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Research Article

Forecasting CO_2 Emissions in China's Construction Industry Based on the Weighted Adaboost-ENN Model and Scenario Analysis

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As a pillar industry of national economy, China's construction industry is still facing the status of substantial energy consumption and high CO_2 emissions, which is a key field of energy conservation and emission reduction. In CO_2 emissions research, it is essential to focus on analyzing the present and future trends of CO_2 emissions in China's construction industry. This article introduces a novel prediction model, in which the weighted algorithm is combined with Elman neural network (ENN) optimized by Adaptive Boosting algorithm (Adaboost) for evaluating future CO_2 emissions in China's construction industry. Firstly, logarithmic mean Divisia index (LMDI) is used to decompose CO_2 emissions into economy, structural, intensity, and population indicators, posing as inputs to the weighted Adaboost-ENN model. Then, through comparison with other three models based on the data of total CO_2 emissions in China's construction industry during 2004-2016, there is evidence that the proposed model makes a favorable prediction performance. On this basis, we employ scenario analysis to predict future trend of CO_2 emissions in China's construction industry. It can be found that the peak of CO_2 emissions in China's construction industry will be achieved before 2030 in high carbon scenario (HS) and baseline carbon scenario (BS), whereas it will not be realized in low carbon scenario (LS). Finally, the specific policy recommendations related to energy conservation and emission reduction in China's construction industry are proposed.

1. Introduction

1.1. Research Background. The greenhouse gas emissions, especially CO_2 emissions, are regarded as the dominant cause of global warming, which has become a consensus of human society. As the biggest energy consumer and CO_2 emitter in the world [1], China is facing mounting international pressure to curb domestic CO_2 emissions, which needs tremendous efforts from various industries. With the acceleration of urbanization and industrialization, the average annual growth rate of China's building energy consumption has exceeded 10% in the past two decades [2]. And, Chen et al. noted that the construction industry contributed 28% of China's total CO_2 emissions in 2011 and projected to be 35% by 2020, with construction industry playing an increasingly large role [3]. Considering the increasing impact of construction industry on CO_2 emissions, it is necessary to study the factors affecting CO_2 emissions in construction industry and predict CO_2 emissions in construction industry to provide recommendations to policy makers.

The choice of construction industry as the research topic can be attributed to the following three reasons.

First, it is one of the most carbon-intensive and resource-intensive industries in China. Both energy consumption and the production of building materials generate massive CO_2 emissions, which should be included into CO_2 emissions in the construction industry [4]. With the increasing demand for construction facilities, the huge consumption of resource and substantial CO_2 emissions highlight its importance in research field.

Then, both the consumption of resource and related CO_2 emissions in China's construction industry have shown an

upward trend over the years. China has promised to reach a peak of carbon emissions around 2030 or even earlier [5]. And the Fourth Intergovernmental Panel on Climate Change (IPCC) Assessment Report concluded that the construction industry has the largest potential for energy saving and emission reduction. Therefore, it is important to predict future CO_2 emissions of the construction industry to answer whether China can achieve the goal reaching the peak of carbon emissions.

Final, there is still a gap in the study of carbon emissions from China's construction industry, which results from two reasons. On the one hand, previous studies on the construction industry focused more on a province or a region, and few researchers focused on construction industry from a national perspective. On the other hand, when some researches come to study the construction industry, most of them only focus on energy consumption, scarcely involving scenario analysis of carbon emissions. Therefore, the paper can fill this gap by studying influencing factors and peak value of CO_2 emissions in China's construction industry.

1.2. Contribution and Innovation of This Study. Based on the above research background, the innovations and contributions of the present study mainly lie in the following aspects. Firstly, the study uses the decomposition method combining logarithmic mean Divisia index (LMDI) method with Cobb-Douglas production function (C-D production function) to derive CO_2 emissions in China's construction industry into economy, structural, intensity, and population factors, which is a fine way to develop the Kaya identity. Secondly, the factors are grouped into several feature sets by correlation analysis, which can effectively avoid information redundancy, and fully play the role of each factor. Thirdly, the factors in each feature set are put together as input to the Adaboost-ENN model, respectively, and the prediction results of each feature set are weighted to get the final results of CO_2 emissions. Through comparison with other three models, there is evidence that the weighted Adaboost-ENN model makes a favorable performance. Then, the weighted Adaboost-ENN model is used to estimate future CO_2 emissions from the construction industry in three different scenarios. Finally, specific policy recommendations on energy savings and emissions reductions in the construction industry are provided. The above work can answer whether the control of major factors affecting CO_2 emissions in the construction industry can effectively reduce CO_2 emissions to achieve the goal of emission peak.

1.3. Structure of This Paper. The rest of this paper is organized as follows. The literature review is given in Section 2. Section 3 describes methods involved in this article. In Section 4, the weighted Adaboost-ENN model is applied, and the performance of this model is evaluated. Then, the proposed model is employed to estimate future CO_2 emissions from China's construction industry in three different scenarios in Section 5. Section 6 summarizes the findings and provides policy recommendations.

