Scenario Analysis of Carbon Peak Based on PSOBP

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Abstract. To investigate the carbon peak scenario and corresponding time in China, this paper firstly employed the grey correlation test to determine the factors influencing carbon emissions; Secondly, PSO-BPNN neural network combined with scenario analysis was used to construct a unique scenario analysis model of China's carbon emissions; Results revealed that: the actual amount of foreign capital utilized, diesel consumption and China's urbanization rate are the three most influential factors on China's carbon emissions. The "double carbon" goals have a long way to go and achieving the carbon peak ahead of schedule requires accelerating the low-carbon energy transition and actively optimizing and upgrading industries but also relies on technological innovation and the promotion of advanced technologies.

Keywords: China, Carbon peak, Scenario analysis, PSO-BPNN.

1. Introduction

The remarkable recovery and expansion of the world economy and the extremely rapid population growth are the primary cause of the impact of global warming and the frequent occurrence of extreme weather. In addition, the scarcity of traditional energy sources and their negative impact on the overall ecological environment is of global concern. China's goals of "peak carbon by 2030" and "carbon neutral by 2060" have captured the world's attention. Consequently, China has worked hard to advance its emission reduction goals through various means, such as carbon trading policies, green power, ultra-high voltage transmission, renewable energy policies, etc. Based on these policies, it is essential to estimate the future trend of China's carbon emissions and propose feasible recommendations to accelerate the peak of the carbon emission target.

In recent years, many scholars in China have conducted research on peak carbon prediction. Nonetheless, most of these studies are based on two methods, factor analysis, and trend analysis. In particular, factor analysis describes the unobserved variables with a low potential number of relevant variables. Liu Yanhui and Li Yang (2022) decomposed the principal contributors to carbon emissions using the LMDI decomposition method. then revealed that total carbon emissions are primarily determined by carbon intensity, energy intensity, economic output, and population based on the Kaya formula [1]. Xu Guoquan, Liu Zeyuan, and Jiang Zhaohua (2006) modeled the decomposition of carbon emission factors per capita in China using LMD based on the basic carbon emission formula and showed that the contribution of economic development to per capita carbon emissions in China had increased exponentially. In contrast, the contribution of energy efficiency and energy mix to reducing carbon emissions per capita in China is inverted u-shaped[2]. Trend analysis, on the other hand, concentrates on analyzing historical observations and forecasting future development trends. Yehong Liu, Zhen Zhang, Hongwei Chen, Jia-Nan Zou, and Bo Hu (2021) employed a time series approach to predict and estimate carbon emissions in Jiangsu Province for 2019 - 2060 using an ARIMA model and proposed the relationship between carbon emissions and vegetation cover under a carbon neutral scenario[3]. Hu, Jianbo, Luo, and Li, Feng (2021) estimated the carbon emission intensity of China under the "peak carbon" target by using the ARIMA-BP model and estimated that the carbon emission intensity of China in 2030 would be 66.93% lower than that in 2005[4]. Wang, Jingjing, and Wei, Jiajia (2021) demonstrated that the carbon emission factors of electricity and heat in Beijing are decreasing annually under the time series of carbon emission characteristics and scenario simulation of building operation in Beijing[5]. Furthermore, the fundamental prediction models are BP neural network and SVR. jinlin, ma zhongyun, and wang honghong (2019) established BP neural network for carbon trading price prediction and concluded that it performed well in short-term prediction and could accurately represent carbon trading price trends and stochastic fluctuations[6]. Huiru Wang, Xuejun Feng, Jinxing Shen, Yan Zhang, and Haipeng Wang (2022) forecasted carbon emission

peaking in Jiangsu province based on SVR and predicted that carbon peaking needs to be delayed until 2036 even in an intensified setting[7].

However, analyzing the future trend of carbon emissions is a very complicated issue, which is limited by various other influences and historical trends, as well as by policy-related regulations and the international situation. Therefore, the research framework of this paper mainly adopts the BP neural network based on PSO improvement and the scenario analysis method to structure the carbon emission scenario forecasting model in China and analyze the relevant policy documents and historical trends of the Chinese government to allocate appropriate parameters to each influencing factor, and then set up three scenarios: baseline, low carbon and enhanced. Through understanding the corresponding year of each scenario of carbon peak and total carbon emissions, the model also proposes feasible recommendations for China to accelerate efforts to reach a carbon peak by 2030.

