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Carbon Emission Prediction: A Classification and Evaluation of Traditional and Data-Driven Methods

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Abstract. Accurate carbon emission forecasts are extremely important for climate policy formulation and carbon emission assessments. This paper divides prediction technologies into three categories: traditional statistical models, machine learning and deep learning models, and hybrid frameworks. Existing models such as STIRPAT, ARIMA and GM(1,1) are highly explanatory but difficult to deal with nonlinear mechanisms or data analysis. On the contrary, data-driven methods represented by Long Short-Term Memory (LSTM) have high prediction accuracy but usually lack transparency. The hybrid approach combines grey neural networks with the Economic Complexity Index (ECI) and Green Complexity Index (GCI) to improve prediction accuracy and overall performance and transcend the constraints of a single country's context. Interpretability tools such as SHAP and LIME are increasingly used to clarify model logical transparency and support strategy development. In short, integrating interpretability, multi-source data fusion and policy-oriented scenario simulation are of great significance to improving the scientificity and practicality of carbon emission prediction tools.

Keywords: Carbon emission forecasting, Machine learning, Deep learning, Hybrid modeling, Model interpretability.

1. Introduction

Accurate prediction of carbon dioxide (CO2) emissions is extremely important for formulating effective climate policies and evaluating progress in decarbonization strategies. As the world attaches increasing importance to carbon neutrality goals, researchers and policymakers urgently need powerful models to understand the complex dynamics of emissions changes in different economic and industrial contexts. Traditional statistical methods, especially models based on social and economic indicators or time series data, are interpretable and can provide policy-related results, but they lack the ability to cope with nonlinear characteristics and structural fluctuations. Advances in machine learning and deep learning have given rise to a new generation of intelligent predictive models that perform well in predictive performance but are often criticized for their lack of interpretability.

This paper comprehensively reviews carbon emission prediction methods and divides them into three categories: traditional methods, machine learning/deep learning models, and hybrid methods. This paper analyzes the evolution from socio-economic regression models and time series

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technologies to integrated learning and deep neural networks, and focus on the emerging trend of hybrid modeling frameworks that combine the advantages of various paradigms. Finally, this paper discusses the importance of interpretation and visualization techniques in improving the transparency and practicality of predictive models to better serve practical applications. China intends to achieve its carbon neutrality goal by 2060. Given the relatively short time window for China's transformation and its high dependence on fossil fuels for its emission structure, this task is undoubtedly extremely challenging [1].

2. Analysis of traditional prediction methods

2.1. Socioeconomic indicator modeling approaches

Modeling methods based on social and economic indicators are widely used in the field of carbon emission prediction because they are highly correlated with policies and easy to describe. The extended STIRPAT model proposed by Costantini et al. simulates the actual carbon emissions of 117 countries by introducing 12 social and economic variables such as GDP, energy consumption, urbanization and industrial structure. The model also incorporates relevant indicators such as the Economic Complexity Index (ECI) and the Green Complexity Index (GCI) to reflect the level of economic structural development and technological maturity. Although these models are conceptually attractive, they still have some obvious limitations. Linear assumptions make it difficult to accurately describe complex nonlinear relationships among socio-economic drivers. Multiple collinearity issues, data differences in different regions, and a lack of reliable cross-border data may also weaken the predictive power of models. These limitations are relatively evident in the structured domain, but in other language environments they are similar to earlier named entity recognition (NER) systems based on non-adaptive rules.

