Method for analyzing carbon emission intensity of regional power system based on carbon emission impact factor and systematic perspective

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Abstract: All countries have set the goal of achieving "carbon peak and carbon neutrality," in which carbon emission assessment is the basis for developing carbon reduction measures. A method for calculating and analyzing the carbon emission intensity of regional power systems based on carbon emission influencing factors and a systematic perspective is proposed in this paper, which identifies the main influencing factors of carbon emissions and implements relevant policies and regulations to achieve carbon peak. Firstly, carbon emission impact factors are provided, considering the energy-economy-electricity-environment (4E) balance system. To support accurate carbon emissions monitoring, relevant data are collected, including energy consumption, economic growth rate, electricity production, and carbon emission indicators. The influence contribution is quantified using methods such as the improved Kaya constant equation. Logarithmic means the Divisa Index approach (LMDI), which selects the divers with solid correlation. Secondly, the carbon emissions data are pre-processed using the Ensemble Complementary Empirical Modal Decomposition (ECEMD) method. Finally, the future carbon emission trend is predicted using the Particle Swarm Optimization Long and Short-Term Memory Network (LSTM) algorithm. Some real power system data are used to verify the method's effectiveness and perform predictive analysis for the example.

Keywords: Carbon emission impact factor decomposition; prediction method; energy-economy-electric-environment balance system

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1. Introduction

Due to the limitation of emission reduction technology and the increasing consumption of fossil energy, carbon dioxide emissions have been increasing yearly, seriously impacting global warming and environmental damage [1]. In response to the greenhouse effect caused by high carbon emissions, all countries are beginning to explore ways to save energy and reduce emissions. China has become the world's largest carbon emitter and should actively shoulder the burden of reducing its emissions. In order to achieve the carbon emission reduction target and improve energy use efficiency and environmental protection, it is necessary to study the energy-economy-electricity-environment (4E) balance system in depth, analyze the factors influencing carbon emissions, and build a carbon emission prediction model that can take into account multiple influencing factors, so as to provide a scientific basis for formulating and implementing carbon emission reduction policies and improving energy use efficiency and environmental protection [2].

Carbon emission factor decomposition refers to the decomposition of carbon emissions into the contributions of various factors to carbon emissions in order to better understand the sources of carbon emissions and ways to control them. Presently, domestic and foreign research on carbon emission factor decomposition has made some progress. The literature [3] used GDP, per capita energy consumption, urbanization rate, and carbon dioxide emission intensity to decompose and predict the carbon emission factors in China, and analyzed the contribution of different influencing factors by the error decomposition method. The literature [4] used a grey model and support vector regression model to predict the effects of energy consumption, industrial structure, and population growth. It proposed a carbon emission reduction policy led by energy structure adjustment and technological progress.

In the case of China, the driving factors behind the new changes in carbon emissions and the changes in the main contradictions leading to the growth of China's carbon emissions in the context of industrial relocation and increasing inter-provincial trade. Considering power generation, transmission and distribution, and final consumption, the carbon emissions of the power system are mainly divided into ten influencing factors: emission factor, energy structure, power structure, conversion efficiency, transmission and distribution loss, economic size, population size, industrial design, power intensity, and residential consumption. Magnus Lind Mark has studied the effects of different factors on carbon emissions in the light of technological development, different energy prices, and economic development. He found that agglomeration and carbon emissions would affect the Environmental Kuznets Curve (EKC) effect [5]. The relationship between income, energy consumption, and carbon emissions changed, and the results of the Organization for Economic Co-operation and Development (OECD) and non-OECD countries were different. There is a turning point between income and energy consumption, and carbon emissions in OECD countries, but there is no turning point in non-OECD countries. Energy consumption and carbon emissions cannot be solved by turning points alone in the literature [6]. The literature [7] verified that environmental quality and economic growth have an inverted U-shaped relationship regarding income and environmental degradation. Based on the environmental Kuznets curve model, the scale effect, structure effect and carbon emission intensity effect of economic development are studied. [8] found the changing relationship between economic growth and carbon emission is an N-type curve relationship, and the curve’s shape refers to the letter’s shape. The economic and carbon emissions relationship did not conform to the EKC curve but showed an "N-type" curve relationship is proposed. A new inflection point appeared after the EKC curve [9]. There is a "positive U-shaped" curve relationship between the economy and carbon emissions with economic development, and carbon emissions first decrease and then increase [10]. In the literature [11], the relationship between carbon emission and the economy in 30 provinces in China is analyzed, and the results show that there is an inverse N-curve-type relationship between the two. Some parameter estimation models find an inverse N-type economic development and carbon emissions are correlated. China's industrial structure, dominated by secondary industries, significantly reduces carbon emissions [12]. It further confirms that the conclusion of a significant inverted U-shaped relationship between the digital economy and carbon emission levels is robust [13].

The above literatures studied the impact factors of carbon emission. The relationship between carbon emission and these factors is researched, inspiring this article's second part. The multiple impact factors as the basis for the third part of carbon emission forecasting are used. Carbon emission forecasting refers to the use of various models and methods to predict and anticipate carbon emissions in a future period. A time series model and a grey correlation model were used to forecast and analyze carbon emissions and their influencing factors, and it was concluded that energy consumption, population size, economic growth rate, and energy structure have the most significant impact on carbon emissions [14]. The literature [15] used grey correlation analysis and time series analysis to investigate the relationship between China's carbon emissions and factors such as energy structure, industrial structure, economic growth, and scientific and technological innovation and predicted China's future carbon emission trends.

However, there are still some problems and challenges in the current decomposition and prediction of carbon emission factors. Firstly, the existing carbon emission factor decomposition and prediction models still need improvement, such as the influence of oversimplified factors, missing data, and insufficient sampling capacity. Secondly, the factors influencing carbon emissions are very complex, and the interaction and effects of multiple factors need to be considered, so how to effectively extract and analyze the information of each influencing factor still needs to be studied in depth.

In response to these problems, this paper further clarifies the research objectives:

(1) A carbon emission prediction method is proposed: the energy-economy-electricity-environment balance system comprehensively considers factors such as energy consumption, economic growth, power generation, and environmental impact and considers the interaction and effects of multiple factors to achieve accurate carbon emission prediction.

