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A Review of the Research Methods of Carbon Emission Driving Factors Analysis and Carbon Peak Prediction

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ABSTRACT

With the growing severity of global climate change, accelerating low-carbon transition and emission reduction has become urgent. A key research focus is how to identify the main mechanisms driving carbon emissions and to accurately predict the timing and pathway of future carbon peaking. This paper systematically reviews and synthesizes two core methodological strands, and examines their respective strengths and limitations. The results indicate that, in decomposition of emission drivers, combined models help overcome the constraints of single methods, while in carbon peaking prediction, machine learning models can improve forecasting accuracy. Nevertheless, both types of approaches still have considerable room for improvement. Building on the summary of existing methods and current applications, this study proposes suggestions and directions for future research.

KEYWORDS

Carbon emission; Carbon peak; Model building; Factor decomposition.

1. INTRODUCTION

The proposal of the “dual carbon” targets marks a new stage in China’s economic and social development, with green and low-carbon transition at its core.[1] Against this background, accurately identifying the main drivers of carbon emission changes and reasonably predicting future emission evolution trend and peaking processes has become a fundamental issue for supporting national and regional mitigation decisions.[2]

In this context, this paper focuses on two key aspects: the analysis of carbon emission drivers and the prediction of carbon peaking. This paper systematically reviews the main methodological frameworks and their evolution, compares the theoretical foundations, data requirements and application scenarios of different approaches, and analyzes the advantages and limitations of various methods in terms of interpretability, prediction accuracy and policy relevance. The aim is to provide methodological guidance for building a multi-scale analytical framework for carbon emissions.

2. METHODS FOR THE ANALYSIS OF CARBON EMISSION DRIVERS

Decomposition of carbon emission drivers is a core technique for revealing the evolution of emission patterns and identifying key influencing factors. In the existing research framework, the main approaches include structural decomposition analysis (SDA), index decomposition analysis (IDA), and production-theoretical decomposition analysis (PDA). In addition, various combined decomposition methods have been developed and widely applied to overcome the limitations of single-method approaches.

2.1. Main decomposition methods for emission drivers

A comparative summary of the three mainstream decomposition methods is presented in Table 1. SDA relies on input-output tables to decompose the effects of production and consumption activities in each sector of the economic system on carbon emissions. It can effectively distinguish the contributions of technological effects and final demand effects, and is therefore suitable for decomposing carbon emissions in multi-sector macroeconomic systems[3]. However, SDA has high data requirements, including complete input–output tables and detailed information on energy consumption and emission factors. Within IDA, the logarithmic mean Divisia index (LMDI) is regarded as the most suitable method. By using logarithmic mean weights, it achieves a perfect decomposition of carbon emission drivers[4], and allows the absolute and relative contributions of each factor to be calculated separately. As a result, LMDI has become the most widely used approach for carbon emission decomposition. Compared with SDA and IDA, PDA has the key advantage of separating technological effects from conventional drivers such as economic scale and industrial structure[5]. PDA further decomposes the energy intensity effect into potential energy intensity, energy technology progress and energy technology efficiency, thereby providing a systematic identification of the contribution of technological factors. Liu et al.[6] developed a dynamic spatial-temporal production theory decomposition analysis (DST-PDA) model based on panel data for 30 Chinese provinces to investigate the drivers and regional spatial-temporal differences of carbon intensity changes. Their results show that energy intensity and technological progress in carbon emissions are the main driving forces behind the reduction in carbon intensity, while carbon emission efficiency exerts an opposite effect.