The latest research further confirms the challenges mentioned above. Research conducted by Salari et al. showed that although carbon dioxide emissions increased for the first time due to economic growth, high income levels and emissions showed opposite trends in various U.S. states [2]. Using the emerging inverted U-shaped Environmental Kuznets Curve (EKC), they revealed the complex interactions between policy-related indicators and nonlinear dynamics, and demonstrated a specific pattern. Similarly, Aftab et al. used the autoregressive distributed lag (ARDL) boundary test and Granger causality analysis to simulate the interrelationship between carbon emissions, energy consumption and economic growth in Pakistan, emphasizing that there is a two-way causal relationship between energy use and emissions [3]. This highlights the limitations of the linear assumption in traditional socio-economic models. Research by Sun et al. also confirmed the existence of a nonlinear relationship between the Environmental Kuznets Curve (EKC) and OECD countries and countries along the Belt and Road Initiative. Their research shows that carbon dioxide emissions increase significantly in the early stages of economic growth, but begin to decline once a certain critical point or threshold for economic development is reached [4]. Recent research has also highlighted the subtle impact of globalization on emissions, with political globalization helping to reduce carbon dioxide emissions, while economic globalization exacerbating environmental degradation [5].

2.2. Time series forecasting techniques

Time-series models such as ARIMA and SARIMA focus on the temporal dynamics of emission data and perform well under relatively stable environmental conditions. Faruque et al. once used the

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ARIMA model to predict Bangladesh's carbon dioxide emissions and achieved relatively reliable short-term prediction results [6]. Gray system theory (such as GM(1,1)) also shows advantages in small sample data cases. For example, in the actual application process of China's cement industry, its prediction accuracy can exceed 95%. However, these models can encounter challenges in non-stationary environments, structural ruptures, or policy shocks. They struggle to handle multiple interacting variables, nor can they adapt to sudden shifts in emission trends. Similar to hidden Markov models in early named entity recognition (NER) systems, these deterministic methods perform well in predictable models but are inadequate when faced with complexity and volatility. Recent studies, such as that by Yuping et al., have shown that globalization has exacerbated carbon dioxide emissions in Latin American countries, including Argentina, which is in sharp contrast to some studies that feel that globalization may alleviate environmental degradation [7].

3. Intelligent modeling approaches for carbon emission forecasting

3.1. Conventional machine learning techniques

Zhou and Chen also adopted a similar method. They combined trend decomposition, Webbrit decomposition, empirical modal decomposition (EMD), and long-term memory neural networks (LSTM) to significantly improve the accuracy of energy consumption predictions (the average absolute percentage error reduced to 0.64%) [8]. They proposed a three-level decomposition and integration approach that demonstrated the potential of mixed-frame complex nonlinear models to process emissions-related data.

In recent years, Costantini et al. have built a global modeling framework that uses multiple regression analysis to predict carbon dioxide emissions in 117 countries [9]. By introducing new indicators such as the Economic Complexity Index (ECI) and the Green Index (GCI), the framework not only enhances the explanatory power of traditional GDP indicators, but also improves the predictive power of emission models and can effectively capture non-linear correlations. This framework has a high degree of cross-border applicability and can predict the emissions of different economies under a unified framework, demonstrating very strong promotion capabilities. Similarly, Bekhet et al. used a dynamic joint equation model in 2016 to analyze the two-way causal relationship between carbon dioxide emissions, energy consumption and economic growth in the Gulf Cooperation Council (GCC) countries, further verifying the powerful ability of machine learning techniques such as stochastic forest regression (RFR) to understand the complex interactions between socioeconomic drivers [10].

3.2. Advanced deep learning techniques

The rapid development of deep learning provides a powerful tool for predicting neural network emissions. For example, research by Fan et al. in 2022 showed that artificial neural networks are effective in predicting China's carbon dioxide emissions [11]. They emphasized that energy efficiency was an important emission reduction factor between 2005 and 2016, with a reduction of 490 million tons, while economic growth was the main driver of an increase of 858 million tons. In addition to artificial neural networks, other advanced technologies also demonstrate the potential to deal with complex emission models. Farouk Mark proposed a series of time-series prediction systems that integrated economic and energy-related factors and compared four deep learning models. The results show that the highest average absolute error rate for the Convolutional Neural

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Network-Long-Short-Term Memory Deep Neural Network accuracy is 3.678%, followed by the CNN-LSTM error rate of 5.065% and the independent LSTM error rate of 5.377%.