2. Method Principle

2.1. BP Neural Network

The forward propagation of the signal and the backward propagation of the error comprise the two constituents of the BP neural network method. It includes the input layer, output layer and hidden layer. Its learning rule is to adopt the steepest descent method in which the back propagation is used to regulate the weight value and threshold value of the network to achieve the minimum error sum of square[8].

$$X_{k+1} = X_k - \eta_k g_k \tag{1}$$

Based on formula (1) above, the X_k represents the matrix of current weight value and threshold value; g_k represents the gradient of current function; ηrepresents the learning rate. The process of BP neural network is shown in Figure 1.

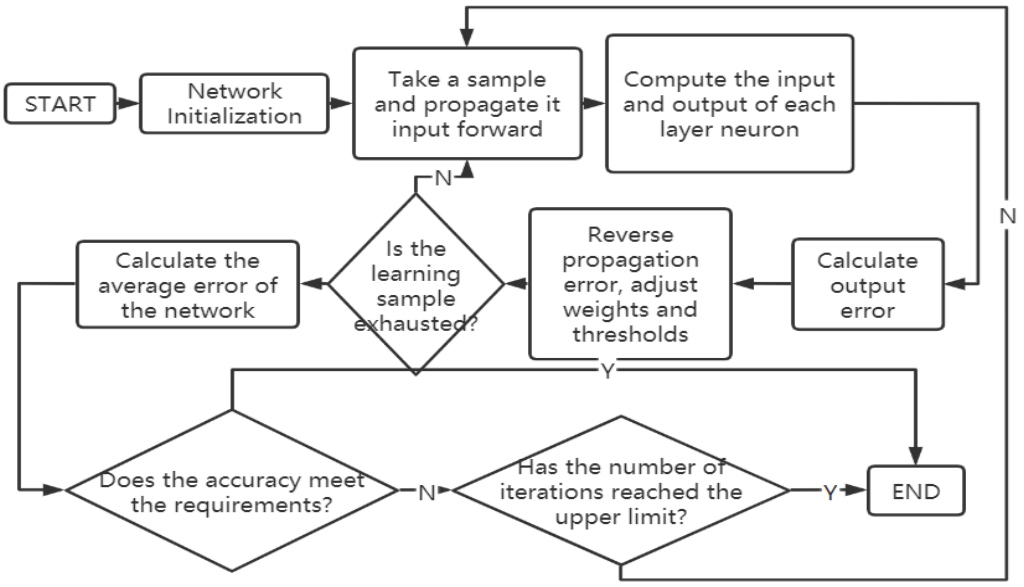


Figure 1. BP neural network flow chart

2.2. Particle Swarm Algorithm

PSO is a stochastic global optimization technique, which each particle represents a different fitness value in the algorithm and represents a feasible solution to the optimization problem, by dynamically adjusting according to its own previous best position and its nearby particle's best position[9]. Each particle is randomly chosen inside of d-dimension place; The position of ith particle is represents as $X_i = [x_{i1}\ x_{i2}\ \ldots\ x_{iD}]^T$ .The velocity of *i*th is represents as $V_i = [V_{i1}\ V_{i2}\ \ldots\ V_{iD}]$. The frontier[$-X_{max}$,$X_{max}$], the biggest velocity [$-V_{max}$,V_{max}].

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 \left(pbest_{id}^{k} - X_{id}^{k}\right) + c_2 r_2 \left(gbest_{d}^{k} - X_{id}^{k}\right) \tag{2}$$

$$X_{id}^{K+1} = X_{id}^{K} + V_{id}^{K+1} \tag{3}$$

Which, $d = 1, 2, \ldots, D$; $i = 1, 2, \ldots, n$; ω is the inertia weight value, which shows the effect of previous velocity vector on the new vector; k is the number of iteration times; c_1 and c_2 are positive constant. r_1 and r_2 are two random variables with uniform distribution between 0 and 1; $pbest_{id}$ represents the best previous position of the ith particle and $gbest_d$ represents best previous position among all the particles in the population. The whole process of PSO algorithm is shown in Figure 2.

