RESEARCH ARTICLE

Using deep learning algorithms to predict and optimize carbon reduction strategies in a green economy

Zhenxuan Chen*

Faculty of Economic, Chulalongkorn University, Bangkok, Thailand.

Received: June 19, 2024; **accepted:** October 30, 2024.

Carbon emissions pose significant challenges to sustainable development, driving the need for accurate prediction models and effective emission reduction strategies. This study focused on developing a method for predicting carbon emissions and optimizing emission reduction strategies. By integrating multi-source data from 2000 to 2020, encompassing carbon emissions, economic growth, energy consumption, population dynamics, and policy factors, the quality of the model input data was ensured through comprehensive preprocessing. Subsequently, a Gradient Boosting Machine-Deep Neural Network (GBM-DNN) hybrid model was utilized to forecast carbon emission trends with optimal hyperparameters determined through cross-validation. The model's predictions, both short- and long-term, accurately captured the trends in carbon emissions. Furthermore, a multi-objective genetic algorithm was employed to explore different emission reduction paths, comparing the allocation of strategies related to energy efficiency improvements, renewable energy usage, carbon taxation, and their respective emission reduction effects, economic costs, and social impacts. A comprehensive evaluation of the environmental and economic impacts of various emission reduction strategies was conducted, providing a quantitative basis for strategic decision-making.

Keywords: deep learning; algorithmic prediction; green economy; carbon emission reduction strategy.

***Corresponding author:** Zhenxuan Chen, Faculty of Economic, Chulalongkorn University, Bangkok 10330, Thailand. Email: zhenxuan_chen@hotmail.com.

Introduction

Global climate change has been one of the most severe challenges that mankind is facing now. According to the International Energy Agency, the energy sector accounts for 73% of global greenhouse gas emissions with the combustion of coal, oil, and natural gas being the main sources [1]. This situation has not only aggravated global warming, but also triggered a series of chain reactions such as frequent occurrence of extreme weather events and sea level rise, which seriously threatens the ecological balance and sustainable development of human society. In response to the crisis, countries around the world have responded to the Paris Agreement's call to limit the rise in global average temperatures to 1.5°C above pre-industrial levels, which requires significant reductions in carbon emissions [2, 3].

In recent years, the rapid development of big data and artificial intelligence technology has brought about revolutionary changes in the field of carbon emission prediction. As a powerful artificial intelligence technology, deep learning is gradually becoming an important tool for carbon emission prediction with its excellent data processing ability and nonlinear modeling ability. Models, such as long-term and short-term memory networks (LSTM), have significant advantages in capturing long-term dependencies in time series data. In addition, multi-objective optimization algorithms, such as genetic algorithm and particle swarm optimization algorithm, have been widely used to explore the optimal emission reduction path [4, 5]. Despite significant progress in the field of carbon emission prediction and optimization of emission reduction strategies, current research still faces many challenges [6, 7]. The first is the issue of data including their availability, quality, and coverage, especially for developing countries. Secondly, the generalization ability of the model is also a problem that needs to be solved. In addition, the trade-off problem in multi-objective optimization, that is how to find the best balance point among economic benefit, environmental benefit, and social benefit, is also a topic that needs to be further explored in future research [8, 9].

The core objectives of this study focused on three interrelated aspects, which included to develop and validate a new deep learning model to achieve high-precision prediction of future carbon emission trends in specific geographic regions, to explore the deep integration of deep learning techniques and optimization algorithms to build a comprehensive strategy optimization framework, and to ensure that the proposed emission reduction measures effectively promote green economy development, ecological balance, and social well-being [10, 11]. The research developed a new deep learning model to integrate multi-dimensional data sources including macroeconomic indicators, energy consumption patterns, policy and regulatory dynamics, *etc*., while combined deep learning technology with optimization algorithms to build a strategic optimization framework, and further, improved the accuracy and practicality of the model through interdisciplinary cooperation [12, 13]. This study provided a new and efficient prediction method for the field of carbon emission prediction, which would help to improve the prediction accuracy and practicality. It also promoted the deep integration of deep learning technology and optimization algorithm in the field of carbon emission prediction and emission reduction strategy optimization and provided new perspectives and methods for research in related fields. Further, this study provided strong support for the realization of global carbon emission reduction targets and sustainable development and helped mankind cope with the challenge of climate change [14].