2. Literature Review

According to current research methods on the influencing factors of carbon emissions, the factor decomposition is a more acceptable method, especially the index decomposition analysis (IDA). The IDA method based on index number theory has much significant superiority, such as easiness to access data, relatively easy calculation and understanding, and multiple decomposition forms. Moreover, IDA is more suitable for time series data to study the temporal changes in CO_2 emissions at sectoral level [6], which is divided into various forms. By comparing various forms of IDA method, Ang [7] found that the LMDI was the preferred method. Specifically, the LMDI method has many features, such as complete decomposition, no residuals and zero values, easy understanding and consistent aggregation [8]. Thus, the method has been widely applied to decompose and analyze the determinants of CO_2 emissions and energy consumption. For instance, Xu et al. [9] used the LMDI method to identify influencing factors of carbon emissions from fossil energy consumption and found that the most major driver of carbon emissions was the economic output effect. And Rocio et al. [10] utilized LMDI method to find the drivers behind the changes in CO_2 emissions between 1990 and 2012 in Colombia. Moreover, Yang and Kong [11] analyzed the driving factors of carbon emissions from China's energy consumption from 2000 to 2014. In recent years, an increasing number of researchers have used LMDI method to study China's CO_2 emissions of specific industry, such as power industry, equipment manufacturing industry, and nonferrous metal industry [12–14]. Similarly, when exploring the influencing factors of CO_2 emissions in China's construction industry, we can also apply LMDI method as a decomposition tool to study related emissions of construction activities.

Recently, the increasing interest in the estimation of CO_2 emissions has heightened the development of CO_2 emissions forecasting method, which are mainly divided into mathematical methods and artificial intelligence (AI). The mathematical methods mainly include Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model [15], grey model [16], time series prediction [17], and logistic regression [18]. However, mathematical methods are generally used to deal with linear problems and are less sensitive to nonstationarity and dynamics in time series. To overcome the limitations of mathematical methods, lots of researches have focused on AI, such as BP neural network (BPNN) [19], radical basis function neural network (RBFNN) [20], Elman neural network (ENN) [21], support vector machine (SVM) [22], and extreme learning machine (ELM) [23]. Particularly, ENN has proved to be helpful for the prediction of discrete-time series due to the advantage of modeling nonlinear dynamic systems and learning time-varying patterns [24], which has been widely used in different fields of prediction, such as wind speed, short-term load, crude oil price fluctuation, and the price indices of stock markets [25–28]. In addition, ENN also has been successfully applied to gas emissions prediction [29, 30]; however, it is rarely used for the prediction of CO_2 emissions. In light of this, this study is motivated to establish CO_2 emission

prediction model for the construction industry based on ENN because it can handle dynamic, nonlinear, and complex discrete-time series.

Although ENN is a kind of single-objective neural network focusing on single-objective functions, there are still deficiencies owing to its inherent characteristics. For example, the self-feedback gain coefficient of ENN is generally determined by the attempt, which leads to low learning efficiency [31]. Fortunately, along with the development of soft-computing technique, abundant optimization algorithms have emerged to improve the deficiency of single-objective neural network in predicting, such as genetic algorithm (GA), particle swarm optimization (PSO), improved particle swarm optimization (IPSO), and whale optimization algorithm (WOA) [32–35]. Although the aforementioned optimization algorithms can improve the prediction performance, they still have some defects of slow convergence speed, local optimum, and long training process.

The Adaboost algorithm puts forward a new idea for optimizing single-objective neural network to improve prediction performance, which quickly becomes a new research hotspot [36]. Liu and Tian et al. [37] applied the Multilayer Perceptron (MLP) neural networks optimized by Adaboost algorithm to predict wind speed, and the prediction results showed that the Adaboost algorithm had promoted the forecasting performance of MLP neural networks considerably and the Adaboost-MLP model was effective for wind speed prediction. And Lu et al. [38] employed the Adaboost-BPNN model to forecast the lifetime of the light-emitting diode (LED) and ultimately achieved a higher forecasting precision. In [39], the Adaboost-BPNN model was used to predict the market demand for refrigerator, which reflected good prediction performance of this model. Besides, Lu and Hu et al. [40] developed a new time series prediction method combining the Adaboost algorithm and generalized radial basis function neural network (GRBF), and actual examples demonstrated that the proposed model was effective and feasible for prediction problems. The increasing application of Adaboost algorithm can be attributed to two aspects. One is that it can improve the prediction performance by combining multiple predictor models; another is that Adaboost algorithm has the advantages of simple calculation and small error. Therefore, the ENN optimized by Adaboost algorithm is applied to evaluate CO_2 emissions from the construction industry, which can maximize the merit of Adaboost algorithms and overcome the inherent defects of ENN model.

3. Methodology

This section aims to provide a brief introduction of the methods used in this study, including the calculation of CO_2 emissions, LMDI method, the partition of feature sets, and the weighted Adaboost-ENN model. The variables involved in the calculation of CO_2 emissions and LMDI method are defined in Table 1.

3.1. Calculation of CO_2 Emissions. The CO_2 emissions sources in the construction industry are defined as two parts: one is direct CO_2 emissions generated by the direct consumption of eight types of energy (coal, coke, gasoline, kerosene, diesel, fuel oil, natural gas, and electricity); the other is indirect CO_2 emissions generated by other industries in the process of producing five types of building materials (cement, steel, glass, wood, and aluminum). According to the carbon emission calculation method provided by IPCC (2006) [41], we can build the calculation model of CO_2 emissions in China's construction industry in the year t, which is illustrated in

$$C^t = C^t_{dir} + C^t_{ind} = \sum_i E^t_i \times F_i + \sum_j M^t_j \times \beta_j \tag{1}$$

3.2. LMDI Method. The CO_2 emissions in construction industry in year t can be expressed as

$$\begin{aligned} C^t &= C^t_{dir} + C^t_{ind} \\ &= \sum_{ij} \left(\frac{C^t_{dir}}{E^t_i} \times \frac{E^t_i}{E^t} \times \frac{E^t}{COV^t} + \frac{C^t_{ind}}{COV^t} \right) \times \frac{COV^t}{GDP^t} \\ &\quad \times \frac{GDP^t}{P^t} \times P^t \end{aligned} \tag{2}$$