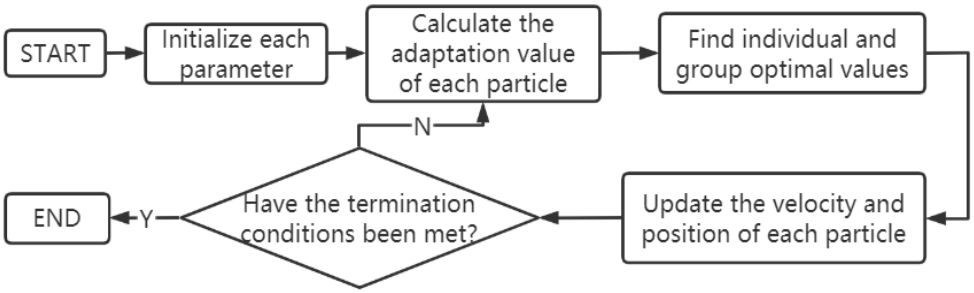


Figure 2. PSO algorithm flow chart

2.3. PSO-optimized BP Neural Network Model

The initial weights and thresholds of the BP neural network are optimized using the PSO algorithm. Firstly, the particle population (velocity and position) is initialized and the initial parameters of the PSO algorithm are set as follows: inertia weight is 0.9, acceleration constant is 1, and the maximum number of iterations is 30. Secondly, the corresponding particle is found to be the optimal solution of the population by global optimization search, i.e., the optimal solution of the neural network weights and thresholds. Finally, the global optimal solution is substituted into the BP neural network to obtain the prediction results of carbon emissions. As a result, improved BPNN process based on PSO is shown in Figure 3[10].

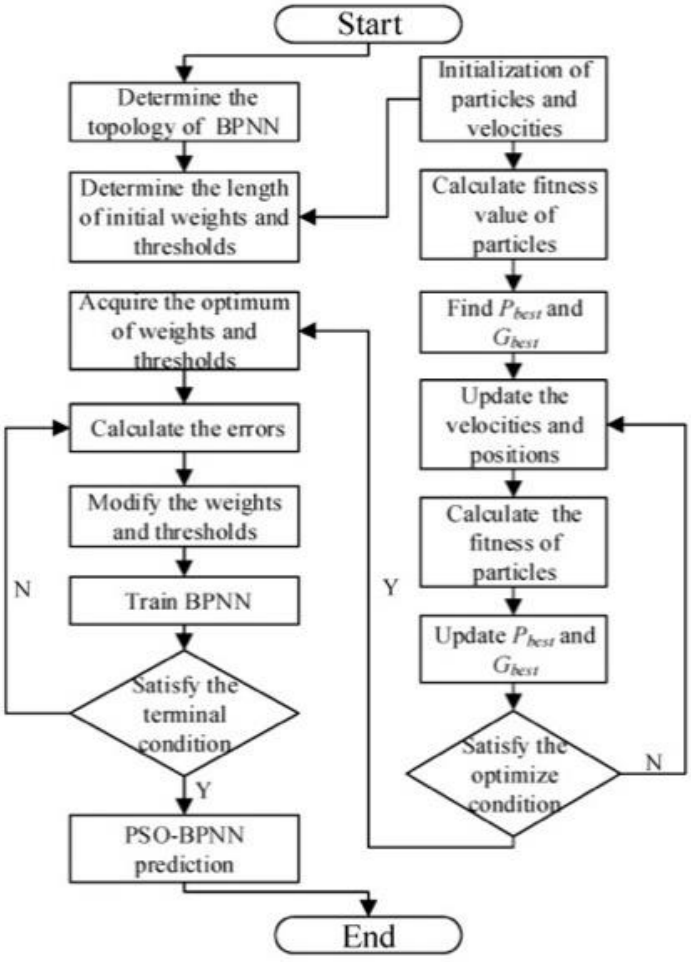


Figure 3. Structure of PSO-BP neural network model

3. Case Analysis

3.1. Index Optimization

According to the previous research literature [11-16], it can be found that most scholars have studied the influencing factors of carbon emissions from the aspects of population size, industrial structure, energy structure and economic scale. Therefore, the index system constructed in this paper is shown in Table 1.

The correlation degree in Table 1 is the grey correlation degree between each influencing factor and China's total carbon emissions. It can be found that the largest correlation with China's total carbon emissions is the actual utilization of foreign capital, and the correlation is 0.8903. However, it is generally believed that the gray correlation greater than 0.6 can be considered to have a strong correlation. According to the results in Table 1, it can be considered that each influencing factor has a strong correlation with China 's total carbon emissions. This shows that by adjusting the actual utilized foreign capital and other factors can have a significant impact on China's carbon emissions.

