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Understanding Transportation Carbon Emission Prediction: Methods, Trends, and Reflections

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Abstract: In the context of the global response to climate change, transportation has received increasing attention as an important source of carbon emissions. The prediction methods for transportation carbon emissions have continued to develop over the past decade, forming a variety of research paths. This paper reviews the primary research methods on transportation carbon emission prediction in the past decade. Based on the systematic sorting and analysis of the existing literature, this paper classifies the mainstream methods into three categories: traditional mathematical models, simulation methods represented by system dynamics, and intelligent models and their coupled models. This paper systematically summarizes the theoretical foundations, applicable scenarios, and technical characteristics of each type of method, points out the advantages and limitations of different methods. At the same time, this paper proposes that future modeling research can be directed toward model coupling, standardization of the construction process, and other development paths. By comparing the applicability of different prediction methods, the results of this paper can help scholars quickly identify and compare different methods for solving specific research problems.

Keywords: Transportation carbon emissions, prediction methods, multi-model coupling, carbon reduction

1. Introduction

Over the past few decades, concerns regarding climate change have escalated in tandem with the growing awareness of its environmental, economic, and social ramifications. The increase in greenhouse gases (GHGs) has been widely recognized as a major driver force of global warming. Therefore, reducing greenhouse gas emissions, especially carbon dioxide, has become a common goal to reduce the impact of climate change. Studies have found that transportation carbon emissions account for 15% of anthropogenic greenhouse gas emissions and 23% of global energy-related emissions [1], accounting for a large proportion of all greenhouse gas emissions. Therefore, how to measure and predict greenhouse gases generated during transportation has become a hot topic in solving environmental problems.

Transportation includes road, rail, air, pipeline, and marine transportation, of which 70% of direct transportation emissions come from road vehicles, followed by air, shipping, and rail [2]. The main subject of this article is the surface transportation system. The impact of transportation on the environment is not only reflected in the transportation process but also indirectly affects the environment through the upstream, midstream, and downstream of the whole transportation industry chain. Therefore, scientifically evaluating the weights of various factors in transportation

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and reasonably measuring the carbon emissions of regions or industries are the focus issues in the field of transportation carbon emission research.

Regarding the prediction of transportation carbon emissions, different scholars have adopted very different methods. For example, scholars who are more familiar with mathematical models have chosen to adopt econometrics to solve such problems. This paper aims to review the carbon emission prediction methods designed in the existing literature, explain the underlying principles and recent research status of each method, and comparatively evaluate the strengths and weaknesses of the different methods and their feasibility. This paper hopes to fill the research gap in this area so that scholars and policymakers can quickly identify and compare different methods to meet their research needs and help solve the problem of decarbonizing transportation.

2. Prediction methods of traditional mathematical models

2.1. IPAT-based econometric analysis

The econometric approach is based on a basic constant equation linking environmental impacts to factors such as population, economic degree, and technological level, also known as the IPAT equation (environmental impact equation), which Ehrlich proposed in the 1970s[3]:

$$\mathrm{I} = \mathrm{PAT} \tag{1}$$

Where I is the environmental impact, P is the number of population, A is the degree of regional economy, T is the level of technology. This equation is widely used in environmental pressure analysis, resource management and other fields. However, this equation sets the relationship between environmental pressure and various influencing factors as an equal proportional relationship, which limits the parameter level of each factor. Therefore, more scholars have proposed the ImPACT model and the ImPACTs model [4] according to specific needs. Among them, the STIRPAT model proposed by research [5] has become the primary method for scholars to study such problems in recent years due to the convenience of its exponential form:

$$\mathrm{I} = \alpha \mathrm{P}^{\beta} \mathrm{A}^{\gamma} \mathrm{T}^{\delta} \varepsilon \tag{2}$$

where α is the constant term, β、γ,、δ are the exponential coefficients of P, A, and T, respectively, and ε denotes the error term, which is usually treated as a logarithmic form to remove the random number error from the model.

