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A Review of Research on Carbon Emission Prediction and Assessment

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Abstract: Abstract: This paper sorts out the current domestic carbon emission influencing factors and forecasting methods, and summarizes the application status of carbon emission forecasting models. forecast period, and the difficulty of modeling are reviewed. It is believed that the promotion and application of the comprehensive evaluation and prediction model should be promoted in the future.

Keywords: Prediction model, Carbon emission, Assessment, Review.

1. Introduction

General Secretary Xi Jinping first proposed in the Sino-US joint statement on climate change in November 2014 that "carbon dioxide emissions will peak around 2030 and will strive to reach the peak as soon as possible", and in September 2020 the 75th United Nations General Assembly General It was further proposed in the debate: "CO2 emissions strive to achieve carbon neutrality by 2060." On March 15, 2021, General Secretary Xi Jinping emphasized at the ninth meeting of the Central Finance and Economics Committee, "Incorporating carbon peaking and carbon neutrality into ecological The overall layout of civilization construction". There is no doubt that my country has entered a new era of development with carbon reduction as a strategic starting point, whether it is the need for ecological civilization construction or sustainable economic and social development. It must be clear that the original intention of addressing climate issues is to achieve high-quality sustainable development, and high-quality sustainable development must find a balanced path of development in the overall coordination of economic growth and CO2 emissions, so as to avoid falling back to a blind economy. Expansion or sports "decarbonization" are two extremes. Carbon emissions can be divided into production carbon emissions, i.e. industrial sector carbon emissions, and living carbon emissions, i.e. household consumption carbon emissions, according to the source and purpose of the emission.

The industrial sector, which is the largest source of carbon emissions, is the key target and main target of carbon emission reduction actions. It is foreseeable that under the rigid constraints of the "carbon peak" target, relevant departments will increase carbon reduction policies and impose direct and mandatory output or cost constraints on the production activities of the industrial sector, so as to promote the industrial sector to accelerate green development. The pace of low-carbonization will change its carbon emissions from rising to falling. However, due to the characteristics of residents' consumption, carbon reduction measures can only be promoted through guidance, and it is difficult to set a clear carbon reduction timetable and target. There is no strong expectation for changes in the scale of carbon emissions in the future, but there is no doubt that carbon emissions from residents' consumption is also an important link in the realization of the "carbon peak" goal that cannot be ignored. It can be seen that the complexity of CO 2 emissions is that it is not only a scientific issue related to climate change, but also an important strategic issue for external development interests and a wide range of domestic impacts on people's livelihood. Rational understanding and expectations of emission trends can more effectively prevent local governments from taking action-type carbon reduction actions or choosing a carbon reduction method of "cutting off the grid" to ensure the bottom line of people's livelihood, development and safety. On the basis of scientifically predicting the carbon emission trend of the industrial sector, the space size of residents' consumption carbon emissions under the goal of "carbon peaking before 2030" can be deduced, which will also help to scientifically formulate corresponding policies to guide residents' low-carbon lifestyles measure.

2. Research Status and Development Trends at Home and Abroad

2.1. Research on Peak Carbon Emissions

Since the carbon peaking goal was proposed, a large number of studies have focused on identifying the influencing factors of carbon emission reduction, predicting the peak volume and time, and analyzing the specific realization path of carbon peaking, aiming to comprehensively analyze the main factors leading to the increase of carbon emissions. Then, it can accurately predict the amount and time of carbon peaking, give a specific realization path, and take targeted actions to promote the realization of carbon peaking.