Table 1. System of influencing factors of carbon emissions in China

Index	Implication	Unit	Reference	Correlation degree
Population	Total population	W	[11]	0.6944
Labor input	The amount of labor actually invested in the production process	W	[12]	0.6797
Gasoline consumption	The number of liters of fuel consumed by a car during a certain mileage	Kilotons	[13]	0.7926
Diesel consumption	Total fuel consumption of diesel engines	Kilotons	[13]	0.8734
Natural gas consumption	Total consumption of natural gas	TMC	[2]	0.7248
Electric power consumption	Total power consumption	TWH	[2]	0.7626
Secondary industry added value	The added value of unit output value of the second industry in a certain period	Billion RMB	[14]	0.7044
Per capita gross domestic product	GDP per capita	RMB	[11]	0.6687
China's urbanization rate	The ratio of urban population to total population	%	[11]	0.7960
Contribution rate of the tertiary industry to GDP	Proportion of increment of tertiary industry in GDP increment	%	[14]	0.7475
Actual utilized foreign capital	Foreign funds actually arrived in China after signing contract with foreign businessmen	Billion USD	[15]	0.8903
CPI of coal mining and washing industry	Mining and washing factory price of anthracite, bituminous coal, and other raw coal	%	[16]	0.6500

3.2. Data Sources

This paper studies the scenario of carbon peak based on China's relevant data from 2000 to 2021. Among them, China's total carbon emissions data are derived from the CEADS database and 2020-2021 *Global Energy Assessment Report*. The population and labor input data are derived from the *China Economic Annual Report*. The energy consumption data mainly comes from Zhou Chuang Information Data Monitoring, China National Energy Administration and *National Economic and Social Development Statistical Bulletin*. The data of the secondary industry added value, per capita GDP, China's urbanization rate, the contribution rate of the tertiary industry to GDP, the actual utilized foreign capital and the CPI of coal mining and washing industry are all from the National Bureau of Statistics.

3.3. Model Construction

3.3.1 Model parameters setting

The BP neural network is constructed with carbon emission as the dependent variable. In this paper, multiple training of different neurons is attempted according to the specific practical situation and the number

of samples, and it is revealed that the best results are obtained when the number of hidden layer nodes is determined to be 25.

The data from 2000-2015 were the training set. Then, testing data from 2016-2021 were used to normalize and train the BP neural network. To identify the optimal weights and thresholds for each neuron, 2016-2021 based on the obtained model and compared with the actual values to evaluate the accuracy of the model.

3.3.2 Model training and testing

The PSO-BP model was fitted and predicted using the training set. We also selected the BP, GM, and SVR models for comparison after training in the same way as the PSO-optimized BP model in order to confirm the reliability of the model. Figure 4 depicts the performance attained for several models.

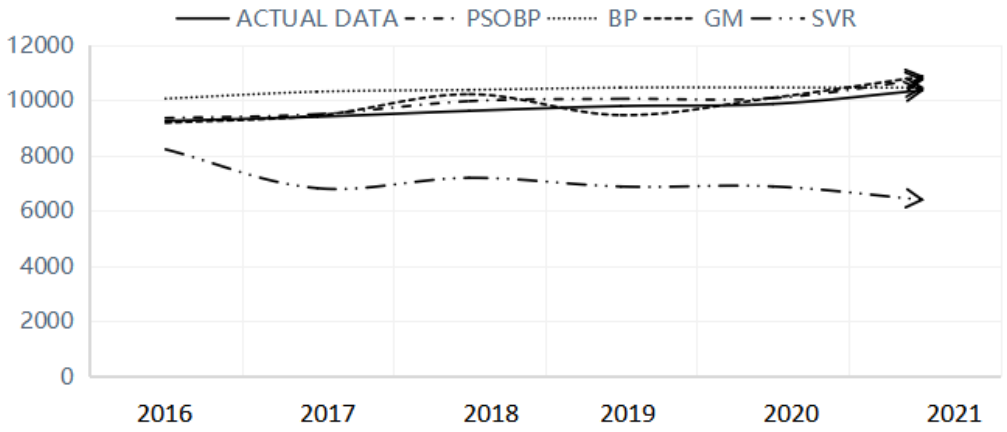


Figure 4. Comparison curves of different models

From Figure 4, the predicted values of the SVR model deviate from the actual values, and the predictions of the PSO-BP, BP, and GM models for carbon emissions in 2016-2021 are closer to the actual data. Among them, GM model showed occasional up and down fluctuations during 2016-2021, BP model presented a flatter trend of rising and then falling, and PSO-BP model's prediction results were most consistent with the trend of actual data, presenting a steady upward trend.

In order to select a more accurate model, error evaluation indexes MAPE and MSE were introduced to evaluate the errors of models respectively, and the results are shown in Table 2. Through comparison, it can be found that the prediction accuracy of PSO-BP neural network model is significantly better than other models.