On this basis, scholars establish various regression models and time series models [6], such as gray models, linear regression models, panel regression models, etc. Zhang[7] et al. used the linear model such as ridge regression to predict the intensity of carbon emissions from transportation in Fujian Province, which provides data support for the low-carbon transportation policy in Fujian, China, but the model is limited to the extended STIRPAT model; Zhong[8] used the seasonal differential self regression moving average model to optimally fit univariate data containing trend and seasonality from 2017-2023, which provides an excellent model for seasonal carbon emission prediction, but the research dealing with carbon emissions from a time series perspective alone has limitations, so econometric models based on panel data have gradually been put into more attention. In the study of panel models, Lv [9] uses a spatio-temporal geographically weighted regression (GTWR) model to determine the panel data in terms of Chinese provinces and conclude the differences in efficiency and impact factors among provinces, but the GTWR model does not have lagged terms in the explanatory variables, and it is possible to consider adding the lag term to the efficiency equation to construct a spatiotemporal panel. Research [10] used Dynamic Panel Quantile in the study, optimized the simulation of the actual situation among different provinces through fractional regression, and the methodology is closer to the actual policy formulation. This method is more advantageous in formulating "stratified classification" regional emission reduction strategies, but the panel model still has shortcomings in numerical accuracy. Other scholars are gradually adopting panel models instead of cross-sectional models to predict changes in data.

Relying on the significant relationship between independent variables and dependent variables, the econometric method is widely applicable to analyze and predict carbon emissions in different scopes. The flexibility of the IPAT equation provides a good basis for the method to be adapted, such as introducing the concept of "economic distance" of spatial econometrics from the study of [11] into the study of carbon emissions, which provides new perspectives on the impact of geospatial factors. For example, introducing the concept of "economic distance" from spatial econometrics in the study of carbon emissions provides a new perspective for the study of the influence of geospatial factors. However, due to the support of traditional mathematical models, the econometric method also has certain limitations. On the one hand, like other macro- or meso-level models, the carbon emission model under the econometrics approach cannot flexibly capture the intrinsic links between factors, nor can it explain why some variables are so significant, and it lacks the ability to analyze in-depth local mechanisms. On the other hand, due to the relatively simple structure of economic models, commonly used regression models and time series models are more sensitive to outliers, and have limited ability to handle abnormal factors, and the results are limited by the analysis methods of traditional models. In addition, when facing specific problems, the applicability of different econometric models varies greatly, and the model selection is highly subjective, which is not conducive to drawing accurate and universal conclusions.

Due to the importance of local dynamic analysis for low-carbon transportation analysis, and the lack of such analysis in econometric models, the application of econometric models in the field of transportation carbon emissions is greatly limited. Therefore, some scholars have also proposed spatial lag models, spatial autoregressive models, and spatial Durbin panel data models to capture these changes in the hope of overcoming this shortcoming. However, the improved models are still incompetent when dealing with multivariate complex interaction and nonlinear dynamic evolution data, which usually leads to biased estimation results. Therefore, in future research, it is necessary to introduce a more systematic and multi-level data modeling framework to improve the accuracy of analysis and policy interpretation. This requires scholars to adopt a multi-scale fusion modeling method, integrate micro-individual travel behavior, meso-level transportation system characteristics and macroeconomic development level, and consider the driving force of transportation carbon emissions from multiple levels. Deep learning and neural networks are also used to help deal with the complex nonlinear and spatial dependencies between modeled variables, overcome the disadvantages of econometric models, and provide strong support for formulating more scientific carbon emission reduction policies.

2.2. Factorization

In addition to econometric analysis, the factor decomposition method is important for studying the role of factors in transportation carbon emissions, and is usually used in combination with the IPAT model and the Kaya model. Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA) are the most commonly used factor decomposition methods.

In general, the structural decomposition method is based on the input-output table and decomposes the analysis object into multiple basic factors. It is suitable for systematic analysis, but has high requirements for data collection. In addition, the index decomposition method has lower data requirements and is suitable for models with fewer basic factors and is more suitable for processing time series data. According to the difference of decomposition terms, there are three main types of index decomposition methods: Laspeyres Index Decomposition, AMDI Index Decomposition (Arithmetic Mean Divisia Index), and LMDI Decomposition (Logarithmic Mean

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Divisia Index). In the decomposition process of Laspeyres index decomposition method, there will always be residual items that cannot be merged and ignored, which will have side effects on the decomposition results. At the same time, when decomposing more than three influencing shadows, the calculation process of Laspeyres will be very complicated; AMDI decomposition method has the problem of residuals, and is not suitable for the existence of zero-value in the data [12]; and the LMDI index model does not produce unexplained residuals after decomposition of the object, and has better explanatory power than the other methods in dealing with the issue of macro-carbon emissions. The LMDI model does not produce unexplained residuals after decomposing the object and has better explanatory power than other methods in dealing with the macro carbon emission problem.