(1) Research on influencing factors of carbon emissions

Identifying the key drivers of carbon reduction can help to break through the carbon reduction bottleneck, so that targeted action can be taken. Many studies mainly consider key influencing factors such as economic growth, economic (industry) structure, urbanization rate, energy intensity, energy structure and technological progress when analyzing the realization of China's carbon peaking goal. Liu et al. (2014) identified carbon emissions under different GDP growth rates through the "Economy-Energy-Carbon Emissions" model. The results show that higher economic growth rates will lead to greater energy consumption and carbon emissions. Yu et al. (2018) constructed a multi-objective optimization model by considering factors such as industrial structure adjustment, economic growth and employment protection. The results proved that through industrial structure adjustment, China is most likely to achieve the carbon peaking goal in 2023. Fang et al. (2019a) found through the STIRPAT model that urbanization, population, per capita GDP, economic structure, energy structure and energy intensity are important influencing factors of carbon emissions in 30 provinces and cities in China, and urbanization will promote the reduction of provincial carbon emissions. increase. Liu et al. (2014) investigated carbon peaking scenarios under four different energy structures based on the Dynamic GTAP-E model, and found that the achievement of carbon peaking goals from oil, natural gas and non-fossil energy will become more and more important over time. more and more important. Liu Zhenzhen and Ma Yuan (2021) By constructing the GTWR model, it is found that the level of economic development, the degree of opening to the outside world, foreign direct investment, the level of urbanization, and technological progress have a negative impact on carbon emission intensity. In addition, there are also some studies that believe that carbon tax (Ding et al., 2019) and carbon price (carbon trading market) (Xiao et al., 2021) will also affect China's carbon peaking target.

(2) Research on the peak volume and time of carbon

Numerous literatures on carbon peaking in China have studied the peaking time and peak level of carbon emissions in China or Chinese provinces and cities through scenario analysis, environmental Kuznets curve analysis , and model analysis based on input-output data . Martin and Chen Wenying (2016) predict that China will achieve a carbon emission peak of around 100-10.8 billion tons around 2030 . Jiang Kejun et al. (2016) discussed the possibility of carbon peaking in China before 2025, and believed that the carbon peaking of energy activities could be achieved from 2020 to 2022, but it requires strong climate change and energy policy support. Mi et al. (2017) proposed that China's carbon dioxide emissions will peak at 11.2 billion tons in 2026 . In July 2020, the Institute of Climate Change and Sustainable Development of Tsinghua University released a comprehensive report on "China's Long-term Low-Carbon Development Strategy and Transformation Path Research", arguing that my country's carbon dioxide emissions have entered a plateau period around 2025, which can be achieved by 2030. Stable carbon peaks. Du et al. (2017) conducted a study on the trend of carbon dioxide emissions and believed that the carbon dioxide emissions of Beijing and Shanghai have reached their peaks. Gao et al. (2016) predict that Shandong can reach the peak in 2024 under the energy saving scenario . Chongqing (Liang et al., 2014) , Inner Mongolia (Wang Xiaolei, 2017) and Shaanxi (Feng Zongxian and Wang Jingjing, 2016) may not reach their peaks until 2030 or later.

(3) Research on the carbon peak path

There are many studies on the path to achieve carbon peaking in China, mainly from the aspects of economic development mode and residents' consumption behavior, economic (industrial) structure and production process, optimization of energy utilization and other aspects to analyze the realization of the optimal path to carbon peaking.

With the rapid economic development, the proportion of carbon emissions from residents' energy consumption in the total carbon emissions will gradually increase. The accelerated urbanization process leads more residents to increase energy consumption to achieve a high quality of life , which also brings greater pressure on energy conservation and emission reduction (Bosetti et al., 2012; Yang and Yu, 2017) . Therefore, the government should vigorously introduce the concept of "low-carbon city", raise awareness of low-carbon economy, and cultivate a low-carbon lifestyle (Zhao et al., 2015) . In addition, China should also take fundamental measures such as optimizing the economic structure, promoting a sustainable low-carbon economic model, abandoning the outdated development model that is overly dependent on high-energy-consumption and high-emission industries, and expanding the tertiary industry represented by a low-energy-consumption economy.

China has entered a period of deep adjustment of its industrial structure, and industrial upgrading is also one of the main ways to reduce emissions. As a large agricultural country, agricultural production is both a carbon source and a carbon sink for China. Change land use patterns to reduce carbon emissions, and increase carbon sinks through land consolidation and intensive use. Industry is the main force for the growth of my country's real economy, but it is still characterized by high energy consumption, high emissions and low efficiency. The tertiary industry represented by transportation and tourism has gradually become an important support for China's modern economic growth. Therefore, optimizing the industrial structure is of great significance for saving energy, reducing consumption, improving energy efficiency and reducing emissions.

