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A Review of Carbon Emission Prediction

1 Introduction

There is a positive correlation observed between global carbon emissions and economic growth [1]. However, the balance between "growth and consumption" is disrupted. Researchers agree that the primary cause of the temperature increase over the past 50 years is the rise in greenhouse gases, such as carbon dioxide [2]. Scientists and policymakers agree on the necessity to limit global warming to 1.5°C above pre-industrial levels for maintaining environmental sustainability [3]. BRICS countries (Brazil, Russia, China, India, and South Africa) have contributed a substantial portion of these emissions, particularly China, India, and Russia [4]. China, the world's leading carbon dioxide emitter, has experienced remarkable growth in carbon emissions during its rapid economic expansion, emitting over 6 billion tons of carbon dioxide annually [5]. As the global population continues to grow and to combat global warming, there is an increasing need for sustainable solutions to reduce carbon emissions and mitigate the effects of climate change. Carbon emissions must eventually be reduced to near zero, given their long half-life as a greenhouse gas.

The prediction of carbon emissions plays a vital role in understanding and addressing the challenges associated with climate change, as well as informing policymaking and sustainable development strategies. Accurate carbon emissions predictions can provide valuable insights for various stakeholders, including governments, industries, and researchers, allowing them to make informed decisions regarding carbon pricing mechanisms, emission trading systems, and the allocation of resources for research and development of low-carbon technologies in the pursuit of mitigating climate change and its adverse impacts. Given the imminent climate change threats and slow progress in reducing carbon emissions, further scientific research is necessary to understand the exact nature of these threats.

2 Literature Review

2.1 Global Carbon Emission Research Overview

Abeydeera et al. [6] conducted a global study on carbon emissions by analyzing 2,945 bibliographic records from the Web of Science Core Collection database, spanning the years 1981 to 2019 . Their study identifies an increasing trend of research on carbon emission research, with the most significant contributions coming from China, the United States, and England. Evaluating greenhouse gas emissions and estimating the carbon footprint were found to be popular research topics. Climate change and the environmental effects of carbon emissions were also significant points of concern. Shi and Yin [7] conducted a literature review and scientometric analysis of carbon footprint research based on 7,450 articles in the Web of Science Core Collection. The research scope has shown a trend from small to large, and the theme of carbon footprint research has evolved from ecology and botany to international trade and household behaviors. The year 2008 was found to be the main node in carbon footprint research, and the research after 2008 shows a significant trend of diversification and interdisciplinary development. Chinese research institutions and scholars have shown an explosive trend after 2008. Their study also found that most international cooperation occurs between North American and European countries while developing countries such as China are still in the marginal area.

2.2 Prior Research On Carbon Emission

The literature on carbon emissions showcases a variety of purposes and models including statistical models such as regression techniques and machine learning models like support vector machines and backpropagation neural networks (BPNN) employed to improve estimation accuracy.

2.2.1 Various Purposes

Wu, Zhou, and Wang [8] predict the spatial pattern of carbon emissions in Nanjing, China under different land use scenarios using the CLUE-S model. Huang and Zhou [9] analyze the relationship between land use and carbon emissions using data on agricultural production activities, land use, and energy consumption. It calculates carbon emissions and absorption and analyzes trends using the carbon emission coefficient method and tendency value. It also analyzes fairness and difference using the Gini coefficient, ecological support coefficient, and economic contributive coefficient. Cai et al. [10] calculate China's transportation carbon emissions using a top-down approach from 2003-2019, and then use a logarithmic average weight decomposition approach to examine factors affecting the emissions. The Tapio decoupling model is applied to investigate how transportation carbon emissions are dynamically decoupled in various provinces. Yin, Bai, and Xiao [11] examine the relationship between economic development and carbon emissions in Chinese cities from 2000 to 2017. An allometric growth model was constructed to analyze the spatial-temporal evolution of their growth, and the geographical detector model was used to identify the driving mechanism.

