (MT)	Peak time (Year)	Peak (MT)	Peak time (Year)	Peak (MT)	Peak time (Year)
Mining industry	224.638	2029	258.314	2031	296.245	2032
Light industry	205.317	2029	212.139	2030	232.966	2031
Textile industry	70.035	2026	72.822	2029	90.547	2033
Petroleum industry	193.285	2027	225.591	2030	231.25	2034
Chemical industry	302.863	2026	325.369	2028	445.499	2031
Cement Industry	1,435.692	2026	1,469.764	2030	1,556.672	2033
Steel industry	2,267.120	2028	2,431.595	2029	2,644.93	2032
Electricity industry	5,670.572	2025	6,231.411	2027	6,296.866	2032

In the low-carbon scenario and benchmark period, except for the mining industry, which achieved its peak in 2031 under the benchmark scenario, the peak years of other industries are consistent with China's 2030 peak goals. Among them, the peak time of the power industry in these two scenarios is slightly earlier than that of other industries, which is in line with China's call for the power industry to be the first to achieve peak. However, in the high energy consumption scenario, various industrial sectors cannot achieve the 2030 peak goal. Therefore, if it is not to cope with the impact of future uncertainty risks, the constraints on industrial and energy transformation cannot be relaxed. To analyse the emission reduction potential and increase potential of industrial sub sectors, the peak time and peak value can be compared between the low-carbon scenario and the baseline scenario, as well as the high energy consumption scenario and the baseline scenario. The emission reduction potential and increase risk of the eight major industrial sectors are shown in Table 6.

The emission reduction potential of the petroleum and power industries is greater than the emission reduction risks, while the emission increase risks of the mining industry, light industry, textile industry, chemical industry, cement industry, and steel industry are all greater than the emission reduction potential. The electricity and steel industries have the greatest potential for carbon reduction, both exceeding 100 million tons. Especially, the electricity industry has a carbon reduction potential of over 500 million tons and can

reach its peak two years ahead of schedule. In contrast, the emission reduction potential of light industry, textile industry, and chemical industry is relatively small, all below 30 million tons. Among them, the carbon emission reduction potential of light industry is the smallest, only 0.028 million tons, and it can also reach its peak three years ahead of schedule.

Table 6 Emission reduction potential and risk of increasing emissions in China's eight major industrial sectors

<i>Industry</i>	<i>Emission reduction potential/billion tons</i>	<i>Early peak time/year</i>	<i>Risk of increased emissions/billions of tons</i>	<i>Delayed peak time/year</i>
Mining industry	0.337	2	0.379	1
Light industry	0.068	1	0.208	1
Textile industry	0.028	3	0.177	4
Petroleum industry	0.323	3	0.057	4
Chemical industry	0.225	2	1.201	3
Cement industry	0.341	4	0.869	3
Steel industry	1.645	1	2.133	3
Electricity industry	5.608	2	0.655	5

This is related to its characteristic of smaller energy consumption. The risks of increased emissions in the chemical industry and steel industry are 120.1 million tons and 213.3 million tons respectively, both above 100 million tons. The risks of increased emissions in the light industry, textile industry, and petroleum industry are relatively small, all below 30 million tons. Among them, the risk of increased emissions in the petroleum industry is the smallest, only 0.057 million tons. The peak time of the textile industry and petroleum industry has been delayed by five years, while the risk of increased emissions in the power industry is 0.655, far less than its emission reduction potential, but it has been delayed by five years to achieve peak.

5 Conclusions

Based on the above analysis, the following conclusions can be drawn:

- 1 This study successfully combined IoT technology with blockchain and established a carbon trading model based on blockchain. This model has the characteristic of ensuring the transparency of transaction information and ensuring the security of transactions through smart contracts. When allocating quotas to government agencies, the debt situation of enterprises can be verified through historical transaction information. Smart contracts are responsible for implementing quota allocation and loan repayment functions. Therefore, the carbon emissions trading model based on blockchain has the characteristics of information traceability, fast and accurate transaction execution, ensuring the financial security of carbon trading and carbon finance loan transactions.

- 2 This study applied the grey prediction model to improve the BP neural network and achieved accurate prediction of the peak carbon emissions of enterprises. A prediction was made for the carbon emissions of the eight major industrial sectors from 2020 to 2050. According to the prediction results, under the low-carbon scenario, all industrial sectors are expected to reach their peak targets before 2030. Among them, the power sector achieved its peak target as early as 2025, reaching 56.7057 million tons. The mining industry and light industry were the latest to reach their peak, reaching their respective peaks in 2029. In the benchmark scenario, except for the mining industry, all other industrial sectors can reach their peak by 2030. However, in high energy consumption scenarios, none of the eight industrial sectors were able to reach their peak targets by 2030, with the latest being the oil industry achieving peak emissions of 2.3125 million tons in 2034.

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