Table 1. Comparison of factor decomposition methods

Decomposition method	advantage	disadvantage
SDA	Applicable to multi-sector macroeconomic carbon emission analysis; effective in distinguishing technological effects and final demand effects[7]	High data requirements; supports only additive decomposition; limited ability to capture dynamic process effects[8]
LMDI	Perfect decomposition with no residuals; able to handle zero and negative values; unique decomposition results; data easily accessible; suitable for long time-series dynamic analysis[9]	Limited ability to isolate technological effects from a production efficiency perspective; weak in capturing dynamic processes such as technological change and factor substitution.
PDA	Able to isolate technological effects independently; decomposition based on production frontier shifts and efficiency changes[10]	Computationally complex; limited ability to quantify the effects of changes in industrial structure and energy composition[11]

2.2. Combined decomposition methods for emission drivers

Although single decomposition methods can analyse carbon emission drivers from different perspectives, there are still some limitations, and it is difficult to achieve a comprehensive identification of driving factors. To address this issue, scholars have gradually explored joint methods to build a more comprehensive decomposition model of carbon emission drivers through the complementary advantages of different methods. Lin et al.[12] constructed an IDA-PDA combined framework that decomposes changes in industrial energy intensity in China into multiple effects, including industrial structure, energy structure and technological progress. This framework compensates for the weakness of PDA in quantifying changes in industrial and energy structure, while preserving the sensitivity of LMDI methods to structural adjustments. Dong et al. [13]coupled PDA with the LMDI method and introduced a Shephard distance function to expand factors such as potential carbon intensity, energy structure and potential energy intensity into ten decomposition terms. The analysis shows that potential GDP is the key driver of industrial carbon emission growth, whereas potential energy intensity and technological progress in carbon emissions exert significant mitigating effects. The main advantage of this approach lies in its ability to place shifts in the technological frontier, changes in technical efficiency and industrial restructuring within a unified analytical framework, and to reveal differences in emission reduction potential across sectors. Zha et al.[14]further proposed an IDA-PDA-MMI combined method that couples index decomposition, production frontier analysis and the Malmquist productivity index. Using provincial data for China from 2000 to 2016, this method decomposes regional CO_2 emission changes into nine driving factors, including economic scale, energy technology efficiency, output technology efficiency and technology gap. The results highlight the roles of technology gaps and regional development stages in explaining differences in emission trends, making this approach particularly suitable for scenarios with pronounced regional heterogeneity.

3. METHODS FOR CARBON PEAKING PREDICTION

In the early stage of carbon peaking research, prediction methods were mainly built on economic theories and energy system analysis frameworks. These traditional models have clear advantages in explaining the mechanisms of emission evolution, but they show limitations when dealing with high-dimensional data and complex nonlinear relationships. With advances in computing technology and the accumulation of large volumes of activity data, machine learning models based on statistical learning and data-driven approaches have been increasingly applied to carbon emission and carbon peaking prediction, helping to overcome these shortcomings.

3.1. Traditional prediction models

3.1.1. Macroeconomic system models

Macroeconomic system models are grounded in general equilibrium theory and macroeconometric analysis, and treat carbon emissions as the joint outcome of economic growth, industrial structure and energy consumption. A representative approach is the computable general equilibrium (CGE) model, which describes the behavioural constraints of economic agents and captures the links among prices, output, energy demand and emissions. By simulating energy use and carbon emission trajectories under different scenarios, CGE models infer the possible timing and level of the emission peak. Jiang et al.[15] developed a CGE model with a detailed power sector module, focusing on four emission reduction options to simulate changes in GDP, residents ' welfare, energy structure and pollutant emissions along different pathways, thereby assessing the macroeconomic and environmental impacts of these mitigation strategies.In macroeconometric analysis, the Environmental Kuznets Curve (EKC) assumes an inverted U-shaped or N-shaped relationship between environmental pressure and per capita income, and highlights the systematic link between stages of economic development and trends in carbon emissions. Using panel data for 30 Chinese provinces, Feng et al.[16] introduced a cubic term of per capita GDP and extended the EKC to three curve types. The study shows that the long-run direct EKC and the total EKC exhibit a "lying S-shape", and that spatial spillover effects of economic growth cause the turning point of the total EKC to appear earlier than that of the traditional EKC, revealing differences between the direct and indirect effects of control variables such as population, urbanisation and energy intensity.