In addressing carbon emissions, the research on the factor decomposition method mainly covers three dimensions: the energy-oriented national dimension, the city dimension oriented by consumption level and vehicle number, and the transportation industry dimension with transportation mode as the universal key factor. The study [13] analyzes from the perspective of energy structure, and through the study of Tapio decoupling state of different energy types, it screens out the main role factors in differentiated areas so that the government can propose decisions on future policies from the perspective of energy structure adjustment. However, the research did not consider the comprehensiveness of factors when identifying decomposition factors, which may be biased. Therefore, the study [14] proposes using the entropy weight method (EWM) before identifying the factors of LMDI to ensure the rationality of factor selection. Meanwhile, due to the inadequacy of the traditional LMDI decomposition method in identifying the causes of regional differences and the mechanisms driving spatial changes, more and more scholars have adopted bilateral regional analysis or multilateral regional analysis to draw more reasonable conclusions. For example, the study [15] quantifiedd the differences in carbon emissions among regions in the Yangtze River Economic Belt based on the two-layer LMDI decomposition method and the Terrell Index, and Wang [16] analyzed the main driving factors and decoupling effects of carbon emissions in the Silk Road Economic Belt. Some scholars [17][18] also link the decomposition method with the clustering technique and Terrell's coefficient to propose a more reasonable decomposition strategy.

With the deepening of research, the factor decomposition method has been widely used to analyze the impact of carbon emissions at different levels. The exponential decomposition method has changed from the initial limitation of only one absolute factor to the present day, when more adjustable factors are introduced into the model. However, there are still problems to be solved. Since index decomposition requires the introduction of mutually offsetting factors, it is not easy to include a single new variable in the analysis. In addition, the factor decomposition method still has difficulty capturing the interaction effects between variables, which limits the comprehensive understanding of complex systems. Therefore, when building the model, it is necessary to consider a more reasonable framework that can include multiple absolute factors, or try the principal component analysis (PCA) method for dimensionality reduction, the Marshall-Edgeworth with Structure Effects (MESE) method of assuming the mean to provide explanations, and other methods, to solve the analytical obstacles posed by the offsetting nature of the factors, and to enhance the model's inclusiveness and explanatory power. For the interaction problem between variables, combining the decomposition model with other dynamic models may be a more reasonable way to capture the relationship between variables in the future.

3. Simulation methods represented by system dynamics

With the deepening of research, simulation has been gradually applied to the field of transportation carbon reduction. As stated in the study [19], the system dynamics method is a modeling tool

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applicable to studying energy transition and sustainable transition for analyzing the feedback effects of key factors among different subsystems under a complex system. This method breaks down the object of study into underlying subsystems and considers that the key factors in the system act on the subsystems to force dynamic changes in the subsystems, which in turn result in changes in the parent system [20], empirical functions and qualitative analyses are commonly used to characterize this set of changes. In essence, it is to construct and analyze dynamic models that reflect the internal structure and feedback mechanism of the system, and using system flow diagrams (stock and flow diagram) and causal loop diagrams (causal loop diagram) to hypothesize all the complex research objects as units to understand, simulate and predict the behavior of complex systems to provide scientific bases for the decision making.

In transportation emissions, SD modeling is a standard methodology for predicting carbon emissions and identifying emission reduction pathways because it can be linked to observed system patterns, microstructures, and decision-making processes. The study [21] reviewed the underlying models of system dynamics in the areas of alternative fuel vehicle promotion and supply chain transportation, and illustrates the advantages of combining qualitative and quantitative aspects of the models in the field of transportation carbon emissions reduction, while pointing out the limitations of this approach in solving the allocation problem. In order to solve the limitations of the SD model in dealing with the distribution problem and the spatial problem, the study [22] proposed the choice of combining the SD method with at least one other method to evaluate the rationality and feasibility of the system, which provides a new way of thinking for the solution of the transportation carbon emission reduction problem. In recent years, with the broad application of the multi-intelligent body model (ABM) to urban complex systems, some scholars have also discussed the urban transportation low-carbon problem by combining the ABM with the SD model. Research [23] provided quantitative data for the formulation of emission reduction policies for large cities by simulating the travel choices of different income groups under policy intervention. However, in the system dynamics model proposed in the study [20][23], the boundary is usually set to a certain city or a certain region, and long-term and cross-regional issues are weakened. Therefore, the model is difficult to draw satisfactory conclusions when dealing with these two types of problems. Therefore, Ren [24] used the ARMA method to predict historical data and established a system dynamics model with a span of 20 years to simulate the impact of policy changes on regional carbon emissions under medium and long-term spans, filling the research gap of the SD model in this regard. However, in this study, historical data was simply fitted, and the reliability of the model needs to be verified.