Materials and methods

Data resources

Carbon emission data mainly came from government public reports, databases of international organizations, and research results of scientific research institutions. The World Bank's World Development Indicators (WDI) database (https://data.worldbank.org/indicator/EN.ATM.CO2E.KT) provided historical and projected CO_2 emissions data for countries including total, per capita, and by sector. In addition, the International Energy Agency's (IEA) Energy Statistics (https://www.iea.org/data-and-statistics/statistics-databases/energy-balances) and the Global Carbon Project (https://globalcarbonproject.org/carbonbudget) provided detailed carbon emissions data and analysis. For specific country or regional research, official data published by the National Bureau of Statistics and environmental protection departments were used. For instance, in the case of China, the National Bureau of Statistics published annual statistical yearbooks (http://www.stats.gov.cn/tjsj/ndsj/), and the Ministry of Ecology and Environment provided policy documents and regulations (http://www.mee.gov.cn/hjzl/) [15, 16]. Economic development data, which covered GDP, per capita income, employment rate, industrial structure, and many other aspects, were obtained from the databases of the World Bank WDI, the United Nations Statistics Division (UNSD), and the Organization for Economic Cooperation and Development (OECD). For more

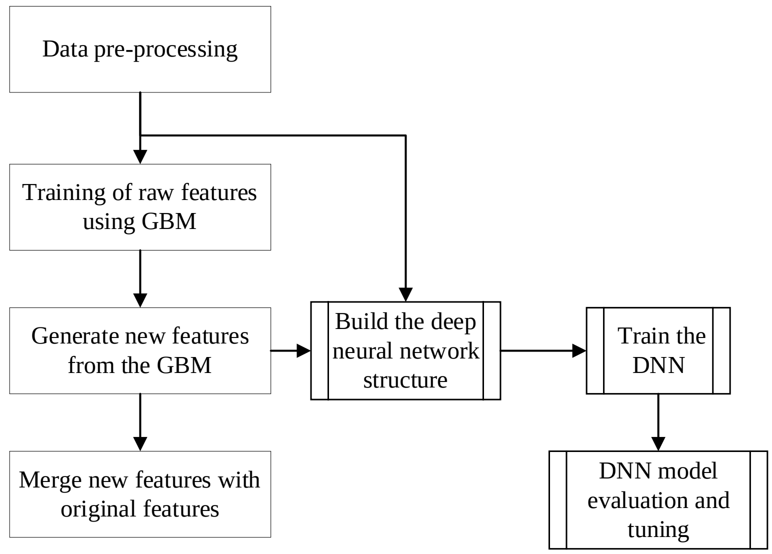

Figure 1. Model framework.

micro-level economic activities such as industry output, corporate financial statements, *etc*., the commercial databases such as Thomson Reuters and Wind Information were employed [17, 18]. For this study, the historical data from the past 30 years including macroeconomic indicators, energy consumption data, policy documents, *etc*. were collected with a total of approximately 100,000 data points, of which 80% was used for model training and the remaining 20% for model validation. The training data used in this study covered a country's carbon emissions, economic growth indicators (such as GDP), energy consumption (including coal, oil, natural gas, and renewable energy consumption), population data, and policy changes from 2000 to 2020. Data were mainly from the International Energy Agency (IEA), the World Bank, and national statistical offices. Data preprocessing included missing value processing (forward filling or backward filling), outlier detection (based on IQR method), and normalization processing (Z-score normalization), which ensured the quality of data and the effectiveness of model training. Research results summarized the key variables in the training dataset used in this study, covering time series information, carbon emissions, economic development indicators, detailed composition of energy consumption, population data, and policy factors from the reliable data sources including international authorities. The preprocessing steps ensured data quality, which included handling missing values, detecting and handling outliers, and normalizing, laying a solid foundation for model training.