In this article, we try to explore the impact of investment and labor on CO_2 emissions in construction industry. Nonetheless, the C-D production function is mainly used to reflect the impact of the number of two or more inputs on the number of output that can be produced by those inputs, particularly the inputs of physical capital and labor [42]. Therefore, this paper describes GDP and COV through production function. So the GDP and COV can be expressed as the following:

$$GDP = A\left(K^t\right)^\alpha \left(L^t\right)^\beta \tag{3}$$

$$COV = A\left(K_c{}^t\right)^\alpha \left(L_c{}^t\right)^\beta \tag{4}$$

where α, β, A are unknown constant parameters. GDP and COV on the right of (2) can be replaced by (3) and (4), and the following can be obtained.

$$\begin{aligned} C^t &= \sum_{ij} \left(\frac{CD^t_i}{E^t_i} \times \frac{E^t_i}{E^t} \times \frac{E^t}{COV^t} + \frac{CI^t_j}{COV^t} \right) \\ &\quad \times \frac{A\left(K^t\right)^\alpha \left(L^t\right)^\beta}{A\left(K_c{}^t\right)^\alpha \left(L_c{}^t\right)^\beta} \times \frac{GDP^t}{P^t} \times P^t \end{aligned} \tag{5}$$

$$C^t = \left(C^t_r \times C^t_n \times C^t_e + C^t_j\right) \times \left(\frac{K^t_c}{K^t}\right)^\alpha \times \left(\frac{L^t_c}{L^t}\right)^\beta \times C^t_a \times P^t \tag{6}$$

Based on the LMDI method proposed by Ang [7], the change of CO_2 emissions in the construction industry between the base year 0 and the target year t can be explained by the following seven factors: the energy structure effect (ΔC^t_n), direct energy intensity effect (ΔC^t_e), indirect carbon intensity effect (ΔC^t_j), construction fixed asset investment ratio effect (ΔC^t_k), construction labor input ratio effect (ΔC^t_l),

Table 1: Definition of the variables.

Variable	Definition
C^t	CO_2 emissions in construction industry in year t (10^6 t);
C^t_{dir}	direct CO_2 emissions in construction industry in year t (10^6 t);
C^t_{ind}	indirect CO_2 emissions in construction industry in year t (10^6 t);
E^t_i	total energy consumption of ith type of energy in year t (10^6 t);
F_i	the CO_2 emission factors of ith type of energy;
M^t_j	total consumption of the jth type of building material in year t (10^4 t);
β_j	CO_2 emission factors of jth type of building material;
E^t	total energy consumption in year t (10^4 t);
COV^t	construction output value in year t (10^9 yuan);
GDP^t	gross domestic product in year t (10^9 yuan);
P^t	total population in year t (person);
K	fixed asset investment (10^9 yuan);
L	labor input (person);
K^t_c	fixed asset investment of construction industry in year t (10^9 yuan);
L^t_c	labor input of construction industry in year t (person);
$C^t_r = CD^t_i/E^t_i$	carbon dioxide coefficient of ith type of energy in year t;
$C^t_n = E^t_i/E^t$	energy structure of ith type of energy in year t;
$C^t_e = E^t/COV^t$	direct energy intensity in year t;
$C^t_j = CI^t_j/COV^t$	indirect carbon intensity in year t;
$C^t_a = GDP^t/P^t$	GDP per capita in year t (10^9 yuan/person);
$C^t_k = K^t_c/K^t$	construction fixed asset investment ratio in year t;
$C^t_l = L^t_c/L^t$	construction labor input ratio in year t;
$coal^* = E^t_{coal}/E^t$	energy structure of coal in year t;
$coke^* = E^t_{coke}/E^t$	energy structure of coke in year t;
$gasoline^* = E^t_{gasoline}/E^t$	energy structure of gasoline in year t;
$\mathrm{kero}sene^* = E^t_{\mathrm{kero}sene}/E^t$	energy structure of kerosene in year t;
$diesel^* = E^t_{diesel}/E^t$	energy structure of diesel in year t;
$fueloil^* = E^t_{fueloil}/E^t$	energy structure of fuel oil in year t;
$natural\mathrm{gas}^* = E^t_{naturalgas}/E^t$	energy structure of natural gas in year t;
$electricity^* = E^t_{electricity}/E^t$	energy structure of electricity in year t.

Note: $*$ indicates energy structure.

GDP per capita effect (ΔC^t_a), and population effect (ΔC^t_p), as shown in the following.

$$\Delta C^t = \Delta C^t_n + \Delta C^t_e + \Delta C^t_j + \Delta C^t_k + \Delta C^t_l + \Delta C^t_a + \Delta C^t_p \quad (7)$$

Although production function combined with LMDI is an innovative way to develop the Kaya identity, there are still some disadvantages of using the C-D production function in calculating the influencing factors. When calculating ΔC^t_k and ΔC^t_l, there exist unknown constant parameters of α and β, which may exaggerate or abbreviate influencing factors [42].

3.3. The Partition of Feature Sets by Correlation Analysis. In previous study, the influencing factors obtained by LMDI method are put together as input to the same prediction model, whereas information redundancy will occur when there is correlation among the factors. Information redundancy often leads to some problems, such as overfitting and poor generalization ability, and the degree of correlation among the factors has a great impact on the training of prediction model. Therefore, it is of great significance to group influencing factors into different feature sets according to the correlation among influencing factors.

In this paper, the specific process of the partition of feature sets is as follows. First, assume X_1, X_2, X_3, X_4, X_5, and X_6 are the influencing factors. The correlation among the influencing factors is analyzed (Table 2) and the correlation coefficient between X_i and X_j is recorded as $\rho_{ij}(i = 1, 2, \cdots, 6; j = 1, 2, \cdots, 6; i > j)$. Second, the threshold of the correlation coefficient is set to $\mu(\mu = 0.9)$. Then, the two influencing factors are grouped into different feature sets when the absolute value of their correlation coefficient is greater than μ.