Although system dynamics models have unique advantages in understanding and simulating complex systems, there are limitations if used as a single research method, such as the lack of the model's ability to deal with spatial regions as well as its ability to express itself to cope with localized problems. The deduction direction of the model depends on the input values of all parameters and constants in the simulation, and the feedback mechanism itself cannot be changed. If used to analyze the simulation of medium- and long-term trends in the region, it will be greatly limited by the data provided by the researchers and the speed of policy changes, which will bring difficulties to the interpretation of the results. The model is based on the determined equations established by the researchers, and it is difficult to accurately simulate random events and uncertainties in real systems. This limits the prediction accuracy of the model when dealing with systems with highly random factors (such as new energy market factors, weather factors, and emergencies).

Future research should focus on remedying these deficiencies: try to combine the SD model with Agent-Based Modeling4041 and Discrete Event Simulation, etc. Establish a system dynamics model that includes random variables and probability distributions, so that the model can more comprehensively simulate the dynamic behavior of complex systems when dealing with high-randomness scenarios and improve the accuracy of predictions. Try to incorporate spatial factors into the model (such as setting up route planning in a multi-region interactive system) and use dynamic real-time data to improve data quality. Use machine learning, deep learning, Monte Carlo models, etc. to process input data and feedback data to build a data set that is more in line with the actual situation.

4. Intelligent models and multi-model coupled prediction methods

As mentioned earlier, regression and time series models are commonly used to predict transportation carbon emissions. Although these two types of methods are characterized by a transparent modeling process and strong interpretability in forecasting, they have problems such as limited explanatory power in explaining nonlinear relationships and insufficient ability to handle high-dimensional data. Therefore, some scholars have proposed a coupling paradigm between intelligent models and traditional models, where traditional models are responsible for dealing with linear trends and basic variable screening, while machine learning algorithms resolve complex relationships through nonlinear mapping mechanisms, and this division of labor significantly improves the robustness of the prediction system.

As a result, scholars are gradually introducing machine learning into traditional models. Gökalp Çınarer [25] used various machine learning algorithms to predict transportation-related energy demand and CO_2 emissions in Turkey and found that Multilayer Perceptron (MLP), Extreme Gradient Boosting (XGBoost), and Support Vector Machine (SVM) algorithms yielded the desirable results. Ji [26] compared ANN, support vector machine, deep learning DL and traditional mathematical models, and concluded that all machine learning algorithms have good advantages over traditional models in predicting transportation carbon dioxide emissions and energy use. For the problems that a single intelligent model cannot solve, some scholars adopt the method of multi-model combination. For problems that cannot be solved by a single intelligent model, some scholars use a combination of multiple models. Research [27] discussed the application of multiple intelligent models in carbon emissions problems, and based on the STIRPAT model, used genetic algorithm-based support vector machine optimization GA-SVM, particle swarm optimization support vector machine optimization PSO-SVM, and grid search support vector machine optimization prediction model GS-SVM to predict and analyze China's transportation carbon emission data from 1995 to 2016. The study[28] further introduced partial least squares (PLS) on this basis, successfully reduces the dimensionality of the eight original impact factors to remove multicollinearity, retains the factor interpretability under the policy scenarios while solving the variable redundancy problem under the high dimensionality of the small samples, and integrates the three social scenarios of "standard-high-carbon/low-carbon" to provide a more accurate prediction of the carbon emissions of China's transportation industry. It also integrates the three social scenarios of "standard, high carbon, and low carbon", which provides a quantifiable basis for decision-making in peak carbon planning under small-area, multi-data, and short- to medium-term scenarios. The study [29] compared the advantages of various intelligent models over traditional models, and summarizes the advantages and disadvantages of BP neural network, SVM and other models in terms of prediction accuracy, but unfortunately does not consider the coupled models, and the model summarization in the article is limited to a single method.

In contrast to traditional carbon emission forecasting methods, intelligent models offer significant advantages in terms of efficiency and accuracy, especially when dealing with high-latitude, data-heavy samples, and this advantage is further amplified. However, due to their inherent learning approach, these models are not easily modifiable, leading to shortcomings, such as the contradiction between the limited interpretability of the results and the transparency

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requirements needed for policy decision-making. Given this, in-depth research can be carried out in the following aspects: developing an interpretable neural network based on the attention mechanism, which enhances the visual resolution of feature importance while maintaining the prediction accuracy; constructing a hybrid prediction system that includes a dynamic weight adjustment mechanism, and attempting to couple the traditional model with intelligent algorithms adaptively; strengthening the empirical research at multiple scales, and promoting the carbon emission prediction problem for special regions such as urban agglomerations Build model.