Deep learning model construction and training

When exploring deep learning applications for carbon emission reduction strategies in a green economy, model selection should consider data characteristics and the complexity of prediction tasks. Because carbon emission prediction involved time series analysis, multivariate interaction, and nonlinear relationship, this study adopted a hybrid model of Gradient Boosting Machine (GBM) and Deep Neural Network (DNN) in ensemble learning method. GBM exceled at dealing with complex interactions between features, while DNN exceled at capturing nonlinear relationships. The combination of the two models enhanced the generalization and prediction accuracy of the model [19]. The specific binding framework of DNN and GBM was shown in Figure 1. The gradient lifters were used as base learners to reduce prediction errors step by step through iteratively adding weak learners such as decision trees. Each new tree focused on the residuals of the previous model, allowing the entire model to gradually approximate the true distribution. The key parameters of GBM included learning rate, number of trees, maximum depth of trees, *etc*., which needed to be optimized according to the results of cross-validation. A deep neural network model was then constructed, which consisted of multiple hidden layers with each layer containing multiple neurons. The input layer of DNN received the preprocessed eigenvectors. After a series of weight matrix transformations (W) and nonlinear activation functions such as ReLU, the final output layer gave the predicted values [20]. The model was expressed as follows.

$$y = f(W_n \sigma(W_{n-1} ... \sigma(W_1 X + b_1) + b_{n-1}) + b_n) \quad (1)$$

where *X* was the input feature. *W* and *b* were the weight matrix and bias term for the ith layer, respectively. *f* was the activation function for the output layer such as linear function or sigmoid, depending on the prediction task [20]. The selection and optimization of hyperparameters are critical to the performance of the model. In this study, Bayesian Optimization was used as the super parameter optimization method. Compared with grid search and random search, Bayesian Optimization found the optimal configuration by establishing a proxy model of the objective function with fewer experiments. Specific to the proposed hybrid model, the key hyperparameters to adjust included (1) the number of hidden layers and nodes of DNN, which determined the complexity of the network. Too many layers or nodes might lead to overfitting, and too few might fail to capture complex patterns in the data; (2) learning rate that controlled the step size of parameter update. If the initial learning rate was too high, it might cause unstable training, otherwise it would prolong the training time; (3) the number and depth of the tree of the gradient hoist, which affected the expression ability and training efficiency of the model and needed to weigh the prediction performance and the risk of overfitting; (4) regularization strength such as L1 or L2 regularization used to control model complexity and prevent overfitting [21]. The mean square error (MSE) was chosen as the primary evaluation criterion for loss functions because it was sensitive to errors between model predictions and actual values and was widely used in regression problems. For DNN part, linear activation function was adopted as output layer activation function to directly output prediction value considering continuous property of prediction value. Adam was chosen as the optimization algorithm, which combined the advantages of momentum and RMSProp, adjusted the learning rate of each parameter automatically, avoided local optimal solution effectively, and accelerated convergence speed. Adam estimated the first moment (mean) and second moment (uncentered variance) of the gradient by maintaining two empirical variances as shown below [22].

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \quad (2)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \quad (3)$$

$$m_t^{corrected} = \frac{m_t}{1-\beta_1^t} \quad (4)$$

$$v_t^{corrected} = \frac{v_t}{1-\beta_2^t} \quad (5)$$

$$w_t = w_{t-1} - \alpha \frac{m_t^{corrected}}{\sqrt{v_t^{corrected}} + \grave{o}} \quad (6)$$

where, β was the gradient. v_{t-1} was the first and second momentum estimates, respectively. m_t was the decay rate. α was the learning rate. $\grave{o}$ was a small constant added for numerical stability [23]. 5-fold cross validation was applied to ensure the generalization ability of the model. The dataset was randomly divided into five subsets with one subset at a time as the test set and the remaining four subsets being combined as the training set. Each subset was used as a test.

