Research on Methods for Predicting Carbon Peak Scenarios

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Abstract. With the proposal of the "carbon peak" and "carbon neutrality" goals, and the implementation of related policies, an increasing number of scholars have conducted research and predictions on energy transition and carbon emissions reduction pathways. This paper examines the latest research progress in this field. Firstly, it summarizes and analyzes the characteristics of carbon peak prediction. Then, it mainly introduces the principles of macroeconomic models, integrated energy-economic system models, and other prediction models, while summarizing their advantages, disadvantages, and applicability. Finally, suggestions are provided for optimizing future research. This paper aims to provide valuable references and guidance for the academic community and government agencies by reviewing and studying the methods for predicting carbon peak scenarios.

Keywords: Peak Carbon · Scenario Prediction · Prediction Method · Model Application

1 Introduction

In 2020, China proposed the strategic goals of "carbon peak" and "carbon neutrality" with the aim of actively addressing climate change and mitigating resource and environmental constraints. In order to predict the timing and peak of carbon emissions, different scholars have used diverse methods and models to analyze carbon emissions in different regions such as national, provincial, and municipal levels, as well as different sectors including industry and transportation [1]. However, existing methods and models vary, and the rationality, scientific basis, and feasibility of their pathways still lack in-depth validation [2].

This paper compares and analyzes various modeling methods, and reviews and studies their principles and application scenarios, with the aim of assisting relevant scholars in further conducting research and practice on predicting carbon peak scenarios and providing references and insights for relevant departments.

S. Tehseen et al. (Eds.): ICEDBC 2023, AEBMR 258, pp. 662–671, 2024.
https://doi.org/10.2991/978-94-6463-246-0_80

2 Characteristics of Carbon Peak Prediction

Carbon peak prediction refers to the analysis and prediction of carbon emission trends in different geographical areas, such as specific countries or regions, or different industries such as industry and transportation. It involves assessing the peak level, timing, and trends of carbon emissions. Carbon peak prediction has the following characteristics:

High complexity: Carbon peak prediction involves multiple factors, such as policy directions, economic and social development, energy activities, and technological progress. These factors interact and influence each other, making the prediction process highly complex.

High uncertainty: Carbon peak prediction is a medium to long-term forecast that requires extensive investigation and research on relevant factors, assessing development trends, and calculating their contribution to carbon emissions reduction. The scientific and precise nature of the prediction results is difficult to ascertain.

Data processing challenges: Carbon peak prediction relies heavily on extensive data from various sectors and levels. This includes factors such as population growth and urbanization at the societal level, gross domestic product (GDP) and industrial structure at the economic level, energy production, energy consumption, and carbon emission factors at the energy level. However, due to inconsistent data definitions and updates, ensuring data quality is challenging, requiring research algorithms to govern the data.

3 Summary of Carbon Peak Forecasting Methods

Currently, carbon peak forecasting methods can be roughly categorized into three types: macroeconomic models, integrated energy-economic system models, and other prediction models. The main characteristics are shown in Table 1.

3.1 Macro-economic Models

Macro-economic models are primarily used to describe the objective economic processes and patterns of the entire national economic system. These models include econometric models, input-output models, optimization models, system dynamics models, and simulation models.

The advantages of macro-economic models lie in their ability to better reflect the macro-level interactions between the energy and economic sectors. They capture the relationships between economic indicators such as gross domestic product, national income, total investment, total consumer expenditure, money supply, price levels, population growth, employment levels, and trade in relation to energy consumption. However, a drawback is that the estimation of the energy sector is relatively simplistic, and the established economic-energy coupling relationships are somewhat abstract.

There are various macro-economic models available today, with typical examples being the Environmental Kuznets Curve model, input-output models, and the Cobb-Douglas function model. Initially used for economic development forecasting, these models have expanded their application scope to the energy and environmental domains.

Table 1. Comparative Analysis of Major Simulation Methods for Carbon Peak Scenario Prediction

Method Type	Applicability	Representative Models	Comparison Analysis	
			Advantages	Disadvantages
Macroeconomic Model	Study of energy systems based on economic changes	Environmental Kuznets Curve (EKC) model, Input-Output model, Cobb-Douglas function model	Captures the macro-level interactions between energy and economic sectors effectively	Descriptions of the energy sector can be relatively abstract
Integrated Energy-Economic System Models	Energy forecasting across multiple domains such as comprehensive economic, social, technological, and energy development	Energy-economic models (MARKAL-MACRO), energy system optimization models (ChinaTIMES), and long-term energy alternative planning system models (LEAP)	Sufficiently detailed descriptions of energy technologies and energy sectors	Requires a significant amount of data input and model parameter configuration
Other prediction models	Long-term strategic planning, uncertainty analysis, and economic forecasting	Dynamic scenario analysis, Monte Carlo method, grey prediction model, neural network model, etc.	Combining qualitative and quantitative analysis for a more comprehensive analysis	The calculations require a large amount of data, and the accuracy can be affected by limited or incomplete data samples