5. Discussion

Although there are abundant research models and practical achievements in the field of transportation carbon emission prediction, and scholars have continuously made breakthroughs from traditional mathematical models, system simulation methods to intelligent algorithmic models in response to different raw data structures and regional differences. However, different methods still have obvious limitations in theoretical basis, applicable scenarios, data dependence and policy orientation.

Traditional prediction models (e.g., STIRPAT, regression models, etc.) were widely applied to carbon emission prediction in early studies due to their good interpretability and structural transparency, but the linear form of modeling determines that they are inflexible and can only deal with cross-sectional problems. Therefore, dynamic panel models, spatial Durbin models (SDMs), spatial lag models (SLMs) and spatial error models (SEMs) have been widely used to reveal the spatial heterogeneity and proximity effects of regional transportation carbon emissions, in order to solve the problem that the original models cannot deal with the problem of combining with spatial data. However, such models still rely on subjective judgments in modeling and are difficult to reveal the nonlinear feedback mechanisms and complex interactions between multiple variables in the transportation carbon emission system. Therefore, methods such as Bayesian time series have also been gradually applied to traditional models this year. In general, traditional models are limited by the inherent form of the model and high data dependence, and their scalability needs to be improved under the current emerging multidimensional data environment.

The simulation method represented by system dynamics has an advantage over the prediction model based on a mathematical model in dealing with the dynamic evolution of complex systems, and it can better describe the trend of carbon emission under variable shocks. However, most of the current SD modeling still relies on the structural assumptions of the researchers for the causal setting of variables and loop drawing, and lacks the automated modeling mechanism and data-driven feedback mechanism for the data. At present, the logic of system dynamics modeling still tends to the traditional mode of "static structure + scenario simulation", which makes it difficult to integrate dynamic data from multiple sources such as the Internet of Things and mobile monitoring, resulting in limited timeliness and situational adaptability of simulation results. Secondly, in recent years, some scholars have attempted to couple the SD methodology with the multi-intelligent body modeling (ABM), reinforcement learning, and metacellular automata, but the coupling paths are mostly lack of unified specification, and the research in this aspect is still in the exploratory stage.

The application of machine learning and deep learning methods (e.g., SVM) has become an emerging hotspot for transportation carbon emission prediction in recent years. These intelligent models have shown good prediction accuracy in high-dimensional and large-sample scenarios. However, they still have obvious shortcomings in terms of interpretability, and their "black box" characteristics make it difficult to meet the transparency and controllability requirements in the relevant formulation process. The current research focuses on optimizing model performance indexes, ignoring the logical adaptation and operability between model outputs and policy contexts, which limits the application of the model in actual governance. Meanwhile, some scholars have tried multiple model coupling strategies (e.g., PLS-GA-SVM, SD+ABM, LMDI+cluster analysis) to compensate for the black box characteristics of a single intelligent model. However, in the actual prediction process, the coupling weights of the multiple models mainly rely on the scholars' experience, and there is a lack of a set of universal prediction frameworks.

6. Conclusion

For the research of traditional models, the research means should be shifted from the basic methods, such as static regression, to the more flexible methods, such as the dynamic spatial measurement model, and at the same time, the variables are pre-screened by the pre-screening algorithms in order to improve the explanatory ability of the model. For simulation models, it is necessary to construct a reasonable automatic modeling process that integrates data-driven and structural settings, which will significantly enhance the dynamic processing ability of simulation models. At the same time, through integration with the multi-intelligence body, graph neural network, and other methods, we can expand the model's adaptability in complex scenarios, such as city cluster, policy simulation, and multi-scenario deduction. For intelligent models, future research should focus on solving the "black box" problem and improving the interpretability of the models. For coupled models, developing a hybrid prediction system with dynamic weight adjustment and process transparency is necessary.

In addition, each method has its limitations in determining the most appropriate method for assessing carbon emissions in a particular region or sector; for example, the system dynamics method is suitable for predicting the long-term evolution of carbon emissions under policy interventions. However, it is often difficult for a single model to address multiple needs simultaneously. Therefore, building a coupled class of models with synergistic advantages and constructing a closed-loop decision-making system that integrates prediction -interpretation -response-decision-making may be an excellent solution for more complex transportation scenarios in the future. Therefore, constructing a coupled model with synergistic advantages to build a closed-loop decision-making system integrating "prediction-interpretation-response-decision" may be an excellent solution to cope with more complex traffic scenarios in the future.

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