2.2.2 Statistical Methods

Wu et al. [12] employed the STIRPAT model to predict future carbon emissions in Qingdao, while Deng [13] introduced the grey forecasting model, an effective approach for small sample data. A novel dynamic time-delay discrete grey forecasting model, referred to as DTDGM(1, N, t), is proposed for predicting systems with dynamic time-lag effects [14]. Specifically, a time-lag driving term encompassing both the interval and intensity of time lags is formulated to represent the lag process of various factors affecting carbon emissions. Comprehensive experimental results on carbon emissions prediction from 1995 to 2017 demonstrate that the DTDGM(1, N, t) model, which accounts for delayed relationships, significantly enhances the model's fitting and predictive performance compared to six benchmark models. Ning et al. [5] focus on four representative provinces and cities, specifically Beijing, Henan, Guangdong, and Zhejiang, to analyze their carbon emissions from 1997 to 2017 and construct appropriate ARIMA models to forecast carbon emissions and trends for the subsequent three years. Gao et al. [15] developed a novel fractional grey Riccati model to examine carbon emissions in the United States, China, and Japan, demonstrating strong estimation performance in all instances.

2.2.3 Machine Learning Methods

Li et al. [16] utilized the SVM-ELM model to forecast carbon emissions in specific regions. Liu et al. [17] identified key factors influencing carbon emissions and developed a BP neural network model to predict Beijing's carbon emissions over the next five years under different development scenarios. Sun et al. [18] combined principal component analysis (PCA) and regularized extreme learning machine (RELM) in a hybrid prediction model to forecast China's carbon emissions. Heydari et al. [1] focused on integrating renewable energy sources into microgrids to minimize carbon emissions, using Generalized Regression Neural Network and Gray Wolf Optimization for long-term forecasting in Iran, Canada, and Italy. The proposed method demonstrated superior performance compared to other approaches. Zhou et al. [19] developed a new ENN model to estimate carbon emissions in China, which outperformed other models and showed potential for further improvement. Qiao et al. created a hybrid algorithm combining a lion swarm optimizer and a genetic algorithm, using carbon emissions data from countries with different development levels between 1965 and 2017 [20]. The algorithm's performance was compared to eight other algorithms, revealing its superiority in reducing the mean absolute percentage error. Ren and Long [21] proposed a hybrid Fast Learning Network–Chicken Swarm Optimization (CSO–FLN) model for predicting the carbon emissions of Guangdong province between 2020–2060. The model's superiority over other estimation models was demonstrated using three error indicators: MAE, MAPE, and RMSE. Aksu and Demirdelen [22] focus on minimizing errors in carbon emissions prediction in Turkey by proposing a new optimization method and developing a forecasting model. ANN-based hybrid models were employed, and the study highlighted the effectiveness of optimization methods in estimation techniques.

2.3 Neural Networks In Carbon Emission Prediction

As a branch of machine learning techniques, neural networks have demonstrated their potential in modeling intricate patterns and relationships within extensive datasets. By applying neural networks to carbon emission prediction, researchers can more effectively capture the complex interactions among various factors that influence emissions. As such, we examined the use of neural networks specifically for carbon emission prediction [23, 24, 25, 26, 27, 28] and outlined the challenges faced by the community in terms of application scenarios, data availability, and model construction. For additional information, please see Appendix A.

2.3.1 Application Scenario

In the context of neural networks related methods and insights from the literature:

i. Provinces, regions, and a certain country are typically popular research objects, with very few focusing on a specific industry, city-level, or global-level carbon emissions trend prediction.

ii. Research for carbon peak and neutrality is quite rare.

iii. There is a significant demand for machine-learning-based software to explore the dynamic characteristics of carbon emissions.

2.3.2 Data Availability

i. Most research have to calculate historical carbon emission data based on formulas, such as the one from IPCC guidelines, but this will generate many errors.

ii. Others estimating carbon emissions data from an industry perspective often ignore emissions from some specific industries such as cement production and carbon sinks.

iii. Large samples of carbon emissions data are often unavailable, which is also why neural networks are better suited for prediction.

2.3.3 Model Construction

i. Compared to a single prediction model or statistical models, a hybrid model composed of neural networks-related methods such as ENN or GRNN and optimization methods like CSO or IPSO can provide better performance in predicting carbon emissions.

2.4 GNNs

Graphs, a data structure consisting of nodes and edges, have become increasingly popular for machine learning due to their expressive power across various fields. Graph analysis focuses on tasks like node classification, link prediction, and clustering. Social science, natural science, knowledge graphs, and other research areas have utilized graphs to represent systems [29, 30, 31, 32].