The performance of the model was based on the average of five iterations. This approach reduced the chance of data partitioning and provided a more robust model performance assessment [24]. In DNNs, inferring feature importance directly from the weight matrix was more complicated because the weight values depended not only on the features themselves but also on the network structure and other weight interactions in the learning process. A simplified approach was to estimate the importance of features initially by analyzing the sum of absolute values of the weights from the input layer to the output layer. To evaluate the importance of the j[th] feature, the sum of the absolute values of the weights of all the output neurons connected to it was calculated as follows.

$$FI_j^{DNN} = \sum_{i=1}^{N_{l+1}} |W_{ij}^{(l)}| \tag{7}$$

where $W_{ij}^{(l)}$ was the number of neurons in layer *l*+1. Although this approach was simple and intuitive, it ignored the complexity of feature interactions in deep learning and was therefore often used as an aid to an initial understanding of feature contributions. In GBM, feature importance was directly related to the gain that each feature contributed across all decision trees, i.e., the performance improvement that the model gained by segmenting that feature. Specifically, for a split node in the decision tree, the gain of feature j could be defined as the decrease in the loss function before and after the split. The importance of a feature j in the entire model FI_j^{GBM} could be calculated as the average of the gains in all trees using that feature as a split node [25].

$$FI_j^{GBM} = \frac{1}{K} \sum_{k=1}^{K} \sum_{t \in T_k} \sum_{\text{splits on } j} G_j(t) \tag{8}$$

where *K* was the number of trees, denoting the k[th] tree. *t* was the node in the tree with feature j as the splitting condition.

Through the above method, the relative importance ranking of each feature in the prediction process of the model could be obtained. Feature importance analysis could identify key influencing factors and guide subsequent data acquisition and model optimization. For identified high-impact features, higher quality or higher resolution data collection might be considered [26, 27].

Statistical analysis

SPSS 27.0 (IBM, Armonk, New York, USA) was employed for statistical analysis of this study. The R-score was calculated as a composite index that considered both the environmental impact (measured by total emission reductions and cost per ton of CO_2) and the economic costs (investment and other direct expenses), as well as the implementation difficulty (social impact scores reflecting policy acceptance and technical feasibility).

Results and discussion

Carbon emission trend projections

The proposed GBM-DNN hybrid model was used to predict carbon emission trends. During model training, the optimal combination of hyperparameters was determined through cross-validation with 5% discount [28, 29]. The configuration of optimal hyperparameters was used to train the hybrid model (GBM-DNN), which was carefully tuned for cross-validation with 50% off to optimize model performance. The number of hidden layer nodes and learning rate of DNN, as well as the number of trees and maximum depth of trees of GBM were included to ensure that the model was neither too complex to overfit nor too simple to ignore important features [30, 31]. The relationship between predicted and actual CO_2 emissions was plotted (Figure 2). The results showed that there were some differences between the predicted and actual values for most of the time, but the overall trend was similar. In the time periods of May, July, and August 2022, the predicted values appeared to be higher than the actual values,

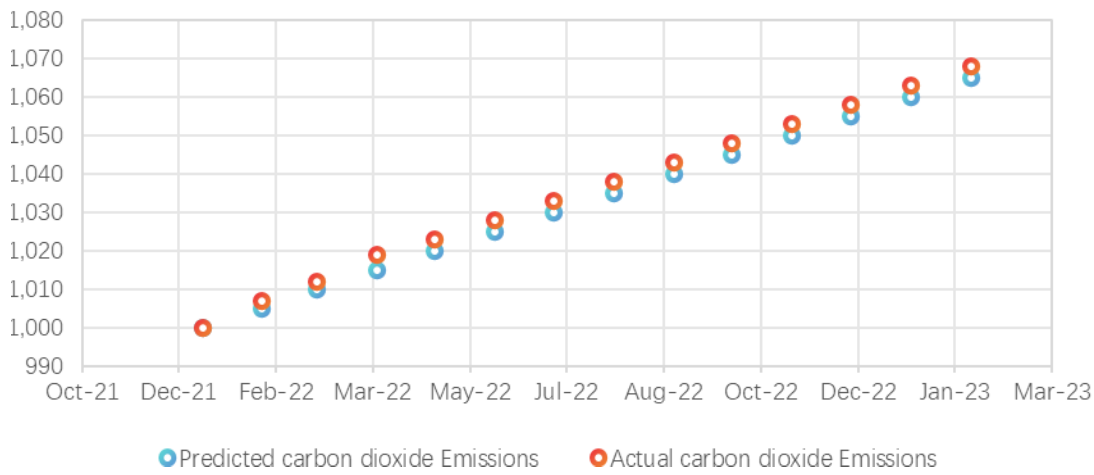

Figure 2. Short-term prediction effect. The vertical axis represented CO_2 emissions.