It can be seen from Table 2 that the absolute value of the correlation coefficient between X_2 and X_1 is greater than μ, indicating that the correlation between the two influencing factors is strong enough. If we eliminate one of these two

Table 2: The correlation coefficient matrix.

	X_1	X_2	X_3	X_4	X_5	X_6
X_1	1.00					
X_2	(ρ_{21})	1.00				
X_3	ρ_{31}	ρ_{32}	1.00			
X_4	ρ_{41}	ρ_{42}	ρ_{43}	1.00		
X_5	ρ_{51}	ρ_{52}	ρ_{53}	ρ_{54}	1.00	
X_6	ρ_{61}	ρ_{62}	ρ_{63}	ρ_{64}	ρ_{65}	1.00

Note: (ρ_{21}) indicates that the absolute value of the correlation coefficient between X_2 and X_1 is greater than μ.

influencing factors, it may cause information loss. Therefore, the influencing factors are grouped into two feature sets; that is, X_1, X_3, X_4, X_5, and X_6 are grouped into one group, and the other group are X_2, X_3, X_4, X_5, and X_6.

3.4. The Weighted Adaboost-ENN Prediction Model

3.4.1. The Adaboost-ENN Prediction Model. ENN is a recurrent neural network, with local memory units and feedback connections. Compared with the forward networks, ENN not only has an input layer, a hidden layer. and an output layer but also has a context layer. Context layer acts as a one-step delay operator to achieve the purpose of memory, so that the system has the ability to adapt to time-varying characteristics. Moreover, it can directly reflect the characteristics of the dynamic process system. Although ENN has been improved on the basis of the forward neural network, a common drawback of ENN is that the recursive part of the hidden layer cannot be adjusted because it is fixed. To overcome this defect of ENN, the Adaboost algorithm is employed to optimize ENN to improve the prediction performance.

Adaboost algorithm, a typical example of boosting algorithm, was developed by Schapire to regress with time series data [43].The Adaboost algorithm can generate different weak learners by training the same data set repeatedly and then combine these weak learners into a powerful learner with high generalization ability. The core idea of the Adaboost algorithm is to raise the weights of the samples with large prediction error and the weak learners with good performance. At the same time, the weights of the samples with good training effect and weak learners with poor learning ability are reduced [44].

The procedure of Adaboost-ENN model is briefly described as follows.

Step 1. Preprocess original data by quantification and normalization.

Step 2. Assume training set $X_i = (x_1, y_1), \cdots, (x_m, y_m), i = 1, 2, \cdots, m$. The initial distribution weight of the sample on the training set is initialized: $D_1(i) = 1/m$. The neural network structure is determined by the input and output dimensions, and the weights and thresholds of ENN are initialized.

Step 3. Find weak predictor $h_j(j = 1, 2, \cdots, T)$. When the jth weak predictor is trained, ENN is also trained with the training set and prediction results are output. And then the sum of prediction error ε_j of the prediction series $h(j)$ can be obtained, which can be expressed as follows:

$$\varepsilon_j = \sum_{i=1}^{m} D_t(x_i), \quad i = 1, 2, \cdots, m\left(h_j(x_i) \neq y_i\right) \tag{8}$$

where $h_j(x_i)$ is the prediction results and y_i is the actual value.

Step 4. Update weight. According to the ε_j, the weight of the series is calculated as

$$\alpha_j = \frac{1}{2} * \ln\left[\frac{\left(1 - \varepsilon_j\right)}{\varepsilon_j}\right] \tag{9}$$

And then, the weight of the next training sample is adjusted; the adjustment formula is

$$D_{j+1}(i) = \frac{D_j(i)\exp\left[-\alpha_j y_i h_j(x_i)\right]}{Z_j}, \quad i = 1, 2, \cdots, m \tag{10}$$

where Z_j is the normalization factor, and $\sum_{i=1}^{N} D_{j+1}(x_i) = 1$.

Step 5. Obtain T strong prediction functions $h_j(x)(j = 1, 2, \cdots, T)$ through T-round training. And a strong prediction function is formed:

$$H_{final}(x) = \operatorname{sign}\left(\sum_{j=1}^{T} \alpha_j h_j(x)\right) \tag{11}$$

3.4.2. The Weight Determination Method. Based on the partition of feature set, the paper introduces the training weight of the feature set by the accuracy of each feature set training model to obtain the output reasonably. According to the study of Zhang and Fu et al. [45], the method of determining weights is obtained. The weight calculation process is as follows.

Step 1. Assume the number of feature sets is $m(m = 1, 2, \cdots, M)$. And the prediction accuracy of each feature set is defined as $E_m(\mathrm{m} = 1, 2, \cdots, M)$. The calculation formula is shown (8):

$$E_m = \frac{\sum_{k=1}^{K}\left(c_{km} - \overline{C_m}\right)^2}{\left(C_{km} - c_{km}\right)^2} \tag{12}$$

where E_m represents the precision quality of the samples in mth feature set; c_{km} is the predicted value of the kth samples in mth feature set; C_{km} denotes the actual value of the kth samples in mth feature set; $\overline{C_m}$ is the average of the actual values in mth feature set.

Step 2. Calculate the output weight of each feature set, recorded as $W_m (m = 1, 2, \cdots M)$. The calculation formula is

$$W_m = \frac{E_m}{\sum_{m=1}^{M} E_m} \tag{13}$$

Step 3. Get final prediction results based on the weights of each feature set, which can be expressed as follows:

$$Y_i = \sum_{m=1}^{M} W_m y_{im} \tag{14}$$

where y_{im} is the predicted value of the ith samples in mth feature set; Y_i is the predicted results based on weighted method.