Graph Neural Networks (GNNs), as deep learning-based methods that operate on graphs and have shown impressive performance has been applied in a variety of settings including supervised, semi-supervised, unsupervised, and reinforcement learning. The applications can be grouped into two categories: structural and non-structural scenarios. Structural scenarios arise from scientific research such as graph mining and modeling physical systems, as well as industrial applications such as knowledge graphs, traffic networks, and recommendation systems. Non-structural scenarios include image and text analysis, which are two of the most active branches of AI research [29].

One of the applications of GNNs is to solve basic tasks in graph mining, such as graph matching and graph clustering. Traditional methods for graph matching suffer from high computational complexity, but GNNs can capture the structure of graphs using neural networks to offer another solution [29]. Graph clustering is achieved by grouping the vertices of a graph into clusters based on the graph structure and/or node attributes [33]. A recent study [34] proposed optimizing spectral modularity to achieve the desirable property of a good graph clustering method.

In addition, two ways of applying GNNs in non-structural scenarios are through the incorporation of structural information from other domains to improve performance, or by inferring or assuming a relational structure in the task and then applying the model to solve problems defined on graphs [35, 29].

2.5 Comparing Traffic And Carbon Emission Forecasting With GNNs

GNN-based traffic forecasting problems share similarities with carbon emission problems tackled by GNNs. Traffic forecasting problems can be grouped according to the data format used, such as time series data, grid data, and graph data. Time series forecasting is the most prevalent type [36, 37, 38], which can be further classified into univariate and multivariate problems, as well as single-step and multiple-step forecasting problems. Common time series models include simple linear regression, ARIMA, and SARIMA, with the latter being superior due to its capability to capture seasonal patterns. Nevertheless, time series data has limitations in representing spatial dependence, prompting the utilization of grid data and graph data formats [39]. Additionally, traffic prediction methods can be sorted into three categories based on the models used: statistical models, shallow machine learning models, and deep learning models [39].

2.6 Critical Evaluation

The literature review highlights the progress made in carbon emissions prediction, particularly in the application of statistical and machine learning methods. However, the use of time series or panel data estimations generates a single parameter, which may not accurately capture the long-term nonlinear relationships between carbon emissions and factors such as GDP per capita, renewable energy consumption, and trade openness [26]. Though linear models are examples of statistical models that offer the benefits of low computational cost and interoperability, their predictive capabilities are inferior to machine learning models which have demonstrated effectiveness across a range of forecasting problems. It has been observed that machine learning methods generally outperform statistical methods in predicting carbon emissions due to their ability to handle complex and non-linear relationships [40, 41, 42].

Machine learning techniques like support vector machines (SVMs), artificial neural networks (ANNs), and deep learning have become increasingly popular for predicting carbon emissions. GNNs, known for their ability to model relational data and capture complex interactions between entities in a network, have emerged as a potent tool [43]. Despite this, research on applying GNNs to carbon emission prediction remains scarce.

Using GNNs to predict carbon emissions offers several advantages. First, GNNs can effectively model spatial and temporal correlations, which are essential for accurately predicting carbon emissions in various regions or industries. Second, GNNs can incorporate additional contextual information, such as social, economic, and policy factors, which may influence carbon emissions. Finally, GNNs can provide an interpretable model structure, allowing researchers to gain insights into the relationships between different factors and their impact on carbon emissions.

In summary, machine learning methods have demonstrated superior performance in predicting carbon emissions compared to traditional statistical methods. While GNNs have not been extensively researched in this context, they hold significant potential due to their ability to model complex relationships and incorporate additional contextual information. Future research should focus on exploring the application of GNNs in carbon emission prediction and leveraging their unique advantages for more accurate and interpretable models.

We aim to explore the application of GNNs in predicting carbon emissions, an area that has not been extensively researched. Our goal is to contribute valuable insights to the field of carbon emission prediction and provide effective methods to support policy-making and environmental strategies. To achieve this, we have outlined specific objectives and research questions that will guide the direction of our research and ensure a comprehensive understanding of the problem.

i. To construct a comprehensive carbon emission dataset for training and testing the GNN model.

ii. To investigate the potential of GNN in predicting carbon emissions.

iii. To identify the key factors and variables that influence carbon emissions and can be effectively incorporated into the GNN model.

iv. To develop a robust GNN model that accurately predicts carbon emissions and outperforms traditional forecasting statistical methods and machine learning methods.

v. To evaluate the performance of the proposed GNN model using appropriate metrics and compare it with existing forecasting techniques.

vi. To provide insights and recommendations for stakeholders based on the GNN model's predictions and facilitate effective carbon emission reduction strategies.