Environmental Kuznets Curve Model. The Environmental Kuznets Curve (EKC) model is an economic model that describes the relationship between the environment and the economy. The EKC model is a typical macro-economic model that reveals the relationship between per capita GDP and carbon emissions [3]. It is commonly used to study the changing trends in environmental pollution as a country's economy grows. In simple terms, the theoretical assumption of this model is that carbon emissions will initially increase and then decrease in an inverted U-shaped curve as the economy rapidly grows. This means that when development reaches a certain stage, the government will implement more environmental policies to reduce carbon emissions. However, this model has been subject to controversy in the academic community because there are still cases of severe environmental problems in some economically developed countries, which renders the model less applicable.

In terms of applications, Xu Hua et al. [4] retested the peak and inflection point of carbon emissions in Shaanxi Province using the EKC model. The results showed that these points varied with the inclusion of related control variables such as industrial structure, institutional factors, and urbanization level. Qian Ping et al. [5] used the EKC model to examine the relationship between energy consumption carbon emissions and economic growth in different provinces. The results showed evident regional distribution and spatial classification differences in per capita carbon emissions and per capita GDP.

The EKC model has a relatively simple construction process and flexible application, but it is highly influenced by variable selection when making carbon emission predictions.

Input-Output Model. The input-output model is mainly used to study the interdependence and impact of economic activities within and between industries. In this model, economic activities are divided into multiple industry sectors, each of which uses the products of other sectors as inputs and generates final products. There are linkages of inputs and outputs between these industry sectors, meaning that the output of each sector is also input for other sectors. Therefore, when the production activities of one sector change, the entire economic system is affected. It not only describes the role of each sector in economic activities but also quantifies the ways in which these sectors interact and influence each other. In addition, the input-output model can be used to assess the impact of economic development on employment, income, and the environment. The input-output model is based on forecasting carbon dioxide emissions through end-use demand and reflects the mutual influence between energy and economic sectors through input-output tables [6].

In terms of application, Feng Zongxian et al. [7], based on energy consumption and carbon dioxide emissions, used the input-output model to predict that Shaanxi Province will reach its carbon emissions peak around 2030. Wang Xianen et al. [8] used a multi-regional input-output model to study carbon emission patterns, carbon transfer, and carbon reduction models based on consumption-oriented approaches at the provincial and industry levels in China. The results verified that carbon emissions from local consumption were higher than imported carbon emissions in 23 provinces.

The advantage of the input-output model is that it considers the interplay between energy and economic sectors, while its limitation lies in the requirement for high data quality.

Cobb-Douglas Function Model. The Cobb-Douglas function (CD production function) is a widely used macro-economic model to describe the relationship of an economic production function [9]. This model is typically used to describe the relationship between output or productivity and input factors such as labor and capital. The model assumes that output follows the Cobb-Douglas function with respect to different production factors and can be used to assess the contribution of each factor to carbon emissions.

In terms of application, Cao Libin et al. [10], based on historical carbon emission data, used the Cobb-Douglas function to predict the peak carbon emissions in the Yangtze River Delta region. The results showed that cities like Shanghai and Zhenjiang have the conditions to implement peak action plans. Zhao Ruotong [11] conducted regression analysis based on the Cobb-Douglas function to study the influencing factors of green and low-carbon agricultural development.

The advantages of the Cobb-Douglas function are its simplicity and intuitive nature, and it is widely applicable. However, due to its assumptions and limitations, it may overlook other influencing factors.

3.2 Integrated Energy-Economic System Model

The integrated energy-economic system model is a tool used to analyze and forecast energy supply and demand, primarily focused on modeling the operation and future development trends of energy systems. Typical approaches include the Energy-Economy Model (MARKAL-MACRO), Energy Systems Optimization Model (ChinaTIMES), and Long-range Energy Alternatives Planning System Model (LEAP).

The advantages of integrated energy-economic system models are that they provide detailed descriptions of energy technologies and sectors. They consider various aspects such as production, transmission, distribution, consumption, and emissions in the energy sector, as well as factors like energy prices, policies, technologies, and markets. These models can help policymakers and energy decision-makers assess the impacts of different policy and technology choices to support energy policy formulation and implementation.