4. Application of the Weighted Adaboost-ENN Model

4.1. Collection of Data. The research period of this paper started in 2004 and ended in 2016. The data of energy consumption in China's construction industry are all derived from "China Energy Statistical Yearbook (2005-2017)" and converted into standard coal consumption (10^4 tce). The consumption data of building materials are obtained from "China Statistical Yearbook on Construction (2005-2017)". GDP, COV, fixed asset investment, fixed asset investment in construction industry, labor input, labor input in construction industry, and population all come from "China Statistical Yearbook (2005-2017)", in which the first four variables are measured in constant 2004 price.

4.2. Decomposition Analysis. Based on the LMDI method in its additive form given in Section 3.2, the decomposition results about CO_2 emissions in the construction industry are presented in Table 3. The results show that there are four influencing factors driving CO_2 emissions in construction industry. According to the order of cumulative effect from large to small, the four influencing factors are GDP per capita, construction labor input ratio, population and energy structure, among which the former two have greater impact. The reason may be that the increase in GDP per capita and population boosts the demand for building facilities and infrastructures, which raises CO_2 emissions. Besides, the construction industry is the labor-intensive industry, which expands the demand for and investment in the labor force. It also can be seen from Table 3 that the remaining three influencing factors play an important role in decreasing CO_2 emissions, which are construction fixed asset investment ratio, indirect carbon intensity, and direct energy intensity. The root cause for these results is that the widespread application of energy-saving technology and the advancement of management level increase the investment in new equipment and the development of new technology.

4.3. The Partition of Feature Sets. In order to fully consider the influencing factors of CO_2 emissions from the construction industry, the energy structure obtained by LMDI method is further subdivided into eight types of energy structures, namely, coal∗, coke∗, gasoline∗, kerosene∗, diesel∗, fuel oil∗, natural gas∗, and electricity∗. The specific definitions of the eight types of energy structures are shown in Table 1.

The partition of feature sets is to group the influencing factors into different feature sets by analyzing the correlation among influencing factors. The correlation analysis is performed on fourteen influencing factors to obtain a correlation coefficient matrix, as shown in Table 4. It can be seen from Table 4 that the absolute value of the correlation coefficient varies from 0.004 to 0.994, which indicates that there is strong correlation among some influencing factors. Therefore, to avoid information redundancy, the obtained fourteen influencing factors are grouped into six feature sets with μ set to 0.9. The composition of influencing factors in each feature set is presented in Table 5.

4.4. Simulation

4.4.1. Parameter Selecting and Evaluation Criteria. It is Adaboost algorithm that optimizes the ENN to form strong predictor, and the strong predictor is used in each feature set to predict CO_2 emissions from the construction industry. Each feature set includes thirteen years of data, in which the first nine years of data are used as training set and the last four years are tested as test set. In Adaboost-ENN model, the number of iterations is set to 330 and the learning rate is 0.0001. Moreover, the main parameters of the weighted Adaboost-ENN model in each feature set are listed in Table 6.

To compare the forecasting performance of models effectively, this study selects the coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) to measure the precision of the models involved in this paper. The equations of the aforementioned evaluation criteria are as follows:

$$R^2 = 1 - \sum_{t=1}^{n} \frac{(\hat{y}_t - y_t)^2}{(y_t - \overline{y})^2} \tag{15}$$

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{\hat{y}_t - y_t}{y_t} \right| \times 100\% \tag{16}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left| \frac{\hat{y}_t - y_t}{y_t} \right|^2} \tag{17}$$

where y_t is actual value of CO_2 emissions in the year t, $\hat{y}_t$ denotes the predicted value of CO_2 emissions, $\overline{y}$ is mean value of the predicted value, and n reflects the test sample size.

4.4.2. Estimation Results. The integral procedure of weighted Adaboost-ENN is executed by MATLAB2014a. To further demonstrate the validity of the splitting of feature sets, the proposed model is compared with the direct prediction model that puts fourteen influencing factors together as input to the Adaboost-ENN model. Then, the present study also

Table 3: The decomposition of different factors on CO_2 emissions change in China's construction industry during 2004-2016.

Year	ΔC_n^t	ΔC_e^t	ΔC_j^t	ΔC_k^t	ΔC_l^t	ΔC_a^t	ΔC_p^t	ΔC^t
2004-2005	-22.3	-227.7	-4384.0	0.0	2560.7	5531.5	334.0	3792.1
2005-2006	-16.8	-567.3	-5380.1	-5058.5	4903.9	15817.3	691.6	10390.0
2006-2007	17.0	-1109.3	-12512.7	-18480.4	4650.1	27123.0	1040.1	727.8
2007-2008	21.0	-1756.8	-7728.2	-26365.2	4737.1	42642.0	1541.7	13091.7
2008-2009	19.6	-2424.0	-20729.2	-32068.9	10548.8	56993.5	2015.2	14355.0
2009-2010	14.4	-2633.8	-14208.4	-38303.8	15862.2	74013.0	2749.3	37492.9
2010-2011	49.2	-3053.2	37690.8	-38818.7	53221.4	125034.1	4554.6	178678.3
2011-2012	61.6	-3789.9	54820.2	-35521.9	78939.6	169982.3	6084.4	270576.4
2012-2013	57.6	-4029.2	-17907.0	-38239.4	88464.4	141520.7	5268.1	175135.3
2013-2014	93.5	-4399.2	-19797.7	-59813.6	91397.8	160535.3	6191.2	174207.4
2014-2015	42.1	-4566.2	-51839.4	-54554.5	70468.5	143320.9	5763.8	108635.2
2015-2016	33.5	-4698.5	-52654.7	-46403.6	67605.7	153396.9	6532.2	123811.5
2004-2016	370.5	-33254.9	-114630.4	-393628.5	493360.3	1115910.5	42766.1	1110893.6

Table 4: The correlation coefficient matrix between 14 influencing factors.