(2) The internal logic of carbon emission data is analyzed by integrating the complementary empirical mode decomposition (CEEMD) method. The improved extended short-term memory network algorithm predicts future carbon emission trends. The actual study data verify the feasibility and accuracy of the proposed method.

(3) By identifying the major contributors to carbon emissions, policymakers can implement policies and regulations targeting the most important emissions sources and reduce the overall carbon footprint to achieve earlier carbon peaks.

The remainder of this paper is organized as follows. Section 2 analyzes carbon emission impact factors and Section 3 presents the carbon emission trend forecast based on the particle swarm algorithm optimized LSTM. In Section 4, we discuss the case study. The paper concludes with Section 5.

2. Analysis of carbon emission impact factors

This section first selects typical influencers representing the four directions from the 4E system and constructs the improved Kaya identity. Then, the LMDI additive algorithm is used to quantify the contribution rate of different influencers of carbon emission changes and select the influencers with a more significant impact.

2.1 Status of Carbon Emission and Digital Management System

Carbon dioxide emissions are not the same as carbon emissions, an umbrella term for all greenhouse gases. Suppose the actual measurement conditions are not widely available. In that case, the government proposes a default value based on several units' measurement results to represent most teams' average level. However, according to the calculations of several parties, this method has many influencing factors, and the representativeness of the default value needs to be improved.

Although the introduction of intelligent methods has improved the calculation efficiency of carbon emission assessment and the visualization of assessment results to some extent, most of these methods simulate and predict carbon emissions from various dimensions before or after project construction, rather than real-time monitoring at the construction site stage [11]. Moreover, many methods use quotas or bills of quantities to calculate carbon emissions, which can lead to discrepancies in the calculation results. Because the percentage can only represent the national or industry average, it cannot reflect the actual level of each specific project.

2.2 Evaluation Indicators and Algorithm Design

(1) Evaluation indicators

Since the optimization process in this paper involves three objectives, time, cost, and carbon emission, how to evaluate the pros and cons of each feasible solution has become a problem that needs to be solved before the algorithm design. In the research process of this paper, the meanings represented by each objective are different. For each sub-objective function, the relative deviation is used to measure the pros and cons of the feasible solution, which is the deviation of the actual value of a particular goal from the minimum value of all possible target explanations [16]. This paper adopts the random and dynamic weighting method, and a comprehensive, objective function is constructed by combining the related concepts of the aggregation function. This effectively simplifies the multi-objective solution, speeds up the solution progress, and ensures the accuracy of the solution results [17].

For the model in this paper, each ant corresponds to a feasible solution, and the evaluation of an ant's advantages and disadvantages includes three indicators: time, cost, and carbon emissions. The degree of deviation of the time index of the k^{th} ant corresponding to the feasible solution can be expressed by the formula (1).

$$A_{Tk}=\frac{E_{Tk}-E_T^{\min}}{E_T^{\max}-E_T^{\min}} \tag{1}$$

where E_{Tk} represents the time index of the k^{th} ant. $E_T^{\min}$ represents the minimum time index; $E_T^{\max}$ represents the maximum time index.

In the same way, the cost of the k^{th} ant corresponding to the feasible solution and the deviation degree of the carbon emission index are shown in formulae (2) and (3).

$$A_{Ck}=\frac{E_{Ck}-E_C^{\min}}{E_C^{\max}-E_C^{\min}} \tag{2}$$

$$A_{Bk}=\frac{E_{Bk}-E_B^{\min}}{E_B^{\max}-E_B^{\min}} \tag{3}$$

where E_{Ck} represents the cost of the k^{th} ant, E_{Bk} represents the carbon emission index of the k^{th} ant.

Formulas (1) to (3) have given the evaluation method of the pros and cons of each ant corresponding to the sub-goals of feasible solutions. Therefore, for the evaluation of the pros and cons of the overall goal, based on the pros and cons of the sub-goals, the corresponding weight coefficient w is introduced for the calculation to obtain the comprehensive, objective function expression as shown in formula (4):

$$\begin{aligned} F(k) &= \omega_T A_{Tk}+\omega_C A_{Ck}+\omega_B A_{Bk} \\ &= \omega_T \frac{E_{Tk}-E_T^{\min}}{E_T^{\max}-E_T^{\min}}+\omega_C \frac{E_{Ck}-E_C^{\min}}{E_C^{\max}-E_C^{\min}}+\omega_B \frac{E_{Bk}-E_B^{\min}}{E_B^{\max}-E_B^{\min}} \end{aligned} \tag{4}$$

Meanwhile, in order to achieve the optimal global effect, this paper draws on the practice of previous research. The random dynamic weighting method provides weighting coefficients for the comprehensive, objective function so that the model can continuously change the search direction during the optimization process, and does not fall into a local optimum [10]. For a comprehensive function with m sub-objectives, the distribution of weight coefficients follows the formula (5).

$$\omega_n=\frac{b_n}{b_1+b_2+\cdots b_n} \tag{5}$$

where b represents the corresponding sub-weight coefficient.

(2) Algorithm design

Under the given construction mode and construction conditions, it is necessary to find the construction scheme with the minimum time, cost, and carbon emission, to control the construction process effectively. The specific algorithm flow and algorithm design include the following parts:

It prevents the solution process from falling into a local optimum and ensures the rationality and globality of the optimal solution [11]. The comprehensive objective function assigns weight coefficients, as shown in formula (6).

$$\omega_i=\frac{b_i}{b_1+b_2+\cdots b_n} \tag{6}$$

Suppose the function value is smaller for the comprehensive objective function. In that case, it indicates that the corresponding feasible solution has less consumption in terms of "time, cost and carbon emission," which means that the feasible solution is better [17]. According to this principle, we need to calculate the value of the comprehensive objective function in the solution process as shown in formula (7).

$$F(k)=\omega_T \frac{E_{Tk}-E_T^{\min}+r}{E_T^{\max}-E_T^{\min}+r}+\omega_C \frac{E_{Ck}-E_C^{\min}+r}{E_C^{\max}-E_C^{\min}+r}+\omega_B \frac{E_{Bk}-E_B^{\min}+r}{E_B^{\max}-E_B^{\min}+r} \tag{7}$$

where, r is a random number between (0,1), which can effectively ensure the validity of the target value. After one cycle's completion, the path's pheromone concentration needs to be updated for the next cycle. The pheromone is obtained by adding the remaining concentration of the pheromone concentration before the current process after the current cycle and the pheromone concentration left by the ants during this cycle, as shown in formula (8).

$$\delta_{mn}(C) = \alpha\delta_{mn}(C-1) + \Delta\delta_{mn} \tag{8}$$

where $\delta_{mn}(C)$ represents the pheromone concentration for this cycle; α represents residual coefficient.