Table 2. Evaluation of prediction methods

Error Evaluation	PSOBP	BP	GM	SVR
MAPE	0.0240	0.0667	0.0298	0.2706
MSE	68968	477942	129788	7826647

3.4. Scenario Setting

In order to forecast carbon emissions more accurately from 2022 - 2035, this paper applies scenario analysis methods to design business-as-usual (BAU), low-carbon (LC) and enhanced (ELC) scenarios with reference to existing research, historical data, and relevant policy. Under BAU, the current pattern of rapid growth in energy consumption, tight supply and demand, low efficiency, and high emissions will continue the trend of increasing energy demand and carbon emissions due to inertial development. According to LC, the main goal is to achieve the carbon peak by 2030, vigorously adjust the industrial and energy structures, significantly improve energy efficiency, and accelerate the development and application of green low-carbon technologies in accordance with China's "14th Five-Year Plan" and other emission reduction plans. ELC is based on LC, with further optimization of energy structure, maturity of low-carbon technologies, and widespread implementation of green production and lifestyles. Based on the description of the above three scenarios, the detailed parameter design is shown in Table 3.

3.5. Results and Analysis

By Implementing the PSO-BP neural network-based China carbon emission forecasting model to explore the development trend of China's carbon emissions under BAU, LC, ELC, and China's carbon emissions from 2022 to 2035 under different scenarios as shown in Figure 5.

Based on Figure 5, under business-as-usual scenario, maintaining the trend of growth in energy demand and carbon emissions due to inertial development, China's carbon emissions are expected to peak in 2034 with a maximum carbon emission of 23,228.5 Mt. To accomplish a carbon peak in 30 years, adjustment of the growth rate industrial and energy structures under business-as-usual scenario, after setting low-carbon scenario, carbon emissions in 2030 are projected to be 19184.18 Mt, which is significantly lower than the maximum carbon emissions under business-as-usual scenario. On account of low-carbon scenario, further optimizing the energy structure, advancing low-carbon technologies, and generally promoting green production and lifestyle, the peak carbon emission year under enhanced scenario is further anticipated by 2026 maximum carbon emissions are reduced to 19,149.60 Mt.

It can be shown that the current policy and technology levels can achieve carbon peak in 2035, but further policy adjustments are expected if China is to reach carbon peak in 2030 and carbon neutrality in 2060. The adjusted growth rates reveal that reducing the diesel consumption and actual utilized foreign capital, and increasing the growth rate of the CPI of coal mining and washing industry are conducive to achieving peak carbon as early as possible, while a moderate raise in secondary industry added value, GDP per capita, China's urbanization rate, and the contribution rate of the tertiary industry to GDP can achieve an elevated national standard of living without delaying the peak carbon year, which is in accordance with the concept of green and sustainable development in China.