Energy consumption and carbon emissions are directly related to the fossil fuel economy. He (2014) and Mi et al. (2017) believe that it is necessary for China to optimize its energy structure in order to achieve the carbon emission peak target and greatly promote the transition to low-carbon development. In addition, China needs to realize the synergistic benefits of carbon emission reduction on energy conservation and environmental protection before carbon emission peaks. Yang and Lin (2016) and Yang and Lin (2016) found that the type and quality of fuel play an important role in reducing carbon emissions. But coal still dominates electricity production and is on the rise. Therefore, encouraging the use of more low-emission-factor fuels in this energy-intensive industry has a huge potential to reduce emissions. Luan Shaosuo (2012) and Wang and Zou (2014) found that reducing energy intensity, optimizing energy structure, and improving energy efficiency have been and will continue to be effective ways to reduce carbon emissions and achieve sustainable development without compromising economic development.

2.2. Research on the Method and Technology of Carbon Emission Peak Forecasting

Accurate prediction and precise control of carbon emission peak is an important means to achieve carbon peak. Prediction technology establishes emission reduction targets for carbon peaking work, and control technology can provide specific emission reduction directions. Most of the existing researches use prediction technology to predict peak volume and time, and provide emission reduction paths based on control technology, and pay less attention to the innovation and development of prediction and control technology itself.

Many studies use carbon emission prediction technology to predict the volume and time of carbon peaks in China . Kuznets curve (Lin Boqiang and Jiang Zhujun, 2009; Zhao Zhongxiu et al., 2013) , grey system theory (Zhao Aiwen and Li Dong, 2012) and other methods, or use modeling techniques to build optimization models, neural network models or econometrics The economic model predicts the volume and time of carbon peaking. The optimization model takes macroeconomic changes and forecasts as the background and constraints, and is divided into the top-down IPAC model according to the relationship between various departments or the optimization of the use cost of the energy sector, etc. , 2006), input-output model (Fan and Xia, 2012), MRIO model (Peng Shuijun et al., 2015), stochastic 3E comprehensive model (Duan et al, 2018), multi-objective optimization model (Yu et al, 2018), etc., And bottom-up MARKAL-TIMES model (Liu et al., 2011), LEAP model (Shan et al., 2012), China TIMES model (Martin, Chen Wenying, 2017) and so on. The econometric model establishes the empirical relationship between carbon emissions and factors such as economy, population, and technology, and extrapolates the values of these factors in a given scenario according to the regression equation. The prediction results mainly include the STIRPAT model (Wang Yong et al. ., 2017; Fang et al., 2019b) and linear regression models (Wang Jingmin and Zhu Yiping, 2012; Du Xiaoyu and Wang Yajing, 2013) , etc. With the development of computer technology, neural network models that imitate the behavioral characteristics of animal neural networks and perform distributed parallel information processing have developed rapidly, mainly including BP (Lu et al., 2020; Zhao Jinyuan et al., 2020) , IFWA- ADDIN EN.CITE GRNN (Niu et al., 2020) , NARX (Xu et al., 2019) and other neural network models and their improved models have shown good performance in carbon emission prediction. Other prediction techniques include support vector regression machine (Song Jiekun, 2012) , Logistic model (Du Qiang et al., 2013) and so on.

2.3. Prediction of China’s Carbon Emission Intensity Under The “Carbon Peak” Target

Related to this part can be roughly classified into four categories: scenario analysis forecasting methods, grey forecasting models, econometric models and neural network models.