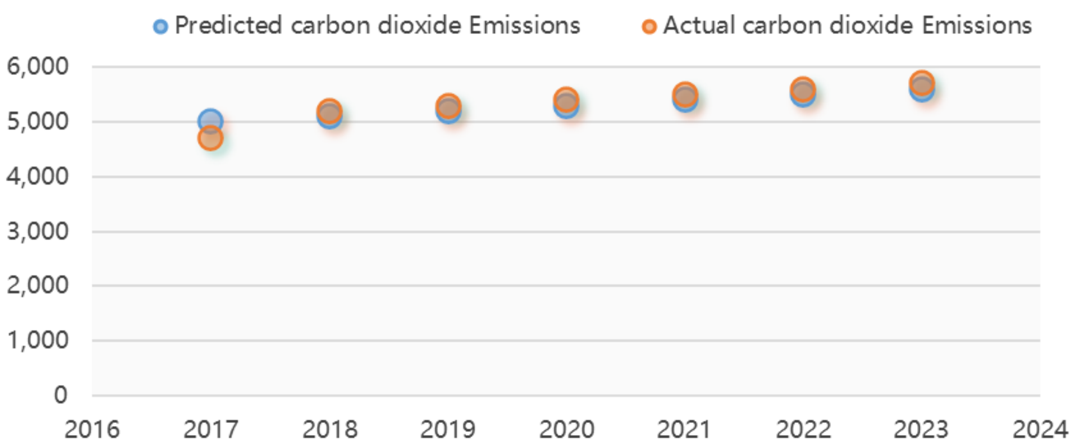

Figure 3. Long-term prediction effect. The vertical axis represented CO_2 emissions.

while, in some other months such as February and March 2022, the predicted values were lower than the actual values. In addition, both projected and actual CO_2 emissions demonstrated an upward trend over time. However, in some cases such as October 2022, the forecasts were lower than the actual values, while the forecasts were usually higher than the actual values. A long-term prediction effect was shown in Figure 3. The value of "Predicted carbon dioxide emissions" was smaller than that of "Actual carbon dioxide emissions", and the difference between the two values gradually increased.

Simulation of emission reduction strategies

Based on the prediction results, multi-objective genetic algorithm (NSGA-II) was used to explore different emission reduction paths. The objective function consisted of minimizing economic costs, maximizing carbon emission reductions, and maintaining social stability such as maintaining the unemployment under a certain threshold. Strategy variables included improving energy efficiency, increasing the share of renewable energy, and imposing carbon taxes. Several emission reduction strategy options were explored based on multi-objective genetic algorithm and compared the allocation of different strategies in terms of energy efficiency improvement, renewable energy use, carbon tax, expected emission reduction effects, economic

Table 1. Comparison of optimization strategies.

Strategy	Energy efficiency	Renewables share	Carbon tax	Projected emission reductions (Mt CO_2)	Estimated economic cost (billion ¥)	Social impact score
S1	15%	10%	50	-120	250	8.5
S2	10%	20%	70	-150	300	7.8
S3	20%	5%	30	-80	180	9.2

Table 2. Integrated environmental and economic impact assessment.

Strategy	Total projected emission reductions (Mt CO_2)	Total economic cost (billion ¥)	Emission reduction cost/ton CO_2 (¥)	Environmental benefit index (1-10)	Economic burden index (1-10)
S1	-120	250	20.83	7.5	5.5
S2	-150	300	20	8	6.5
S3	-80	180	22.5	7	4.5

costs, and social impacts, which provided decision makers with a visual comparison of different emission reduction pathways, allowing for a comprehensive consideration of economic benefits and social acceptability (Table 1).