	Coal∗	Coke∗	Gasoline∗	Kerosene∗	Diesel∗	Fuel oil∗	Natural gas∗	Electricity∗	C_e	C_i	C_k	C_l	C_a	C_p
Coal∗	1.000													
Coke∗	0.748	1.000												
Gasoline∗	-0.835	-0.809	1.000											
Kerosene∗	0.420	0.558	-0.621	1.000										
Diesel∗	0.504	0.648	-0.845	0.490	1.000									
Fuel oil∗	-0.562	-0.448	0.485	0.023	-0.612	1.000								
Natural gas∗	0.194	0.653	-0.484	0.439	0.494	-0.074	1.000							
Electricity∗	-0.794	-0.901	0.757	-0.573	-0.629	0.576	-0.383	1.000						
C_e	0.841	0.950	-0.825	0.547	0.652	-0.548	0.477	-0.976	1.000					
C_i	0.332	-0.024	-0.358	-0.208	0.394	-0.488	-0.233	-0.004	0.085	1.000				
C_k	0.762	0.822	-0.722	0.258	0.631	-0.676	0.313	-0.843	0.884	0.374	1.000			
C_l	-0.667	-0.687	0.736	-0.636	-0.668	0.452	-0.257	0.833	-0.806	-0.122	-0.582	1.000		
C_a	-0.824	-0.828	0.909	-0.671	-0.772	0.495	-0.362	0.907	-0.918	-0.211	-0.757	0.931	1.000	
C_p	-0.865	-0.857	0.914	-0.636	-0.742	0.505	-0.371	0.922	-0.944	-0.224	-0.805	0.901	0.994	1.000

Note: ∗ indicates energy structure.

Table 5: Composition of variables in different features.

Feature set 1	Feature set 2	Feature set 3	Feature set 4	Feature set 5	Feature set 6
Coal∗	Coal∗	Coal∗	Coal∗	Coal∗	Coal∗
Coke∗	Coke∗	Coke∗	Coke∗	Gasoline∗	Gasoline∗
Gasoline∗	Kerosene∗	Kerosene∗	Kerosene∗	Kerosene∗	Kerosene∗
Kerosene∗	Diesel∗	Diesel∗	Diesel∗	Diesel∗	Diesel∗
Diesel∗	Fuel oil∗	Fuel oil∗	Fuel oil∗	Fuel oil∗	Fuel oil∗
Fuel oil∗	Natural gas∗	Natural gas∗	Natural gas∗	Natural gas∗	Natural gas∗
Natural gas∗	C_j	C_j	C_j	Electricity ∗	C_e
C_j	C_k	C_k	C_k	C_j	C_j
C_k	C_a	C_p	C_l	C_k	C_k
C_l	-	-	-	C_l	C_l

Note: ∗ indicates energy structure.

Table 6: Main parameters of the weighted Adaboost-ENN model.

Feature set	Values		
	Weak predictors	Hidden layer	The weight
Feature set 1	16	24	0.076
Feature set 2	17	13	0.054
Feature set 3	10	22	0.051
Feature set 4	15	24	0.195
Feature set 5	30	23	0.290
Feature set 6	11	26	0.334

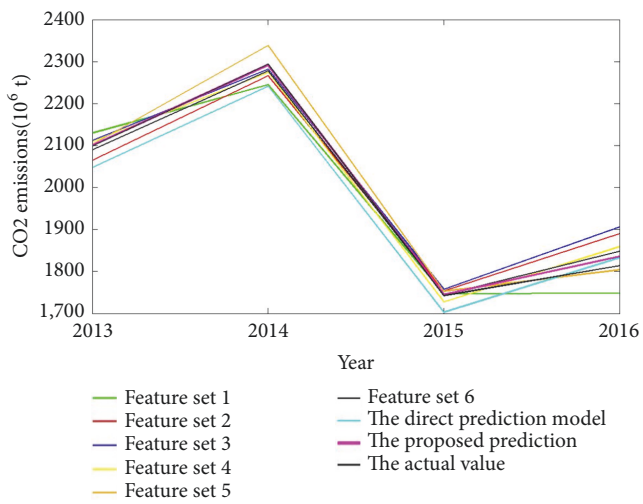

Figure 1: The prediction results and actual values.

Table 7: The estimates errors of prediction results.

	R^2	MAPE(%)	RMSE
Feature set 1	0.9609	1.88	0.0223
Feature set 2	0.9599	1.93	0.0235
Feature set 3	0.9537	1.77	0.0262
Feature set 4	0.9863	1.15	0.0139
Feature set 5	0.9886	0.82	0.0106
Feature set 6	0.9924	0.79	0.0103
The proposed model	0.9977	0.37	0.0059
The direct prediction model	0.9633	2.00	0.0207

Table 8: Error analysis of the compared models.

	The proposed model	PSO-ENN	ENN	BPNN
R^2	0.9977	0.9878	0.9448	0.9417
MAPE(%)	0.37	0.98	1.45	2.10
RMSE	0.0059	0.0126	0.0183	0.0289

makes comparisons with different models, including PSO-ENN model, ENN model, and BPNN model, to testify the effectiveness of the proposed model.

It can be seen from Figure 1 that the fitting curve from 2013 to 2016 of the suggested weighted Adaboost-ENN model is superior to others in CO_2 emissions forecasting from the construction industry. Relatively, the tracks of direct prediction model and the prediction results of each feature set have a worse fitting effect with some predicted points deviating from the actual values. Moreover, to intuitively reflect the forecasting performance of models, the evaluation criteria of prediction results are listed in Table 7. In general, the forecasting performance of the proposed model outperforms others in terms of R^2, MAPE, and RMSE. For instance, the R^2 of the proposed model is 0.9977, but those of feature set 6 and direct prediction model are 0.9924 and 0.9633, respectively. The RMSE of the proposed model is 0.0059, whereas those of feature set 6 and direct prediction model are 0.0103 and 0.0207, respectively.