(1) Scenario analysis and prediction are based on empirical judgment and model setting. Usually, the change trend of carbon emissions under the influence of various factors is summarized by means of mathematical or econometric models, and obtained through empirical judgment and other empirical analysis. The conclusion is to set the change of each influencing factor, so as to infer how the carbon emission will change. Among them, the STIPART model is usually used as a benchmark model for scenario analysis, and is an important framework for predicting the trend of carbon emission scale changes at the national and regional level, while STIRPAT is evolved from the IPAT identity, which decomposes environmental pressure into Affluence and technology share pressures. Due to the needs of research, Waggoner and Ausubel (2002) refined technology into the technical level of unit output value and the pressure caused by unit technology to the environment, namely the ImPACT identity. Subsequently, more and more studies have shown that simple linear fitting cannot well explain the impact of various factors on the environment. For example, the famous EKC described economic output and environmental pressure as an inverted "U"-shaped relationship. York et al. (2003) further extended the STIRPAT model, which characterizes nonlinear and random factors. Qu Shenning and Guo Chaoxian (2010) used this model to make judgments on the influencing trends of carbon emission factors in various provinces, and under the premise that one or both of population, wealth, and technology remain unchanged, forecast by scenarios. The possible peak of China's carbon emissions, it is concluded that the peak will appear in 2020-2045. Peng Xizhe and Zhu Qin (2010) also adopted the model and made some improvements, and believed that in addition to population size, demographic factors should also be included in the analysis, and the empirical result is that the change in population structure has driven my country's carbon emissions increase. exceeds the size of the population. He Xiaogang and Zhang Yaohui (2012) incorporate the factors of industrial characteristics into the model, and the typical fact of China's industrial carbon emissions changes is an "N" type trend. Zhang Guoxing and Su Zhaoxian (2020) set up 8 scenarios based on the STIRPAT model, and predicted that the transportation carbon emissions in the Yellow River Basin in 2030 will be roughly between 200 million and 250 million tons .

(2) The grey prediction method is based on the concept of grey system, which is between the white system with fully known information and the black system which is completely unknowable. Grey theory tends to start from the data, set a lower weight for random interference, and strengthen the information with obvious regularity. The accumulation form is the main method of data generation. Wang Yongzhe and Ma Liping (2016) constructed a GM (1, 1) model based on the historical per capita energy consumption in Jilin Province, predicting that energy consumption will remain high and maintain a high growth rate from 2016 to 2018. Wang Xing et al. (2017) introduced a grey model when analyzing carbon emissions in the southwest region, and estimated that by 2020, the agricultural carbon emissions in this region will reach around 169 million tons.

(3) Econometric methods are commonly used forecasting methods in economic research. This type of method is mainly based on linear models, and recursively predicts by quantitatively analyzing the dynamic relationship of the data itself. Typical methods include vector autoregression (VAR), differential integrated moving average autoregression (ARIMA), etc. Compared with the ARIMA model, VAR considers the potential relationship between multiple vectors (such as the link between unemployment and inflation in macro indicators) , while ARIMA fully exploits the useful information other than noise in the random disturbance term. Qiu Shuo et al. (2016) used the ARIMA model to predict the future energy demand of Shaanxi Province, and believed that Shaanxi Province needs to rationally optimize the energy structure of various industries; Lu Yang (2011) used the VAR model to simulate the impact of carbon tax on output and employment. It is believed that due to the neutral nature of income tax, the introduction of carbon tax may have a certain negative impact on the economy . Xing Yi (2015) constructed a VAR model to examine the dynamic relationship among energy, economy and credit; Yang Yuwen and Wu Ailing (2020) started with structural and quantitative indicators based on panel data of seven provinces or regions from 1997 to 2015 , the three factors of economy, society and energy are incorporated into the VAR model to predict the changing trend of carbon emissions.