Macroeconomic system models can systematically capture the feedback effects of macroeconomic policies on energy demand and carbon emissions, and are well suited to evaluating the overall impacts of policy instruments such as carbon taxes and emission trading schemes. However, its structure and parameter settings iare highly subjective, and the require statistical data of high quality and consistency. As a result, prediction outcomes are often highly sensitive to scenario design.

3.1.2. Energy system models

Energy system models focus on energy balance relations and technological characteristics, and emphasise the physical and energy flows within the system. Representative models include the Long Range Energy Alternatives Planning system (LEAP) and the Integrated Policy Assessment Model for China (IPAC). By taking as inputs primary energy consumption, efficiencies of conversion technologies, efficiencies of end-use equipment and cost parameters, these models solve for the evolution of the energy mix and emission pathways under given requirements and policy constraints.

LEAP is a widely used tool for energy system analysis, suitable for medium and long-term energy and environmental scenario studies at national, regional or urban scales. Zhang et al.[17] used LEAP to construct carbon emission scenarios for public buildings in Shanxi Province over 2021-2050. Building floor area and energy use per unit area were adopted as core activity data, and combined with information on heating systems, power grid structure and fuel types to link terminal energy use in buildings with primary energy consumption, thus enabling simulation of emission trajectories under different scenarios.IPAC is an integrated energy policy and climate change assessment model developed for China's specific context. It consists of several sub-models, including an energy–economy model (IPAC-SGM), a computable general equilibrium model (IPAC-CGE), a dynamic energy–economy model (IPAC-TIMER) and an emission scenario model (IPAC-Emission)[18]. Its main objective is to assess the medium and long-term impacts of energy policies on economic growth, energy consumption and carbon emissions, and to provide quantitative support for policy making. Taking the ammonia industry as a case study, Xiang et al. [19]applied IPAC to examine the effects of three LCOE scenarios and different carbon price policies. The results indicate that carbon emissions from China's ammonia industry peaked before 2020 and could reach net-zero by 2050; under a low LCOE scenario, electrolysis-based technologies could dominate ammonia supply as early as 2038, and the cost of zero-carbon ammonia may fall below that of conventional ammonia after around 2030.

Energy system models represented by LEAP and IPAC provide a systematic description of energy demand, technology choices and fuel structure, and thus offer a solid basis for analysing emission pathways and peaking characteristics under different policy and technology scenarios. However, due to limitations in representing economic feedbacks and parameter uncertainties, it is usually more suitable as a scenario analysis and policy evaluation tool.

3.1.3. Decomposition-econometric models

Decomposition-econometric models are built on the IPAT identity and the Stochastic Impacts by Regression on Population Affluence and Technology (STIRPAT). By decomposing the drivers of carbon emissions and setting future scenarios, these models are used both to explain historical changes in emissions and to predict future peaking trajectories under given assumptions. STIRPAT extends the IPAT identity into an estimable stochastic regression model, in which population, economic level and technological level are regressed to obtain the elasticity coefficients of each factor with respect to emissions[20], thereby overcoming the obvious limitation of IPAT that different factors are implicitly assumed to contribute equally to environmental pressure. The STIRPAT model can be expressed as:

$$I = aP^bA^cT^de \tag{1}$$

where a, b, c, and d represent the model coefficient and the index corresponding to the three types of influencing factors of population (P), affluence (A), and technical level (T), respectively, and e is the error term. Among them, the size of the index value is positively correlated with the degree of influence of the corresponding factors on the environmental pressure ; the error term e is used to characterize the impact of potential factors that are not included. Wang et al.[21] constructed a STIRPAT model including variables such as population, urbanization rate, per capita GDP, energy intensity, and industrial structure, taking the six coastal provinces in the eastern and southern coastal regions as the research object. Referring to national emission reduction targets and regional development plans, four scenarios were set up. The results show that by 2030, carbon intensity can be reduced by 59.7% in some scenarios compared with 2005.

Overall, decomposition-econometric models have relatively simple structures and good interpretability, making it straightforward to link predicted outcomes directly to changes in specific driving factors. However, they have difficulty fully capturing complex nonlinear relationships and interactions among multiple factors, which limits their predictive capability.