The basic calculation formula is shown in formula (9).

$$\Delta\delta_{mn} = \sum_{k=1}^{i} \Delta\delta_{mn}^{k} \tag{9}$$

2.3 4E Impact factor selection

The total coal and fossil energy consumption ratio is used to characterize the energy structure. The degree of electrification refers to the proportion of energy consumption in a country or region that uses electricity. A high degree of electrification means that more energy consumption comes from electricity. Electricity mix refers to the proportion of different energy sources in electricity production. The difference in power structure will significantly impact energy consumption and carbon emissions. Energy intensity is a key measure of carbon emissions, requiring GDP per capita data. Population size determines energy consumption. In a certain period, with a certain amount of energy consumed per capita, the larger the total population base, the more fossil fuels and energy consumed will increase significantly.

Effective prevention and control measures are urgently needed to solve the problem of greenhouse gases, especially carbon dioxide. The first thing to understand is to analyze the specific reasons for the growth of carbon emissions from what aspects, which is the first to figure out the source of influencing factors of carbon emissions.

(1) Energy structure

Research shows that the energy structure transition and carbon emissions all have an inverted U-shaped relationship with economic growth. The turning point of the energy structure transition is earlier than the turning point of carbon emissions, i.e., the transition realizes the double dividend of CO_2 and economic development when the GDP per capita exceeds a certain range [12]. Since the major factor affecting carbon emissions is coal consumption, this paper characterizes the energy structure in terms of the ratio of total fossil energy consumption to total energy consumption, denoted as *M*.

(2) Energy intensity

Energy intensity measures how much energy is used to produce a unit of GDP. A significant spatial spillover of energy intensity and technological progress on energy carbon emissions and the atmospheric environment is denoted as *Q*.

(3) GDP per capita

The carbon emissions of each province are strongly linearly related to the GDP per capita, and the national GDP increases with the gradual growth of carbon emissions, which is also linearly related. For the GDP per capita data of each province from 2003 to 2021, to overcome the effects of economic inflation and other factors, the actual GDP per capita is calculated with 2010 as the base period and is denoted as *G*.

(4) Electrification rate

The level of electrification refers to the share of energy consumption accounted for by electricity use in a country or region. A high degree of electrification means that more energy comes from electricity. For example, developed countries tend to have high levels of electrification, while developing countries have a relatively low level (Ershov 2020). Regions with high electrification tend to have higher energy consumption and carbon emissions because electricity is generated from fossil fuels such as coal, fuel oil, and natural gas. Therefore, this paper expresses the electrification rate as the share of electricity consumption in total final energy consumption, denoted R.

(5) Electricity structure

The percentage of different energy sources used to produce electricity, such as coal, natural gas, nuclear, and renewable, is called the electricity structure. The difference in electricity structure can significantly impact energy consumption and carbon emissions. For example, coal is a carbon-intensive energy source, and the use of coal to generate electricity generates large amounts of carbon dioxide emissions. In contrast, renewable energy sources, such as solar and wind, produce almost no carbon emissions [18]. Therefore, in this paper, the ratio of renewable energy generation to total electricity consumption is used to express the electricity structure's cleanliness, denoted by E.

6) Population size

Population size has a significant positive impact on carbon emissions, and rapid population growth will increase the degree of impact on carbon emissions. Here, the population size is characterized by the total population of each province at the end of the year, which is recorded as P.

2.4 Quantitative Analysis of Influence Factor Contribution

Kaya's constant equation is mainly used for the decomposition of carbon emission impact factors based on carbon emissions (C), total energy consumption (E), gross product (G), and total population (P) to decompose the carbon emission impact factors, expressed as.

$$C = \frac{C}{E} \cdot \frac{E}{G} \cdot \frac{G}{P} \cdot P \tag{10}$$

where $\frac{C}{E}$ denotes carbon emission intensity, and $\frac{E}{G}$ denotes regional energy intensity, $\frac{G}{P}$ denotes regional GDP per capita.

In this paper, based on Kaya's constant equation, carbon emissions are separated into carbon emissions from various energy sources, and the consumption of each primary energy source is added to expand Kaya's constant equation, as indicated in equation (11).

$$C = \frac{G \times P}{Q} \times \sum_{m} M_m \lambda_m + \frac{G \times P}{Q} \times R \times (1 - E) \times \lambda_E \tag{11}$$

The definition of each influencing factor in equation (11) is

(1) Energy intensity $Q = \frac{E}{GDP}$, denotes the level of energy consumption per unit of GDP.

(2) Economic level $G = \frac{GDP}{P}$ denotes the per capita GDP.

(3) Total population P .

(4) The energy carbon emission factor $\lambda_m = \frac{C_m}{E_m}$, which indicates the carbon emission of the *m* energy consumption. The economic level indicates GDP per capita. C_m is the carbon emission of the m energy source, E_m is the consumption of the m energy source.

(5) The energy share $\mu_m = \frac{E_m}{E}$, is the percentage of the m^{th} energy consumption in the total consumption.

Then equation (11) can be rewritten as

$$C = QGP\sum_{m}\lambda_{m}\mu_{m} \tag{12}$$

The Logarithmic Mean Divisa Index (LMDI) decomposition method is widely used to measure the impact of economic growth, industrial structure changes, and energy conservation and reduction measures on energy consumption, and it can also use residual terms. The LMDI decomposition method is divided into two types: multiplicative integral solution and additive and decomposition. The multiplicative integral solution focuses on the rate of change, and the index represents the side contribution rate. The additive and decomposition focus on the amount of change, and the indicator represents the contribution value. In this paper [19], the LMDI additive decomposition model is mainly used for analysis.