Energy-Economy Model (MARKAL-MACRO Model). The Energy-Economy Model (MARKAL-MACRO Model) is a comprehensive energy-economic model used for energy policy and technology analysis. It is considered a representative hybrid model that combines the MARKAL model and the MACRO model. This model can predict the production and consumption of various fuel combinations, optimize the collection, conversion, and utilization of energy resources to achieve environmental sustainability, safety, and maximize benefits [12]. In terms of carbon peak prediction, the MARKAL-MACRO model is one of the commonly used nonlinear models that can forecast carbon emissions during the planning horizon [13, 14].

In applications, Zhou Wei et al. [15] made predictions based on the MARKAL-MACRO model, and the results showed that under the baseline scenario, China's carbon emissions would peak in 2036 at 10.753 billion tons. Under the optimized scenario, the peak would be reached in 2029 at 9.527 billion tons. Chen Wenyin et al. [14] constructed the China MARKAL-MACRO model and studied China's future energy development, carbon emission baseline scenarios, and the impact of carbon reduction on the energy system. Meng Xiangfeng [12] used the MARKAL-MACRO model to predict China's total carbon dioxide emissions during the carbon peak planning period. The study also explored and researched China's future energy structure and the construction of a carbon trading market.

The MARKAL-MACRO model has advantages in terms of comprehensiveness, technological detail, and flexibility. However, it also faces limitations such as high data requirements, complex modeling, and less precise short-term predictions.

Energy Systems Optimization Model (ChinaTIMES). The Energy Systems Optimization Model (ChinaTIMES) is an energy system optimization model based on linear programming developed by the Energy Analysis and Decision-making Laboratory at Tsinghua University. This model uses linear programming techniques to model various factors of the energy system, considering the entire process of energy production, transmission, trade, consumption, and emissions, in order to solve for the optimal operation of the system.

In applications, Martin et al. [16] used the ChinaTIMES model to couple energy demand forecasting with CO2 emission projections. The research results indicate that China's carbon emissions will peak around 2030, with a peak value ranging from 10 to 10.8 billion tons. The power sector will contribute to a 70% to 80% reduction in emissions in the year of carbon peak. Chen Hua et al. [17] conducted an analysis considering both economic and carbon emissions aspects. They established an objective function incorporating both direct operational costs and comprehensive carbon costs, and verified that the optimized results from the model have significant low-carbon comprehensive benefits.

ChinaTIMES model has several advantages, such as high scalability, allowing it to tackle complex system problems in different scenarios. It also has fast calculation speed, enabling quick response to decision-making needs and providing decision-making solutions.

Long-range Energy Alternatives Planning System Model (LEAP). The Long-range Energy Alternatives Planning System model, also known as the LEAP model, is a comprehensive multi-sectoral complex system model based on scenario analysis. It is considered a typical example of a "bottom-up" simulation approach [18]. The LEAP model is mainly used for long-term energy planning and policy-making. It helps decision-makers and planners evaluate the substitutability and sustainability of various energy technologies to determine the optimal energy development pathways for unconventional transformation and sustainable development.

In applications, Yang Nan et al. [19] used the LEAP model to analyze the energy consumption and carbon emission trends in steel production in Tangshan City from 2010 to 2030. The results showed that under multiple emission reduction measures, the carbon emissions in steel production would peak in 2018. Xie Jiaoyan [20] used the LEAP model combined with scenario analysis to predict the timing and peak level of carbon emissions in public buildings in Chongqing City. It was found that with the deepening of scenarios, the carbon peak time would gradually advance, and the peak level would gradually decrease. Long Yan et al. [21] used the LEAP model to predict the energy consumption and carbon emissions in Hubei Province from 2013 to 2030. The results showed an increasing trend in energy demand and carbon emissions along with economic growth.

The advantages of the LEAP model lie in its comprehensive consideration of the energy system as a complex system spanning economic, environmental, and social domains. However, the model's drawback is its extensive complexity, as it cannot simply separate the energy system during the prediction process. This may overlook the dynamics of the overall energy system and potentially lead to subjective conclusions.

3.3 Other Prediction Models

Other prediction models mainly include dynamic scenario analysis, Monte Carlo method, grey prediction model, neural network model, etc., which are applicable for predicting carbon peaks. The advantages of these models are that they can conduct qualitative and quantitative analysis. However, they also have disadvantages such as a high number of variables, demanding assumptions, and large data computation.