Policy evaluation

A comprehensive assessment of the proposed strategy that considered the environmental impact (emission reductions), the economic costs (direct costs such as investment, tax adjustments, *etc.*), and the difficulty of implementation (social impact scores that reflected policy acceptance, technical feasibility, *etc.*) was conducted. Three strategies named S1, S2, and S3 that represented three distinct strategies for emissions reduction were compared in this study. Each strategy encompassed a unique combination of environmental impact, economic costs, and implementation difficulty, aiming to balance these factors effectively. The results showed that, although S1 had lower economic costs, its emission reduction effect and social impact score were slightly lower than that of S3, while S3 had higher environmental benefits and social acceptance, but required a larger initial investment (Table 2). The performances of different emission reduction strategies in terms of environmental benefits, economic costs, and implementation difficulties were comprehensively evaluated, which provided quantitative basis for strategy selection through quantitative indicators to clearly identify which strategy had the least impact on the economy while achieving emission reduction targets and was easy to implement, providing scientific basis for policy planning [30, 31]. LSTM, as a common model for time series prediction, performed well in this task, but its MSE and MAE were relatively high, indicating that its prediction accuracy was slightly inferior to GBM-DNN hybrid model (Table 3). XGBoost and random forest as representatives of reinforcement learning and ensemble learning performed well, but lag significantly in MSE and MAE indicators, indicating that accuracy needed to be improved. As a benchmark model, the ability of linear

Table 3. Comparative analysis of prediction effect of models.

Model name	MSE	MAE	R^2 score
GBM-DNN hybrid model	100.56	2.15	0.89
LSTM	105.2	3.1	0.86
XGBoost	120.1	4.5	0.83
random forest	150.3	5.8	0.77
linear regression	200.7	8.2	not apply

regression model to deal with complex data relations was limited because of its simplicity. All indicators were at the bottom, reflecting the limitations of nonlinear models in complex forecasting tasks. The GBM-DNN hybrid model was constructed to predict carbon emission trends successfully. The effectiveness and superiority of the hybrid model were verified by comparing it with other models. The prediction results showed that the model could effectively track and predict fluctuations and trends of carbon emissions in both short and long term, providing timely and forward-looking information support for decision makers. In terms of emission reduction strategies, this study explored different emission reduction paths by using multi-objective genetic algorithm and provided comprehensive strategy selection basis for decision-makers by comprehensively evaluating the environmental benefits, economic costs, and implementation difficulties of different strategies. The results showed that there were significant differences in emission reduction effect, economic cost, and social impact among different emission reduction strategies, and decision makers needed to weigh and choose according to specific circumstances. The results of this study have important reference value for policy makers.

References

1. Wang ZW, Xu L, Ma JX. 2023. Carbon dioxide emission reduction-oriented optimal control of traffic signals in mixed traffic flow based on deep reinforcement learning. Sustainability. 15(24):25.
2. Ma Q, Tariq M, Mahmood H, Khan Z. 2022. The nexus between digital economy and carbon dioxide emissions in China: The moderating role of investments in research and development. Technol Soc. 68:10.
3. Long Z, Chen XZ. 2023. Early warning research on enterprise carbon emission reduction credit risk based on deep learning model under unbalanced data. Front Energy Res. 11:16.
4. Li ZG, Wang J. 2022. The dynamic impact of digital economy on carbon emission reduction: evidence from city-level empirical data in China. J Clean Prod. 351:12.
5. Meng ZY, Li WB, Chen CF, Guan CH. 2023. Carbon emission reduction effects of the digital economy: mechanisms and evidence from 282 cities in China. Land. 12(4):21.
6. Wang ZH, Zhang ZY. 2023. The carbon emission reduction effect and mechanism analysis of digital economy: Evidence of prefecture-level cities in China. Appl Econ. 2023:18.
7. Lin MA, Zeng HR, Zeng X, Mohsin M, Raza SM. 2023. Assessing green financing with emission reduction and green economic recovery in emerging economies. Environ Sci Pollut Res. 30(14):39803-39814.
8. Xie B, Liu R, Dwivedi R. 2024. Digital economy, structural deviation, and regional carbon emissions. J Clean Prod. 434:11.
9. Zhou SQ, Zhang XM, Chu SW, Zhang TT, Wang JF. 2023. Research on remote sensing image carbon emission monitoring based on deep learning. Signal Processing. 207:10.
10. He XR, Shi JZ, Xu HC, Cai CY, Hu QS. 2022. Tourism development, carbon emission intensity and urban green economic efficiency from the perspective of spatial effects. Energies. 15(20):23.
11. Li J, Sun ZC, Zhou J, Sow Y, Cui XF, Chen HP, *et al*. 2023. The impact of the digital economy on carbon emissions from cultivated land use. Land. 12(3):18.
12. Liu JL, Duan YX, Zhong S. 2022. Does green innovation suppress carbon emission intensity? New evidence from China. Environmental Science and Pollution Research. 29(57):86722-43.