Previous studies have typically divided environmental impacts into three effects: technology, structure, and scale, and measured the extent to which technology, structure, and scale affect carbon emissions. This paper considers eight factors from the 4E system to construct a decomposition model based on the previous research:

Each influencing factor can be decomposed into data using the LMDI decomposition model without leaving residual terms compared to the extended Kaya constant equation, which has the advantages of solid interpretability, impressive results, ease of use, and proven technology. Therefore, following the extended Kaya constant equation, it is applied to the LMDI additive model to decompose the carbon emission impact factors, which is expressed as

$$\Delta C = C_t - C_0 = \sum \Delta C_i \tag{13}$$

where ΔC is the decomposition of the cumulative effect of carbon emissions in a calendar year. C_t and C_0 are the carbon emissions in year *t* and the base year, respectively. ΔC_i is the change in carbon emissions caused by different influencing factors.

The formula for each driver is as follows:

$$\Delta C_i = \ln\left(\frac{\alpha_t}{\alpha_0}\right)\sum_{m}\frac{C_{mt} - C_{m0}}{\ln\left(C_{mt} / C_{m0}\right)} \tag{14}$$

where, C_{mt} and C_{m0} denote the carbon emissions of the m^{th} energy source in year *t* and the base year, respectively. α_t and are the number of influencing factors of the *m* energy source in year *t* and the base year, respectively.

To better analyze how each impact factor affects carbon emissions, the explanatory variable w for the change in carbon emissions is calculated using the following equation.

$$w = \Delta C_t - \Delta C_{t-1} \tag{15}$$

where ΔC_t denotes the cumulative total effect of the decomposition of carbon emissions in year *t*.

3. Carbon emission trend forecast based on the particle swarm algorithm optimized LSTM

This section uses the CCEMD algorithm to analyse the inherent, implicit information in carbon emissions data. The key drivers identified in the previous section are input variables, and the enhanced LSTM algorithm is used to accurately predict carbon emissions.

3.1 The carbon emission intensity of regional power system based on a systematic perspective

Carbon emission intensity (*ct*). The main source of carbon emissions is the use of fossil fuels. Carbon dioxide emissions are calculated using electricity, natural gas, coke, coal, and fuel oil (petrol, kerosene, etc.). Carbon emission intensity (*ct*) is measured by the ratio of total carbon dioxide emissions to GDP, calculated using the following formula:

$$CO_2 = \sum_{m=1}^{M} C_m = \sum_{m=1}^{M} E_m \times SC_m \times CF_m \tag{16}$$

where M is the number of energy types considered. E_m represents the consumption of the m energy type, SC_m is the standard coal conversion factor, CF_m is the CO_2 emission factor of the m energy type.

For node carbon emissions in a power system, the symbol e represents the linear relationship between the carbon flow through a node and the active power flow. The node carbon potential e_n of node n in the system should be described as follows:

$$e_n = \frac{\sum_{i \in N^+} P_i \rho_i}{\sum_{i \in N^+} P_i} = \frac{\sum_{i \in N^+} R_i}{\sum_{i \in N^+} P_i} \tag{17}$$

where N^+ represents is the set of all branches of power flow into node n in the unit connected to node n in the system. i is the branch number. The node carbon potential and the branch carbon flow density ρ_i are both $kgCO_2/(kW \cdot h)$, and numerically equal to the weighted average of the carbon flow density of all branches flowing into node n in terms of active power flow P_i.

The significance of the node carbon potential is that it strongly represents the carbon emission flow corresponding to the power consumption of the part that the branch cannot represent, which is conducive to calculating the point's carbon emission flow consumption. Similarly, for a node with only 4. power plant access, its node carbon potential is equal to the real-time carbon emission intensity of the reactor unit [20].

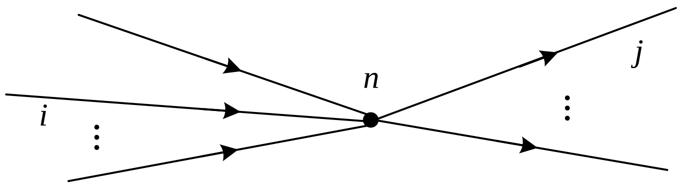


Fig. 1. The relationship between branch carbon flow density and node carbon potential

Node carbon potential and branch carbon flow density are also indicators that describe the relationship between active power flow and carbon emission flow. What is the relationship between them? The following is an analysis of the relationship between them. In a power system, a node n and its adjacent branches are shown in Fig 1.

If the incoming and outgoing power flows of node *n* are and N^{+} respectively, then the active power flows flowing into node *n* from branch *j* and out of node *n* from the second branch are P_i and P_j, respectively. According to the principle of non-selectivity of electric energy, each branch with an outgoing power flow has a component of the incoming power flow from each upstream unit of its starting node. If the element of the first branch of the outgoing power flow branch contains the branch *i* of the incoming power flow branch $P_{j,i}$, then, according to the principle of proportional sharing, there are:

$$R_j = \sum_{i \in N^{+}} P_{j,i} \rho_i \tag{18}$$

$$\rho_j^{'} = \frac{R_j}{P_j} = \frac{\sum_{i \in N^{+}} P_{j,i} \rho_i}{P_j} \tag{19}$$

$$P_{j,i} = P_j \frac{P_i}{\sum_{s \in N^{+}} P_s} \tag{20}$$

where, $\sum_{s \in N^{+}} P_s$ is the sum of the active power flow of all branches with incoming power in all connected branches of node *n*. Then, it can be obtained simultaneously:

$$\rho_j^{'} = \frac{\sum_{i \in N^{+}} P_j \frac{P_i}{\sum_{s \in N^{+}} P_s} \rho_i}{P_j} = \frac{\sum_{i \in N^{+}} P_i \rho_i}{\sum_{s \in N^{+}} P_s} = \frac{\sum_{s \in N^{+}} R_s}{\sum_{s \in N^{+}} P_s} = e_n \tag{21}$$

It can be seen from the above that if the active power flow and the carbon flow of a node are unchanged on all incoming nodes, the carbon flow density on its outgoing branch is constant. This means that the branch carbon flow density of all the carbon flows flowing out from the upstream node on the unit is equal to the node carbon potential of the starting node of the branch.