Furthermore, the proposed model is compared with three other different models. The prediction error of each model is listed in Table 8. As shown in Table 8, the proposed model displays high prediction accuracy in terms of MAPE and RMSE. For PSO-ENN, ENN, and BPNN, the values of MAPE are higher than the proposed model, about 0.61%, 1.08%, and 1.73%, respectively. However, the RMSE value of PSO-ENN is 0.0126, so the results forecasted by PSO-ENN have already exhibited better accuracy. Nevertheless, MAPE and RMSE of the proposed model are 0.37% and 0.0059, which obtains better results.

5. Future Estimation of CO_2 Emissions in the Construction Industry

In this paper, we evaluate the future CO_2 emissions in China's construction industry in 2030. The year 2030 is a crucial time node, because China government promised that China's total CO_2 emissions would peak around 2030 or even earlier. In order to test whether China can achieve this goal, we set three scenarios referring to the previous research on scenario analysis [46–48]. In these researches, the influence of policy is rarely considered, and historical trend of influencing factors is simply reflected by the average growth rate, which makes the setting of scenarios distinguished from fact.

Therefore, we make some improvements to the scenario setting based on the previous researches. Firstly, according to whether the variables are affected by policies on energy conservation, population and economy during 2017-2030, fourteen influencing factors obtained by LMDI method are divided into policy variables and nonpolicy variables. Therefore, C_e, C_j, C_a, C_p, and coal$*$ are determined as policy

variables; the remaining variables are nonpolicy variables. Secondly, the policy variables are divided into positive variables (C_p and C_a) and negative variables (C_e, C_j and coal$*$) to further distinguish the direction and extent of the impact of these variables on CO_2 emissions. And we assume that the future variation tendency of nonpolicy variables in each scenario will be consistent with each other. Thirdly, considering the historical trend of variables, we define the parameters of policy variables by the average growth rate. Moreover, on the basis of historical data and related information of nonpolicy variables, the ARIMA model is applied to predict future trends of nonpolicy variables from 2017 to 2030 in all three scenarios, which can reduce the impact of abnormal data and make prediction performance more stable.

5.1. Scenario Setting. The specific three scenarios include HS, LS, and BS, in which policy variables are set as follows.

(1) Under the HS, according to annual growth rate of C_e and coal$*$ during the 12th Five-Year, the future trends of these two variables are set. The changes in C_p and C_j are determined by the annual average growth rate of the two variables during 2006-2016. The change trend of C_a from 2017 to 2020 is decided by its growth rate during the 12th Five-Year. Considering that China's economy has entered a "new normal", the growth rate of C_a from 2021 to 2030 is reduced by 5% than that from 2017 to 2020.

(2) Under the BS, the variation tendency of policy variables is decided by the relevant national policy regulations. The corresponding data is taken from Research Report on National Population Development Strategy [49], 13th Five-Year Comprehensive Plan for Energy Saving and Emission Reduction [50], the 13th Five-Year Plan [51], and Revolution Strategy of Energy Production and Consumption (2016-2030) [52].

(3) Under the LS, the future change rate of each policy variable is reduced by 5% based on change rate of the BS. Table 9 lists the future change rate of each policy variable under the three scenarios.

5.2. Future CO_2 Emissions in the Construction Industry. The weighted Adaboost-ENN prediction model is used to predict CO_2 emissions in China's construction industry from 2017 to 2030. According to the prediction results, the forecast curves of CO_2 emissions in the construction industry under different scenarios are plotted, as shown in Figure 2. Under HS, CO_2 emissions curve is in the shape of an inverted "V". In BS and LS, CO_2 emissions can be roughly divided into three phases. Firstly, CO_2 emissions will show rapid upward trend from 2017 to 2020. Subsequently, the upward trend of CO_2 emissions will become flat. After 2028, it will present slow downward trend in BS, whereas LS is the opposite. Through comparison, we can see that the time of CO_2 emissions reaching their peak is inconsistent and the peak also varies under HS and BS. Moreover, in accordance with the order of CO_2 emissions, the CO_2 emissions of the construction industry under HS are the highest, followed by BS, and the lowest CO_2 emissions are LS.

From Figure 2, the growth rate of CO_2 emissions will be reduced from 5.51% over the period 2015–2020 to 1.42% over

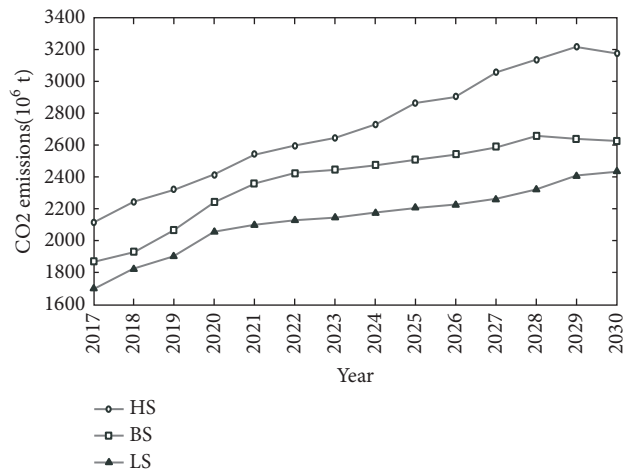

Figure 2: Predicted CO_2 emissions in China's construction industry under three scenarios from 2017 to 2030.