3.2. Machine learning models

3.2.1. Classical machine learning methods

Among classical machine learning methods, support vector regression (SVR), random forest (RF) and gradient boosting tree models are most commonly used. Using panel data for 1,903 county-level cities in China, Zhang et al.[22] applied an RF model that integrates 14 categories of urban governance factors to explore their nonlinear relationships with CO_2 emissions from the residential, industrial and transport sectors. The results confirm that RF achieves higher prediction accuracy than traditional models and provides support for designing low-carbon governance policies under different scenarios.Yang et al.[23] further compared the simulation performance of STIRPAT, RF, extreme gradient boosting (XGBoost) and SVR models, and determined that RF as the most suitable prediction tool. Based on this model, carbon emission trends in 13 cities of Jiangsu Province were projected under three development scenarios to support the formulation of differentiated mitigation policies.

Classical machine learning models have achieved higher accuracy than linear regression and decomposition models in forecasting emissions at regional, urban and sectoral scales. However, their model structures are relatively fixed and have limited ability to handle complex, high-dimensional inputs. They are mainly used for static and short-term prediction, and are less suitable for capturing long-term dynamic evolution.

3.2.2. Artificial neural networks and deep learning models

With the continuous increase in data volume and feature dimensionality, deep learning methods represented by artificial neural networks have been increasingly introduced into prediction studies. Artificial neural networks approximate complex functions through nonlinear activation functions and learn the mapping relationship between inputs and outputs directly from data[24]. Among these methods, BP neural network is most widely applied. This model has a flexible structure and low requirements on the form of input variables, but it suffers from slow convergence and a tendency to become trapped in local optima[25].With the development of deep learning, network architectures with temporal memory have been incorporated into prediction tasks. Long short-term memory (LSTM) networks and gated recurrent units (GRU) are well suited for handling long time-series data and can capture long-term dependencies and lag effects in emission changes to some extent. Huang et al.[26] addressed the increase in carbon emissions caused by rising fossil energy use by selecting

16 potential influencing factors, extracting principal components through principal component analysis (PCA), and constructing an LSTM model to predict carbon emissions in China. Comparisons with backpropagation neural networks (BPNN) and Gaussian process regression (GPR) confirm that LSTM achieves higher prediction accuracy, demonstrating the effectiveness of the model.

The performance of a single machine learning model largely depends on variable selection and hyperparameter settings[27]. As a result, an increasing number of studies have combined factor selection methods, intelligent optimisation algorithms and nonlinear prediction models to improve predictive performance[28].Kong et al.[29] proposed a novel daily carbon emission prediction model in which input variables were selected using a two-stage feature selection approach combining the partial autocorrelation function (PACF) and ReliefF, and prediction was then performed using an improved and optimized extreme learning machine (ISSA-ELM). Empirical results show that the two-stage feature selection method can significantly improve prediction accuracy while reducing redundant information and multicollinearity. Liu et al.[30] took the Yellow River Basin as the research area, constructed the comprehensive evaluation index of digital economy and the traditional economic and social index as input variables, and used the PSO-BP prediction model improved by genetic algorithm. The results show that the model has high accuracy and the prediction performance is better than the single BP model.

4. CONCLUSIONS AND PROSPECT

(1) In the analysis of carbon emission drivers, SDA, IDA and PDA models each focus on different aspects of the driving mechanisms, while combined models overcome the limitations of single frameworks through methodological complementarity and improve the comprehensiveness of the results. Future research may place greater emphasis on extending decomposition analysis toward more dynamic and forward-looking approaches, and on more deeply integrating factor decomposition with emission reduction scenario simulation, in order to provide more practical support for policy formulation.

(2) Machine learning models have become important tools in carbon emission and carbon peaking prediction. Classical machine learning methods and neural network models can effectively improve short-term and medium-term prediction accuracy, while joint models further address issues related to variable selection and parameter setting. However, machine learning approaches still have limitations in scenario design and mechanism interpretation. How to effectively integrate these methods with macroeconomic system models and energy system models remains a key direction for future research.

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