Dynamic Scenario Analysis. Dynamic scenario analysis is a common method for predicting carbon peaks. Typically, it is used in conjunction with models such as LEAP, ChinaTIMES, and Monte Carlo by adjusting input parameters and setting different scenarios to predict the inflection points and peak values of carbon peaks.

In applications, Wang Yong et al. [22] predicted the time and peak values of carbon peaks in Chinese megacities under different scenarios by setting nearly 30 combinations of scenarios. Hong Jingke et al. [23] used the LEAP model to simulate the development path and structural characteristics of carbon emissions in the construction industry chain in the 1.5 °C scenario from 2020 to 2050.

Dynamic scenario analysis has advantages such as considering multiple factors, perspectives, scenarios, and high flexibility. However, it also faces challenges such as high data quality requirements and model complexity.

Monte Carlo Method. The Monte Carlo method is a statistical technique that solves problems through numerical simulation and computation using random samples. Its principle is to estimate and compute complex problems by using a large number of random samples, replacing slow or intractable computations. In the Monte Carlo method, problems are often represented as functions of random variables. A large number of samples are generated using a random number generator, which are then plugged into the function for calculations. The solution or probability of the problem is estimated by taking the average value or probability distribution of the samples. Due to the large number of samples involved, a high level of computational precision can be achieved.

In applications, Dong Feng et al. [24] used Monte Carlo dynamic simulation to assume the distribution of variables such as China's GDP, coal proportion, and tertiary industry proportion. Based on national policy planning, appropriate probabilities were assigned to each variable to predict future carbon intensity. He Yuchen et al. [25] applied the Monte Carlo simulation method to analyze the uncertainty of lifecycle carbon emissions. The results showed that carbon emissions during the operational phase of a substation accounted for about 70% of the lifecycle carbon emissions.

While the Monte Carlo method can achieve high computational accuracy, it requires a large amount of computation and high data demands.

Grey Prediction Model. The grey prediction model, unlike traditional statistical forecasting methods, can make effective predictions with limited data and high uncertainty. The basic idea of the grey prediction model is to divide a system into two parts: known information and unknown information. By processing the known information, the regular changes in the unknown information can be revealed, thus accurately predicting future development trends.

In applications, Zhao Yu et al. [26] applied the grey prediction model to predict agricultural carbon emissions. The results showed a gradual decline in carbon emissions in Jiangsu Province from 2016 to 2030. Huang Xinyi [27] used the grey model to analyze carbon emissions in Jiangsu Province, and the results showed that the absolute values of relative errors were all less than 0.05, validating the accuracy of the grey model.

The grey prediction model is suitable for handling small-sample prediction problems and requires only a small amount of data for prediction [28]. However, it assumes that the original data has certain regularity and is not suitable for long-term carbon emission and energy development predictions.

Neural Network Model. The neural network model is a computational model that mimics the biological neural network. It adopts a data-driven approach and utilizes the iterative process of error backpropagation to improve prediction accuracy.

In applications, Feng Zongxian et al. [6] used a neural network model and scenario analysis to predict the peak value of carbon emissions in the manufacturing industry. The results showed that under an intensified policy scenario, the overall peak value of carbon emissions in the manufacturing industry would advance to 2028, with a peak emission of approximately 7.2 billion tons. Zhao Jinhui et al. [29] employed a neural network model to establish a carbon emission prediction model for Henan Province and designed six development paths.

The neural network model has strong nonlinear mapping capabilities, making it suitable for dealing with the complex nonlinear relationships involved in carbon emissions. However, similar to the grey prediction model, it has high data requirements, and the quantity and quality of data have a significant impact on prediction results.

4 Summary

The carbon peak target is not just a set of numbers; it is also an important achievement of the low-carbon transition that reflects changes in various fields such as society, economy, and energy. Currently, many scholars use different models and data to predict the scenarios of carbon peaks at national, provincial, and city levels. These methods have different approaches and considerations, leading to considerable variations in research results.

In future optimization studies, several key points should be considered. Firstly, different models should be selected based on practical needs, and cross-validation should be conducted to obtain more scientifically grounded results. Secondly, it is important to enhance the assessment of multiple factors such as economic development, energy consumption, and energy efficiency improvements. In-depth analysis of the effectiveness of emission reduction measures such as CCUS and forest carbon sinks should be conducted to propose realistic energy transition paths and recommendations, thereby supporting the achievement of the "carbon peak and carbon neutrality" goals.

Acknowledgments. This work is supported by the Key R&D Program of Shandong Province, China (2022RZB02017).

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