Based on power flow distribution, it is essential to determine the "flow state" of carbon emission flow in a power system. Unlike power systems, power flow calculation focuses on analyzing the mode of operation of the power system. In contrast, carbon emission flow focuses on the production, transfer and consumption of carbon emissions in the power system. Power system carbon emissions and their calculation should have the following characteristics:

(1) The carbon emission flow depends on the power flow, especially the active one. Factors affecting the distribution of power flow, such as the topology of the power system and other primary constraints, will still affect the distribution of carbon emission flows. In addition, the formation of carbon emission flows should be related to the carbon emission characteristics of the generating units connected to the system. Therefore, the factors that directly affect the distribution of carbon emission flows in the power system should include the topology of the power system, the operating state of the power system and the real-time carbon emission intensity of each unit.

(2) In the power flow calculation of the power system, balancing nodes shall be set to ensure that the entire system's performance can be guaranteed. The flow of carbon emissions into and out of the system

corresponding to the power flow will also necessarily be in balance. The production and consumption of carbon emissions in the power system should always be equal. However, since the calculation of carbon emission flow is based on the power flow distribution of a system that has reached steady state equilibrium, it is not necessary to set another equilibrium node.

(3) The carbon emission flow calculation can only be performed with the result of the power flow calculation, which is the condition of carbon flow calculation. After the power flow calculation is completed, all variables in each part of the system are known, and the node classification set at the beginning of the calculation does not affect the carbon flow calculation.

(4) The general conditions for the power flow calculation are the power flow injection of each *PQ* node, the operating status of each node, such as voltage and active power injection of the *PV* node, and the admittance data of the system line. More attention is paid to the carbon emission flow of the power system from the unit's generation to the consumption of each node load.

3.2 Carbon emission data pre-processing based on ECEMD

Existing studies mainly focus on updating forcing factors or improving forecasting methods, and few studies have pre-processed carbon emission data. In 2021, Wen Zhang et al. were the first to apply EMD to carbon emission forecasting in 12 countries. They effectively improved the forecasting accuracy by combining the machine learning algorithms, but the method is difficult to deal with modal confounding. Due to the non-linearity and volatility of carbon emission data, it is difficult to solve this problem by simply improving the forcing factors or forecasting methods. Based on the integrated empirical mode decomposition (EEMD) method, this paper considers Intrinsic Mode Functions (IMF) and residual terms (res) by adding white noise in the form of positive and negative pairs in the original time series, mixing white noise with the original time series multiple times, and taking the average of the decomposition IMF of each noise series as the final IMF, to reduce the information loss during the decomposition. The ensemble complementary empirical modal decomposition (ECEMD) process is as follows.

The original signal is modified by N pairs of positive and negative Gaussian white noise:

$$\begin{bmatrix} M_1 \\ M_2 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} S \\ N \end{bmatrix} \tag{22}$$

where, S is the original signal, N is the Gaussian white noise, M_1 and M_2 are the sum of the original signal and positive Gaussian white noise and negative Gaussian white noise, respectively. Then the EMD decomposition is applied to the target signal, and for each signal, a set of IMF components are produced, where the I component of the *j* IMF is denoted as imf_j. Finally, the sum is averaged to obtain the results of each IMF, which are denoted as:

$$imf_j = \frac{1}{2N} \sum_{i=1}^{2N} imf_{ij} \tag{23}$$

Therefore, the final decomposition of ECEMD can be expressed as follows:

$$x(t) = \sum_{j=1}^{K} \mathrm{imf}_j(t) + res \tag{24}$$

The operational flow of the ECEMD method is shown in Fig. 2.

The ECEMD decomposes the original carbon emission data into several frequency terms of different amplitudes and a residual term. The smooth signal obtained from the decomposition is used as the final input to the prediction model to accurately predict carbon emission trends.

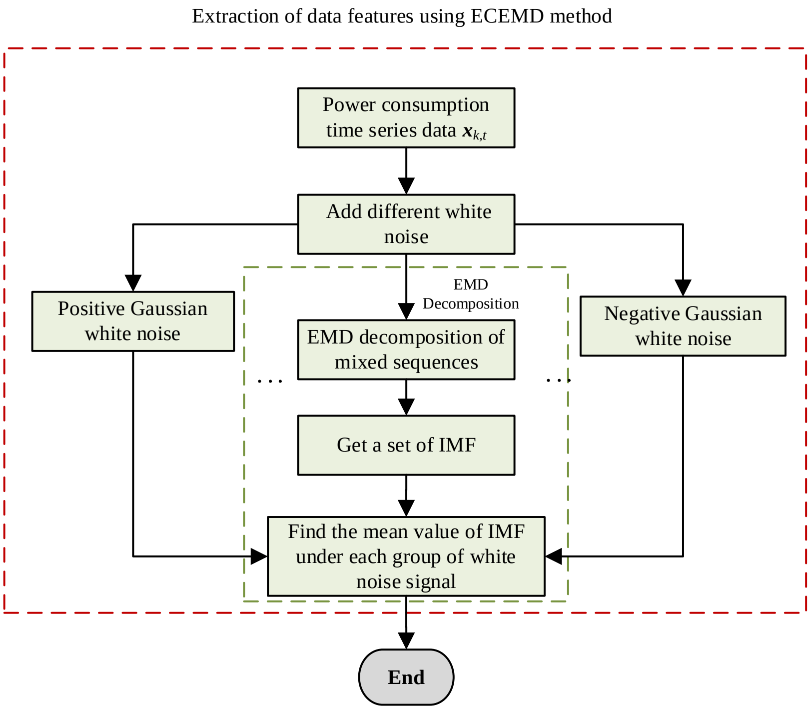


Fig. 2. Flow of the set complementary empirical modal decomposition method

3.3 Carbon emission trend prediction method with particle swarm algorithm optimized LSTM network

The long- and short-term memory network algorithm is a variant of the recurrent neural network (RNN) proposed by Hochreiter et al., which has the ability to store long- and short-term information [21]. The model overcomes the problems of gradient disappearance and gradient explosion in machine learning and has good processing ability for time series data. The cell structure of the LSTM is shown in Fig. 3.