It is worth mentioning that by optimizing the feature selection of existing methods, a performance error rate of 5.541% comparable to LSTM can be achieved, highlighting the importance of data preprocessing. The CNN-LSTM hybrid model uses spatial feature extraction to accurately correct for medium-term emission dependencies affected by LSTM strategies or macroeconomic changes. It can also capture the impact of macroeconomic changes on medium-term emissions. However, these techniques require important label-dependent datasets that are sensitive to hyperparameter adjustments and have limited interpretability. SHAP is often used to improve LIME transparency, but we still face the challenge of alleviating these issues to some extent. Despite these limitations, deep learning models still have the potential to improve the accuracy of emission forecasts and reduce the cost of interpretation. On the other hand, comparative research by Zeroual et al. shows that advanced deep learning models such as LSTM and Variational Autocoder (VAE) perform well in processing complex time series data. Even with limited training data, VAE has demonstrated greater accuracy in predicting COVID - 19 cases [12].

4. Advanced modeling strategies for carbon emission forecasting

4.1. Hybrid modeling framework

Recent research particularly clearly emphasizes that in order to effectively improve spatio-temporal prediction capabilities, multi-source data such as land use must be incorporated into comprehensive models [13]. Hybrid modeling is a method to effectively improve the accuracy of carbon emission prediction. It combines traditional models and intelligent algorithms. The grey neural network model is a typical representative of this framework. It cleverly combines the grey GM(1,1) model and the back propagation neural network. The grey GM(1,1) model is good at processing small samples or weak information. The back propagation neural network has nonlinear learning capabilities. This hybrid framework is highly adaptable in practical applications such as industrial forecasting. More accurate prediction results can be obtained and prediction errors can be reduced. This mixed framework can reduce the prediction error by 1.14% and improve the accuracy of prediction. Recently, Costantini et al. have studied to build a model that considers economic complexity [9]. The model incorporates the Economic Complexity Index (ECI) and Green Complexity Index (GCI) and other indicators, through which the structural and technical characteristics of 117 countries are selected. These subtle differences significantly improve the generalization ability and interpretability of the model. Making this model more advantageous than traditional regression methods deserves attention.

4.2. Model interpretability and visualization mechanisms

Deep learning and integrated models have performed quite well in predicting carbon dioxide emissions, but the lack of interpretability has become a major obstacle to their widespread application, especially in important aspects such as policy formulation and supervision. To solve this problem, recent research has begun to incorporate interpretability artificial intelligence (XAI) technologies, such as SHAP and LIME, to reveal the impact of complex model characteristics. For example, Costantini et al. in recent work used random forest feature importance ranking in 2024 [9]. Successfully identified the main socio-economic drivers of carbon dioxide emissions in 117 countries and regions, improving the transparency of global models. In addition, Faruque et al.

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emphasized in 2022 that when deep neural networks process multivariate time series data, post-mortem interpretation tools are needed, especially in cases involving energy policy intervention and requiring sufficient decision support, by visualizing partial dependence plots, SHAP value distributions or time importance plots, Model users can gain a deeper understanding of which factors such as GDP or electricity consumption have the greatest impact on future emissions [6]. These improvements not only enhance the credibility of the model, but also facilitate cross-disciplinary communication among data scientists, economists and environmental stakeholders.

5. Conclusion

This paper classifies and evaluates traditional data-driven methods in the field of carbon emission prediction. The methods covered range from classic statistical methods to mixed models. Traditional models such as STIRPAT or ARIMA have strong explanatory properties, but there are certain shortcomings in dealing with nonlinear dynamics. Although machine learning and deep learning models such as Random Forest and CNN-LSTM have improved prediction accuracy, they usually lack transparency and interpretability. In order to make up for the shortcomings of these methods, the importance of hybrid models and descriptive tools is becoming increasingly prominent. By combining gray systems, neural networks and social and economic indicators, the correlation between model performance and policies can be enhanced. Future research must focus on the following aspects, achieve multi-level data integration in the context of rapid economic development, improve the transparency of the model itself, and enhance the adaptability of the model to different scenarios. and responding to the challenges posed by sudden environmental pollution.

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