the period 2021–2027 in BS, which can be attributed to a series of practical policies related to direct energy intensity, indirect carbon intensity and coal$*$. There will be further decrease after 2027, and CO_2 emissions will reach peak of 2736.08 million tons in 2028. By 2030, CO_2 emissions in the construction industry will be reduced to 2653.25 million tons. It is probably because the setting of the BS is mainly to take into account national policies. On the one hand, China government promised that China's total CO_2 emissions would peak around 2030 or even earlier, so the government will introduce corresponding policies to achieve this goal as soon as possible while ensuring economic development. On the other hand, with the development of Building Information Modeling (BIM) technology, it will help improve the sustainable and healthy development of the construction industry to reduce CO_2 emissions. In HS, CO_2 emissions will peak in 2029, and the peak value will be about 3218.36 million tons higher than that in BS. The underlying reason is that the setting of HS is based on historical development trend of each variable, so it will be more concerned about economic development than BS. In addition, with the development of clean technology and the use of clean energy, the negative factors inhibiting CO_2 emissions will gradually exceed positive factors. In LS, the CO_2 emissions of construction industry will present slow upward trend from 1702.38 million tons in 2017 to 2438.53 million tons in 2030, with an annual growth rate of 2.80%. The reason may be that the setting of LS further reduces the speed of economic development and increases the degree of inhibiting CO_2 emissions compared to BS. This study only focuses on the node in 2030, so the peak value of LS is uncertain from a long-term perspective.

Furthermore, with respect to the occurrence time of CO_2 emissions peak value in construction industry, the results indicate that it will be achieved before 2030 under HS and BS, whereas it will not be achieved in LS. In other words, it is possible to peak in 2030 for CO_2 emissions in construction industry. Therefore, this further illustrates that the government's policy measures are reasonable.

Table 9: Definition of annual variation rates of policy variables under different scenarios (%).

Policy variable	HS	BS	LS
Population	0.51(2017-2030)	0.54(2017-2020) 0.39(2021-2030)	0.37(2017-2030)
GDP per capita	8.06(2017-2020) 7.66(2021-2030)	6.50(2017-2020) 6.18(2021-2030)	6.18(2017-2020) 5.87(2021-2030)
Direct energy intensity	-4.73(2017-2030)	-5.44(2017-2030)	-5.71(2017-2030)
Indirect carbon intensity	-3.30(2017-2030)	-3.89(2017-2030)	-4.09(2017-2030)
Coal energy structure	-1.01(2017-2030)	-1.32(2017-2020) -1.18(2021-2030)	-1.39(2017-2020) -1.24(2021-2030)

6. Conclusion

6.1. Major Conclusions. This paper employs the decomposition method combining the LMDI and C-D production functions to derive fourteen variables that affect CO_2 emissions in the construction industry. On this basis, fourteen influencing factors of CO_2 emissions in the construction industry are grouped into six feature sets by the correlation analysis. The influencing factors in each feature set are put together as input to the Adaboost-ENN model, respectively, and the prediction results of each feature set are weighted to get the final result of CO_2 emissions in the construction industry under different scenarios. Conclusions can be drawn as follows.

(1) During the study period, influencing factors have different effect both in magnitude and direction. GDP per capita, construction labor input ratio, population and energy structure drive significantly the growth of CO_2 emissions, each of them contributing 100.45%, 44.41%, 3.85%, and 0.03%, respectively. However, construction fixed asset investment ratio, indirect carbon intensity, and direct energy intensity inhibit CO_2 emissions, each of them reducing CO_2 emissions by 35.43%, 10.32%, and 2.99%.

(2) Compared with the direct prediction model, single feature set, and other three models, the weighted Adaboost-ENN model has minimum prediction error, which indicates that the proposed model is effective and promising in CO_2 emissions forecasting.

(3) Under HS and BS, the peak time for CO_2 emissions in construction industry may be 2029 and 2028, respectively, and the peak values are 3218.36 million tons and 2736.08 million tons in that order. Compared with HS, CO_2 emissions in the construction industry in the other two scenarios are lower, indicating that the government's stricter requirements on direct energy intensity, indirect carbon intensity, and coal energy structure will help reduce CO_2 emissions in the construction industry.

6.2. Policy Implications. According to the above conclusions, to reduce CO_2 emissions in China's construction industry, some policy implications are given as follows.

(1) Based on the close relationship between economic growth and CO_2 emissions in construction industry, it is crucial to deepen supply side reform and adjust economic scale of the construction industry. Since the 21st century, the construction industry has made tremendous contributions to the national economy and has also led to rapid growth of CO_2 emissions. Therefore, the government should adjust the industrial structure, such as encouraging leading enterprises in the industry to become stronger and timely transforming and upgrading the types of enterprises.

(2) Improve the overall quality of the workers in the construction industry to further promote the awareness of emission reduction. Human activities play an irreplaceable role in production, whereas they definitely increase CO_2 emissions. Therefore, it is crucial to deal with the relationship between human activities and emission reduction work. In view of this, enterprises should construct cultural atmosphere of energy saving and emission reduction from spirit level and system level and then strengthen publicity and education.

(3) Promote the adjustment of energy production and utilization methods, and optimize the energy structure. On the one hand, the government should focus on energy balances and regional distribution to alleviate the pressure on large-scale and long-distance transmission of primary energy. On the other hand, energy diversification will be realized by increasing the proportion of clean energy, which is conducive to the promotion of high-quality and low-carbonization of energy production and consumption.

The study provides in-depth analysis of the influencing factors of CO_2 emissions in construction industry and scientific prediction model with high accuracy and stability, which may help the government take effective policy measures to achieve emission reduction targets. However, the drawback of this study is clear such that the prediction performance of the weighted Adaboost-ENN model is expected to be further improved due to the availability of research data. In future research, scientific prediction models will continue to be explored.

Data Availability

The dataset tables used to support the findings of this study have been deposited in the figshare repository, https://figshare.com/s/07646ddaa4a2207de699.

Conflicts of Interest

The authors declare no conflicts of interest.

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