(4) Inspired by human neuron structure, the neural network model is characterized by feedback mechanism and activation function, and adopts the search and solution mechanism of gradient descent, which can well capture the nonlinear relationship in the data. In particular, it has significant

advantages in dealing with complex nonlinear, discontinuous and high-frequency multi-dimensional data. Jiang Yu (2012) constructed an evaluation system based on the RBF neural network to measure the coordination relationship between economic development and circular low-carbon in the research on state-owned forest areas, and found that the low-carbon development momentum of state-owned forest areas is weak. Chen Wei (2015) combined ARIMA and neural network models, and proved that the combined method can better improve the prediction error of a single linear model when estimating China's foreign trade volume. The LSTM neural network model was first proposed to make up for the shortcomings of the simple RNN model for long-term dependency mining. Later, it was widely used in the processing of financial time series and audio sequences, and has been compared in the field of economic and financial forecasting. good application. Ouyang Hongbing et al. (2020) compared the prediction effects of various models on time series. The empirical results show that the LSTM neural network model has higher prediction accuracy than other models. Literature comparing the accuracy of neural network models with the accuracy of econometric models is not uncommon, and it is generally believed that neural network models perform better in forecasting than econometric models. Taking GDP as an example, in their research, Zhou Jian and Kuang Ming (2015) found that the prediction error of neural network models, especially LSTM neural network models, was better than that of traditional VAR and BVAR models. It captures the predictable information in the data well, and thus has higher accuracy.

3. Summary

To sum up , many scholars at home and abroad have made extensive explorations in the fields of carbon emission prediction models from different perspectives, and have achieved some useful results in machine learning and neural network construction of carbon emission models. Some models still have shortcomings such as weak stability and interpretability, and difficult to determine parameters. In addition, the carbon emission system is a huge and complex nonlinear system, and traditional prediction methods have no learning process for data samples, so it is difficult to describe the precise nonlinear relationship, and the artificial neural network model in the case of small samples cannot be fully trained. , making it unstable in performance and weak in generalization ability.

The accuracy of scenario analysis methods relies heavily on human subjective judgments. In addition, due to the inclusion of too many factors, on the one hand, although the interpretation of the model can be increased, it is more likely to introduce more uncertainties, especially under the framework of the STIRPAT model, the role of various factors affecting carbon emissions Whether the strength can be more accurately estimated is first of all a problem, and secondly, the judgment of the future trend of each factor itself has a certain uncertainty, which means that the prediction under this framework will have a higher model risk. Although the grey forecasting model has very low data requirements, even a small number of samples can be forecasted, but due to the nature of the exponential forecasting method of grey forecasting, it does not consider the randomness of the system, and the accumulated errors will make medium and long-term forecasting. There is a large deviation. Traditional literature prefers classical econometric time series models such as VAR and ARIMA in forecasting related research. Although VAR and ARIMA models can well capture trends and simple nonlinear characteristics in data, they are not suitable for fluctuations and complex nonlinear characteristics. The characterization is obviously much weaker than the neural network model. On the other hand, while neural networks can improve the accuracy of predictions, they are far inferior to traditional econometric models in terms of economic interpretation. In general, there is considerable debate as to which model is more advantageous. However, there is still room for improvement in existing research in terms of relevant predictions in the field of carbon emissions .

In recent years, Bengbu City, Anhui Province, has pursued a green development path with "Carbon", promoted the construction of green and clean energy projects, and successively formulated and issued a series of policies and measures to promote green development, and promoted the green and low-carbon transformation of the economy and society. Positive progress, low-carbon atmosphere is increasingly strong. Bengbu City actively responded to climate change, adhered to the "double control" of total carbon emissions and intensity, deepened the construction of high-polluting fuel non-combustion zones, and realized the city's zero-burning coal-fired boilers below 35 tons/hour. Looking at the existing literature, how to construct a support system suitable for the prediction and control of carbon peaking in Bengbu City under the premise of comprehensively considering the social and economic development status of Bengbu City and medium and long-term planning, so as to achieve accurate prediction and precise control of carbon peaking. , in order to achieve an early peak and a low peak, is a question that must be answered at present. In the future, it may be possible to introduce a new method combining machine learning and neural network for non-parametric estimation problems under limited samples, and to predict the carbon emissions of Bengbu City by constructing the GCN-LSTM neural network model and the SVM machine learning model . A new method to provide model and algorithm support for energy saving and emission reduction.

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