13. Wang JQ, Tian JX, Kang YX, Guo K. 2023. Can green finance development abate carbon emissions: Evidence from China. International Review of Economics & Finance. 88:73-91.
14. Yao X, Zhang H, Wang XY, Jiang YD, Zhang YX, Na XH. 2024. Which model is more efficient in carbon emission prediction research? A comparative study of deep learning models, machine learning models, and econometric models. Environ Sci Pollut Res. 31(13):19363-19380.
15. Wang SY, Li JX, Tang H, Wang J. 2022. CEA-FJSP: Carbon emission-aware flexible job-shop scheduling based on deep reinforcement learning. Front Environ Sci. 10:13.
16. Wang CQ, Qi FY, Liu PZ, Ibrahim H, Wang XR. 2023. The effect of the digital economy on carbon emissions: an empirical study in China. Environ Sci Pollut Res. 30(30):75454-75468.
17. Liu WJ, Zhu P. 2024. The impact of green finance on the intensity and efficiency of carbon emissions: the moderating effect of the digital economy. Front Environ Sci. 12:18.
18. Bai K, Zhao LK, Che WQ, Guo BJ, Li ZL. 2024. The visual weighing method of mining dump atruck based on resnet. Matrix Science Mathematic. 8(2):38-48.
19. Yu ZX, Liu S, Zhu ZC. 2022. Has the digital economy reduced carbon emissions? Analysis based on panel data of 278 cities in China. Int J Environ Res Public Health. 19(18):18.
20. Sun GJ, Liu YX, Li B, Guo LL. 2024. Road to sustainable development of China: The pursuit of coordinated development between carbon emissions and the green economy. J Clean Prod. 434:14.
21. Ma CS, Hou B, Yuan TT. 2020. Low-carbon manufacturing decisions considering carbon emission trading and green technology input. Environ Eng Manag J. 19(9):1593-1604.
22. Liu YX, Lei P, He DY. 2024. Endogenous green technology progress, green transition and carbon emissions. Int Rev Econ Finance. 91:69-82.
23. Rjoub H. 2022. Sustainable digital economy and trade adjusted carbon emissions: Evidence from China's provincial data. Econ Res-Ekon Istraz. 35(1):5469-5485.
24. Zhang H, Qi R, Liu YY, Wang TT, Zhong F, Zhou Q, *et al*. 2024. The spatial impact of digital economy on carbon emissions reduction: evidence from 215 cities in China. Front Environ Sci. 12:17.
25. Ezenkwu CP, Cannon S, Ibeke E. 2024. Monitoring carbon emissions using deep learning and statistical process control: a strategy for impact assessment of governments' carbon reduction policies. Environ Monit Assess. 196(3):15.
26. Huang HF, Wu XM, Cheng XF. 2021. The prediction of carbon emission information in Yangtze River Economic Zone by deep learning. Land. 10(12):23.
27. Gao XD, Li JB. 2024. China's digital economy: a dual mission of carbon-emission reduction and efficiency enhancement. Sustainability. 16(6):21.
28. Hou J, Bai WT, Sha DC. 2023. Does the digital economy successfully facilitate carbon emission reduction in China? Green technology innovation perspective. Science Technology and Society. 28(4):535-560.
29. Di KS, Chen WD, Zhang XN, Shi QM, Cai QL, Li DL, *et al*. 2023. Regional unevenness and synergy of carbon emission reduction in China's green low-carbon circular economy. J Clean Prod. 420:17.
30. Sun JB, Wu XH. 2023. Research on the mechanism and countermeasures of digital economy development promoting carbon emission reduction in Jiangxi Province. Environmental Research Communications. 5(3):15.
31. Xia AX, Cao JL, Xu YG. 2023. Carbon emission reduction alliance, green technology, and emission reduction performance: an empirical study based on the synergistic perspective of environment and economy. Environ Sci Pollut Res. 30(19):55864-55883.