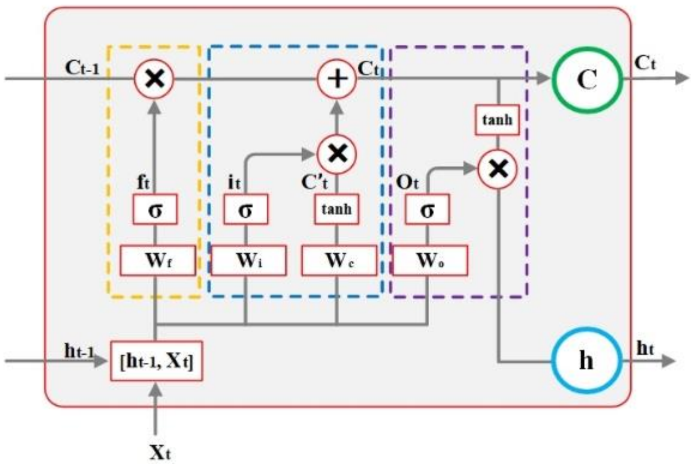


Fig. 3. Cell structure of the LSTM for carbon emission intensity

The specific forecasting process is shown in Fig. 4.

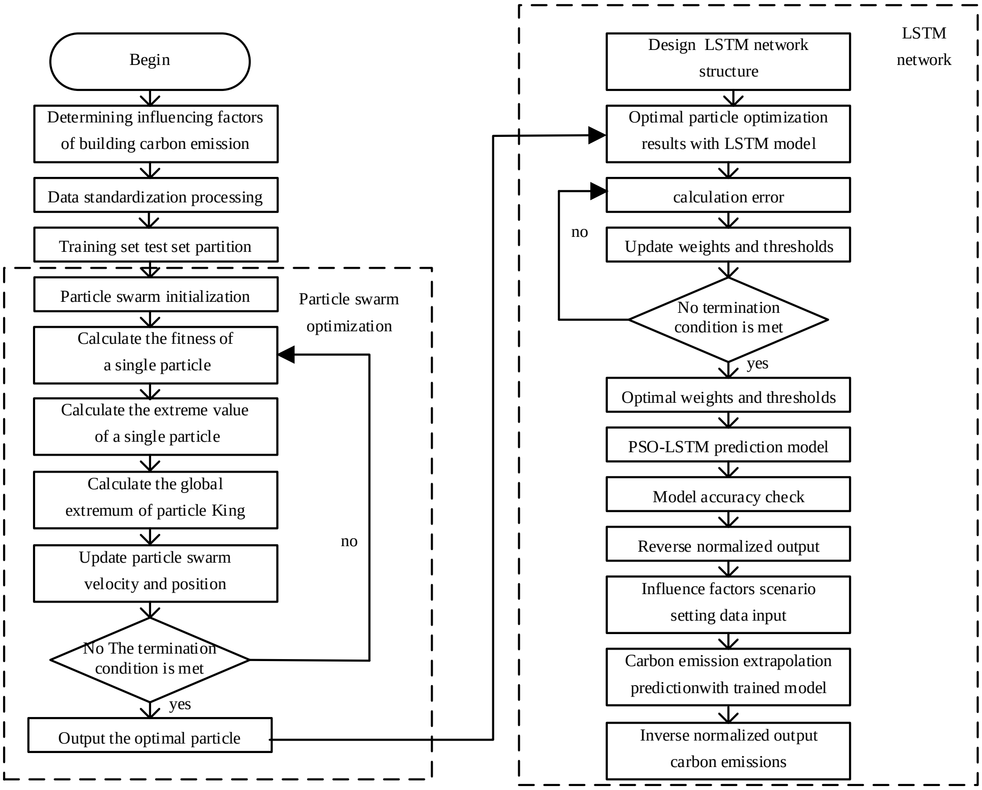


Fig. 4. Flow chart of set complementary empirical mode decomposition method

Although LSTM models have significant advantages in processing time series data, it may be difficult to identify their parameters, and the selection of different parameters significantly affects the prediction results. Since the Particle Swarm Optimization (PSO) algorithm has good global search ability and convergence speed, the particle swarm algorithm is introduced to optimize the LSTM network, which improves the problem that the initial connection weights and parameters of the LSTM model are not accurate enough to obtain, enhances the objectivity of parameter selection, and can make a more accurate prediction of carbon emission data. Accordingly, this paper proposes a combined PSO-LSTM model for carbon emission prediction with the following ideas:

(1) Firstly, the influencing factors of carbon emissions are analyzed. The above contribution rate analysis examines the relationship between each influencing factor and carbon emissions. Then, the input layer data of the carbon emission prediction model are obtained.

(2) To overcome the shortcomings of LSTM parameters that are difficult to determine, an LSTM network optimized by the PSO algorithm is proposed, and the parameters of the LSTM network are optimally searched to improve the reliability and accuracy of the model prediction.

(3) The relevant error indicators and data for 30 years from 1990 to 2019 are used, and the training and test sets are delineated to compare the accuracy of the PSO-LSTM model with that of the traditional LSTM model.

(4) Three scenarios of low-carbon, baseline, and high-carbon are set as the influencing factors, and the trained model is used as the input data for prediction to make extrapolation projections of future

carbon emissions, examine the peak time under different scenarios, and make corresponding suggestions as a result.

4 Case study

Some actual carbon emissions data from a power system in China are used to test the proposed method. The data for each variable were obtained from the regional statistical yearbook and the China Energy Statistics Yearbook. The actual study data is used to verify the feasibility and accuracy of the proposed method. In this paper, Tianjin is selected as the research city to predict its carbon emission trend so as to explore the path of regional low-carbon transformation and realize the goal of carbon peak and carbon neutrality as soon as possible.