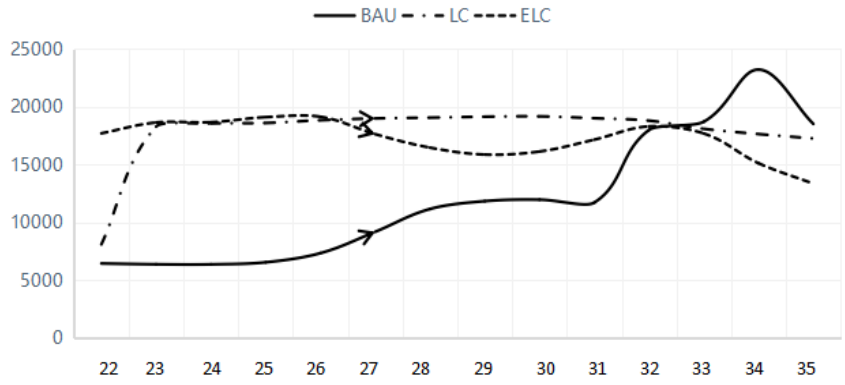


Figure 5. Carbon emission development trend under three scenarios

Table 3. Scenario parameter design

Index	Scenario	2022-2025	2026-2030	2031-2035	Index	Scenario	2022-2025	2026-2030	2031-2035
Population	BAU	0.30%	0.00%	-0.10%	Secondary industry added value	BAU	-2.50%	-2.00%	-1.50%
	LC	0.30%	0.00%	-0.10%		LC	-2.50%	-2.00%	-1.50%
	ELC	-0.10%	-0.20%	-0.30%		ELC	0.35%	0.3%	0.25%
Labor input	BAU	-0.65%	-0.75%	-0.95%	Per capita gross domestic product	BAU	7.00%	5.00%	3.00%
	LC	-0.65%	-0.75%	-0.95%		LC	4.73%	4.13%	3.83%
	ELC	-0.65%	-0.75%	-0.95%		ELC	5.73%	6.13%	7.83%
Gasoline consumption	BAU	0.07%	0.13%	0.23%	China's urbanization rate	BAU	1.20%	0.80%	0.50%
	LC	0.07%	-0.13%	-0.21%		LC	1.20%	0.80%	0.50%
	ELC	-0.07%	-0.23%	-0.31%		ELC	1.40%	1.80%	1.50%
Diesel consumption	BAU	-0.50%	-1.00%	-1.50%	Contribution rate of the tertiary industry to GDP	BAU	2.25%	3.55%	3.95%
	LC	-1.50%	-2.00%	-2.50%		LC	2.25%	3.55%	3.95%
	ELC	-1.70%	-2.30%	-2.70%		ELC	3.55%	4.05%	4.45%
Natural gas consumption	BAU	0.13%	0.23%	0.33%	Actual utilized foreign capital	BAU	5.5%	5.8%	6%
	LC	0.10%	0.20%	0.30%		LC	-2.80%	-3.50%	-3.80%
	ELC	0.10%	0.20%	0.30%		ELC	-3.30%	-4.50%	-4.80%
Electric power consumption	BAU	0.16%	0.26%	0.36%	CPI of coal mining and washing industry	BAU	0.16%	0.26%	0.23%
	LC	-0.33%	-0.26%	-0.36%		LC	0.35%	0.30%	0.29%
	ELC	0.40%	0.50%	0.45%		ELC	0.40%	0.40%	0.39%

4. Conclusion And Suggestion

In this paper, the grey correlation analysis method is used to analyze the influence of population, labor input, gasoline consumption, diesel consumption, natural gas consumption, electricity consumption, the added value of the secondary industry, per capita GDP, China's urbanization rate, the contribution rate of the tertiary industry to GDP, the actual utilized foreign capital and the CPI of coal mining and washing industry on carbon emissions. Additionally, a scenario analysis model developed by PSO-BP is used to examine the trend of China's total carbon emissions from 2022 to 2035 based on three scenarios: BAU, LC, and ELC. The study's findings are as follows:

(1) The actual utilization of foreign capital, diesel consumption, and China's urbanization rate have the greatest correlation degree with China's overall carbon emissions, with correlation degrees of 0.8903, 0.8734, and 0.796, respectively. This shows that these three indicators have a more significant impact on China's carbon emissions.

(2) The assessment of the scenario forecast findings indicates China cannot achieve its carbon peak under BAU before 2030. Rather, the peak will occur in 2033 with 23,228.50 Mt. Nevertheless, under LC, China's carbon emissions peaked in 2029, and peak emissions fell by 4044.32 Mt compared with the BAU. Due to ELC 's more efficient energy structure, advanced green low-carbon technologies, China will achieve a carbon peak in 2025 with 19149.60 Mt, which is further lowered compared to LC.

Nevertheless, through the scenario analysis of the future trend of China 's carbon emissions, it can be found that China 's economy continues to grow, energy demand continues to increase, industrial structure transformation and energy structure adjustment are facing many challenges, and the task of carbon peak is very arduous. This paper proposes the following suggestions in consideration of this:

(1) Accelerate the transition to a low-carbon, environmentally responsible energy system. It is essential to prioritize expanding the development of renewable energy sources, such as wind and solar power generation, boosting hydropower in accordance with regional conditions, and implementing nuclear power aggressively during the "14th Five-Year Plan" period.

(2) Promote the optimization and upgrading of industrial structure. Increase the proportion of tertiary industry and gradually reduce the proportion of secondary industry. Using green manufacturing technology and a new generation of information technology to transform the whole chain of each industry, encourage the penetration of the Internet, artificial intelligence, and green manufacturing technology into various industrial fields, cultivate and develop green financial productive service industries, and improve the level of energy conservation and emission reduction in service industries.

(3) Increase the promotion of scientific and technological innovation and advanced application technologies. Promote high-efficiency solar cells, renewable energy hydrogen production, zero-carbon industrial process transformation and other low-carbon frontier technologies, the widespread use of photovoltaics, strengthen energy storage, ultra-high voltage transportation and other new technology demonstration and industrialization applications.

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