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Appendix A

Table A1. Carbon Emission Prediction using Neural Network Methods: A Comprehensive Overview.

Methods		A feedforward neural network (FLN)	NNEnsemble
Paper		Carbon emission forecasting and scenario analysis in Guangdong Province based on optimized Fast Learning Network	Modeling and spatio-temporal analysis of city-level carbon emissions based on nighttime light satellite imagery
Date & Journal & Impact		2021, Journal of Cleaner Production, 9.297 (2020)	2020, Applied Energy, 9.746 (2020)
Challenges	Application Scenario	1.Very few carbon emission-related research in Guangdong province focused on trend prediction and scenario analysis of carbon emission. 2.The search for carbon peak and neutrality is rare.	1. The utilization of night-time light satellite imagery data in urban-level carbon emissions was rarely considered. 2. A general framework and machine-learning based software is highly demanded for obtaining the relationship between carbon emissions and NSL data in various regions to explore the dynamic characteristics of carbon emissions at urban scales.
	Data	1. Existing research mostly focuses on energy-related carbon emissions without considering carbon emissions from cement production and forest carbon sinks. 2. Carbon emissions data needs to be calculated first.	1. Carbon emission data at urban scales is difficult to estimate because of missing values of statistical variables. 2. Carbon emissions data needs to be calculated first based on IPCC formula.
	Models	1. Compared to hybrid models, single prediction model is always ineffective in its prediction accuracy due to the nonlinear characteristics of carbon emissions.	1. Simple regression methods cannot accurately quantify the relationship between carbon emissions and night-time light satellite data.

Table A2. Carbon Emission Prediction using Neural Network Methods (Part 2/3): Cont.

Methods		A feedforward neural network	A feedforward neural network (MLANN)
Paper		Electricity production based forecasting of greenhouse gas emissions in Turkey with deep learning, support vector machine and artificial neural network algorithms	Forecasting the CO2 Emissions at the Global Level: A Multilayer Artificial Neural Network Modelling
Date & Journal & Impact		2021, Journal of Cleaner Production, 9.297 (2020)	2021, Energies, 3.004 (2020)
Challenges	Application Scenario	1. The number of studies related to forecasting Greenhouse Gases for Turkey is very-limited and only a few studies predicts it based on electricity production. 2. Carbon emissions gets more focus from researchers but other greenhouse gases also have higher global warming potential than that of carbon emissions.	
	Data		1. The long-run relationship between carbon emissions and its predictors, such as GDP per capita, renewable energy consumption, and trade openness is not linear.
	Models	1. DL and SVM algorithms were rarely used in Turkish greenhouse gases prediction.	1. Statistical models are not able to estimate the relationships accurately when the data are uncorrelated, non-stationary, nonlinear and chaotic

Table A3. Carbon Emission Prediction using Neural Network Methods (Part 3/3): Cont.

Methods		A feedbackward neural network (ENN)	A feedbackward neural network (ENN)
Paper		Prediction of direct carbon emissions of Chinese provinces using artificial neural networks	Forecasting CO2 Emissions in China's Construction Industry Based on the Weighted Adaboost-ENN Model and Scenario Analysis
Date & Journal & Impact		2021, PLOS ON, 3.752 (2021)	2019, Journal of Energy, 7.147 (2020)
Challenges	Application Scenario	1. Direct residential carbon emissions were rarely predicted.	1. Previous studies on the construction industry focused more on a province or a region, and few researchers focused on construction industry from a national perspective. 2. Scenario analysis of carbon emissions is not sufficiently studied.
	Data	1. Larbge samples of carbon emission data is not available.	1. Carbon emissions have to be firstly calculated based on direct and indirect consumption.
	Models	1. The neural network models used in research are often single models, which cannot effectively demonstrate the superiority of the prediction methods	1. ENN suffers from low learning efficiency. Though optimization methods such as GA, PSO, IPSO and WOA can improve its efficiency, low convergence speed, local optimum and long training process are still problems.