4.1 Quantitative analysis of the contribution of influence factors

For the different types of drivers proposed in Section I, the contribution rate of each driver to the impact of carbon emissions is analyzed based on historical data from 2010 to 2022. The contribution of the different drivers to the change in carbon emissions is shown in Fig 5 and Table 1.

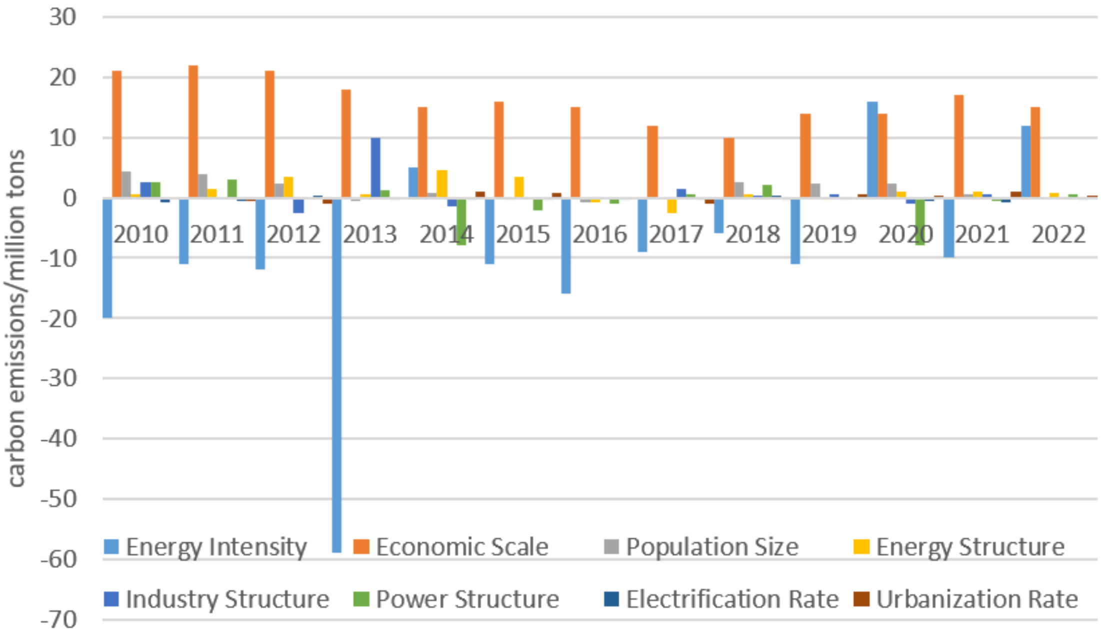


Fig. 5. Contribution rate of each influencing factor from 2010 to 2022

Table 1. Influencing factor contribution rate from 2010 to 2022

Year	*EI*	*ES*	*PS*	*ES*	*IS*	*PS*	*ER*	*UR*
2010	-20	21	4.37	0.5	2.5	2.5	-0.67	0.23
2011	-11	22	3.89	1.5	0	3	-0.44	-0.59
2012	-12	21	2.25	3.5	-2.5	0	0.45	-0.96
2013	-59	18	-0.54	0.5	10	1.2	-0.04	0.21
2014	5	15	0.84	4.5	-1.5	-8	-0.41	1

2015	-11	16	-0.33	3.5	0	-2	-0.4	0.71
2016	-16	15	-0.79	-0.79	0	-1	-0.24	0.18
2017	-9	12	0.19	-2.5	1.5	0.5	-0.43	-0.91
2018	-6	10	2.53	0.6	0.3	2.2	0.27	-0.42
2019	-11	14	2.35	-0.2	0.5	-0.3	0.19	0.49
2020	16	14	2.27	1	-1	-8	-0.51	0.45
2021	-10	17	0.57	1	0.5	-0.5	-0.84	0.91
2022	12	15	0.11	0.8	0	0.6	-0.33	0.28

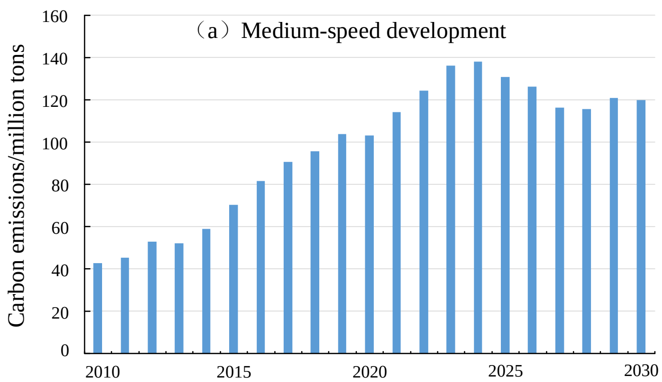
4.2 Carbon Emission Trend Forecast

The influencing factors are set in three scenarios: low-carbon, benchmark, and high-carbon. Future carbon emissions are extrapolated and predicted according to the trained model as input data for the prediction. The peak time under different scenarios is investigated, and corresponding suggestions are made. Table 2 describes the specific parameter settings. We will mainly compare the carbon emissions of three scenarios. The purpose is to analyze the trend of carbon emissions by forecasting three types of carbon emissions and providing ａ reference for decision-makers.

Table 2. The parameter setting of high, medium and low speed in Tianjin area from 2024 to 2030

Scene	Year	G（Rate of increase）	M	T（Rate of increase）	P（Rate of increase）	J（Added value）
High speed	2024-2027	4.90%	0.740-0.690	-1%	0.20%	0.69%
	2028-2030	4.70%	0.670-0.590	-4%	0.10%	0.49%
Medium speed	2024-2027	5.50%	0.740-0.690	-2%	0.22%	0.71%
	2028-2030	4.50%	0.673-0.605	-3%	0.22%	0.43%
Low speed	2024-2027	6.89%	0.745-0.720	1%	0.40%	1.32%
	2028-2030	6.31%	0.701-0.625	0.50%	0.20%	0.889

The improved LSTM algorithm is used to simulate the prediction according to the parameter settings of different scenarios, and the prediction results are shown in Fig 6.



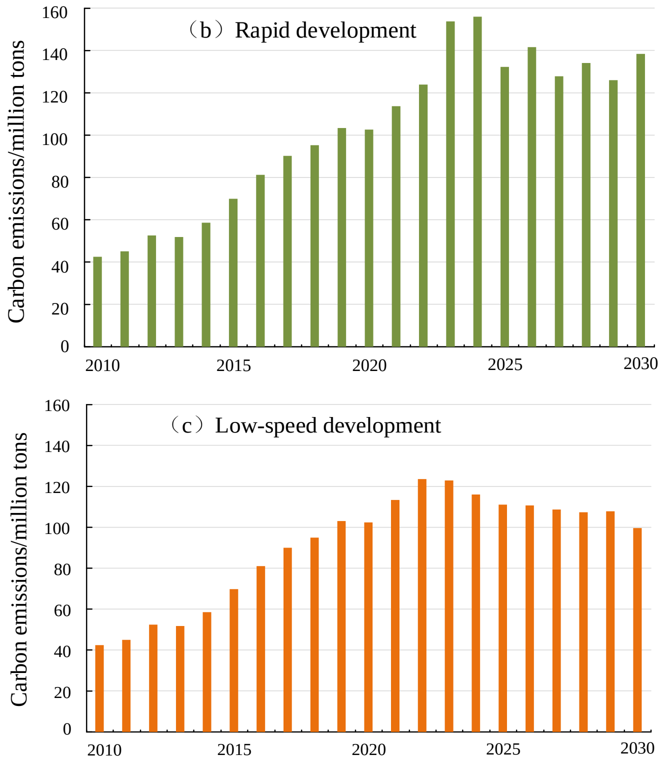


Fig. 6. Carbon emission forecasting in Tianjin area from 2024 to 2030 based on PSO-LSTM model

The analysis shows that the energy structure and energy intensity of coal are large because coal use is increasing rather than decreasing, and there is a significant gap between population growth and the other two scenarios, and the total effect of energy structure on carbon emissions is the largest, followed by population size and energy intensity. These indicators have a non-negligible impact on carbon emissions, leading to a longer peak time and correspondingly prominent peaks in the low carbon peak scenarios.

As the population growth rate has been relatively stable in recent years, controlling the energy structure and intensity has become a top priority to achieve the double carbon target. Technological progress is crucial to achieving the dual carbon target. Reducing coal consumption and increasing the use of non-fossil energy can bring the carbon peak earlier and reduce the peak. Governments need to develop policies to control the relevant indicators, but it is also necessary to increase investment in technology. In controlling indicators such as GDP per capita, population size, and urbanization rate, we should also focus on the development of science and technology, and the focus of carbon emission reduction should be on the technical level and further improve the energy structure and energy intensity.

Considering the influence of the power generation process, power transmission and distribution, and power terminal consumption activities on carbon emissions, the growth of China's electric power carbon emissions is decomposed into emission factors, energy structure, conversion efficiency, transmission and distribution loss, power structure, power intensity, industrial structure, economic scale, residential consumption and population size. In addition, the effect analysis of various schemes and measures on carbon emission investment, including the improvement of emission factor, energy structure, power structure, and so on, are studied. As shown in Table 3, Scheme 1 is to improve the emission factor, Scheme 2 is to improve energy structure, and Scheme 3 is to improve power structure. Scheme 1 has the lowest total investment cost and the highest return on investment but is inferior to Scheme 3 in the comprehensive investment cost index comparison. However, Scheme 2 performs poorly in all aspects.

Table 3. Energy-saving and low-carbon optimization results for Tianjin

Scheme number	Carbon reduction ΔC_p/t	Comprehensive investment cost I/Thousand yuan	Annual yield E/Thousand yuan	Return on investment β
1	115.58	80.2	192.7	22.75
2	77.42	127.2	129.1	1.10
3	183.52	164.4	237.7	1.62

In summary, the Carbon Emission Impact Factor and Prediction Method Considering Energy-Economy- Electricity-Environment Balance System presented in this article helps reduce the carbon footprint by providing a systematic approach to understanding the factors that contribute to carbon emissions in the energy-economy-electric-environment balance system. Meanwhile, the existing carbon emission factor decomposition and forecasting models have been improved. This method allows us to effectively extract and analyze the information of each influencing factor, identify the most significant factors contributing to carbon emissions, and develop effective strategies to reduce these emissions.

Furthermore, the method presented in this article can help policymakers make informed decisions on energy and environmental policies. By understanding the factors contributing to carbon emissions, policymakers can implement policies and regulations targeting the most significant emission sources and reducing the overall carbon footprint.

5 Conclusions

To achieve the carbon peaking by 2030, low-carbon transformation paths for the region need to be explored. The carbon emission impact factors are analyzed. The future carbon emission trend is predicted using the LSTM algorithm. In this paper, Tianjin is selected to construct a 4E balance model, the LMDI method explores how much each influencing factor contributes to carbon emissions, and three scenarios are set up to analyse the future carbon emission trend under different scenarios by using the PSO-LSTM model, and the conclusions are as follows:

(1) The LMDI decomposition results show that energy intensity changes and energy structure changes had significant carbon suppression effects in the region from 2010 to 2020, and population expansion and economic growth influence climate change.

(2) The scenario results show that with low-carbon development as the core and appropriate adjustment of development strategies from 2021 to 2030, the region is expected to reach a carbon peak from 2026 to 2030.

(3) Some quantitative results in the theoretical and numerical example analyses, as well as the influence of the detailed parameter setting of the scenario model, suggest that the predicted results are still not very accurate. In future studies, more accurate predictive analyses of reaching the carbon peak will be conducted based on limited data and more optimized methodological models, such as the influence of complex factors.

Ethical Approval

Not applicable

Consent to Participate

Not applicable

Consent to Publish

Not applicable

Authors Contributions

Yang WANG and Yubo WANG wrote this paper; Tianchun XIANG gave the data curation; Liang ZHAO and Yi GAO are the supervision; Delong ZHANG and Shuai LUO are in charge of re-reviewing.

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Competing Interests

Not applicable

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