Carbon Emission Forecast Based on Multilayer Perceptron Network and STIRPAT Model

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Abstract

INTRODUCTION: It is of great research significance to explore whether China can achieve the "two-carbon target" on time. The MLP model combines nonlinear modeling principles with other techniques, possessing powerful adaptive learning capabilities, and providing a viable solution for carbon emission prediction.
OBJECTIVES: This study models and forecasts carbon emissions in Jiangsu Province, one of China's largest industrial provinces, aiming to forecast whether Jiangsu province will achieve the two-carbon target on time plan and provide feasible pathways and theoretical foundations for achieving dual carbon goals.
METHODS: Based on the analysis of the contributions of relevant indicators using the Grey Relational Analysis method, a comprehensive approach integrating the STIRPAT model, Logistic model, and ARIMA model is adopted. Ultimately, an MLP prediction model for carbon emission variations is established. Using this model, simulations are conducted to analyze the carbon emission levels in Jiangsu Province under different scenarios from 2021 to 2060.
RESULTS: The time to reach carbon peak and the likelihood of achieving carbon neutrality vary under three scenarios. Under the natural scenario of no human intervention, achieving carbon neutrality is not feasible. While under human-made intervention scenarios including baseline and intervention scenarios, Jiangsu Province is projected to achieve the carbon neutrality target as scheduled, attaining the peak carbon goal, however, proves challenging to realize by the year 2030.
CONCLUSION: The MLP model exhibits high accuracy in predicting carbon emissions. To expedite the realization of dual carbon goals, proactive government intervention is necessary.

1. Introduction

As early as the mid to late 20th century, global climate warming has garnered widespread attention from the international community. Issues such as its causes, measurement, consequences, and mitigation measures have become focal points in the scientific community. China, being the world's largest emitter of greenhouse gases and a significant consumer of energy, has witnessed a rapid increase in carbon emissions, with its global share consistently rising in the 21st century. In September 2020, in response to global climate change, President Xi Jinping announced during the 75th United Nations General Assembly that China aims to peak carbon emissions before 2030 and achieve carbon neutrality by 2060. The realization of the dual carbon goals is not only a solemn commitment made by China to address global climate change but also an inevitable choice for the country's future economic structural transformation and sustainable development.

To achieve carbon reduction targets, China must seek a negative correlation between economic growth and carbon emissions. This involves two key aspects. Firstly, improving energy efficiency by reducing the energy consumption per unit of GDP can lead to a negative correlation between economic growth and energy consumption. Secondly, increasing the proportion of non-fossil energy consumption, thereby reducing the carbon emissions per unit of energy, can establish a negative correlation between energy consumption and carbon emissions. To implement these strategies effectively, it is essential to establish mathematical models for the analysis, assessment, and

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prediction of the impact of these initiatives on carbon emissions, ensuring the achievement of China's carbon neutrality goals.

Given the uneven socio-economic development across regions in China, the realization of dual carbon goals ultimately needs to be implemented at the regional level. Jiangsu Province, being one of the economically strongest provinces in China, is also a key region for energy consumption and air pollution. Achieving the carbon peak in this region is crucial for the successful realization of the national dual carbon goals. Therefore, studying the future carbon emission trends in Jiangsu Province and the pathways for carbon reduction under different scenarios holds profound significance for the smooth implementation of Jiangsu Province's dual carbon goals and China's overall carbon reduction efforts.

Existing literature reveals that researchers both domestically and internationally have developed various models for predicting carbon emission changes, but there is still room for improvement. In [1], based on the assumption that "carbon emissions are proportional to energy consumption", a Logistic model is constructed to predict the growth of carbon emissions in China. In [2], by integrating factors influencing carbon emissions, the STIRPAT model is employed to forecast carbon emissions and peak times in Chinese urban clusters under different scenarios. In [3], using the LEAP model, the analysis examines CO_2 emissions and peaks in Shanxi Province from 2019 to 2035 under various scenarios. In [4], relying on macroeconomic indicators, a mixed data ADL-MIDAS model is built to predict and analyze the total and structural carbon dioxide emissions during China's "14th Five-Year Plan". Furthermore, scholars have utilized the system dynamics model [5], nonlinear grey multivariable model [6], grey rolling model [7], and Gompertz's law and fractional grey model [8] to forecast regional carbon emissions and carbon emission intensity. However, environmental impact assessment methods, mainly represented by STIRPAT, are limited to accurately predicting the linear portion of carbon emissions. Their predictive accuracy for the nonlinear part is relatively low, lacking the fitting capability for nonlinear sequences compared to machine learning algorithms.

With the continuous development of artificial intelligence, an increasing number of scholars have applied machine learning and deep learning to the field of carbon emission prediction. In [9], the Aquila Optimizer's Double Support Vector Regression (AO-based TWSVR) is employed to forecast China's net carbon emissions from 2021 to 2035. In [10], utilizing the generalized structure of machine learning (ML) derived group method of data handling (g-GMDH), the analysis and prediction of China's carbon dioxide emission trends from 2020 to 2043 are conducted. Various machine learning techniques, including support vector regression (SVR), random forest (RF), and neural networks, have been widely applied in carbon emission prediction [11][12]. The development of deep learning has led to the emergence of various neural network-based carbon emission prediction models, such as artificial neural networks (ANN) [13] and long short-term memory networks (LSTM)

[14][15][16]. While neural networks can, to some extent, address the shortcomings of traditional methods, such as the need to construct membership functions, the inability to accurately describe changes within the prediction interval, and certain biases in the design process [17], theoretically, neural network models require a large number of data samples. The quantity and quality of publicly available government data are often insufficient to meet the training requirements for accurate predictions. Additionally, in scenarios with significant data noise or low data quality, traditional carbon emission prediction models tend to outperform neural networks. Therefore, as for current research methods, there has been no application of improving the MLP neural network with traditional carbon emission prediction models and establishing prediction models based on multiple carbon emission influencing factors.

The Multilayer Perceptron (MLP) prediction model integrates the concepts of nonlinear modeling and other technologies, exhibiting strong adaptive learning capabilities and generalization performance. It is particularly well-suited for solving various time series prediction problems and can effectively enhance accuracy under current conditions. This study comprehensively considered various factors influencing carbon emissions to obtain a nonlinear fitting model. Building upon the STIRPAT model, Logistic model, and ARIMA model, the MLP prediction model for carbon emission variation was established. By setting natural scenarios, baseline scenarios, and intervention scenarios, a simulation analysis was conducted to project the overall trend of carbon emissions in Jiangsu Province from 2021 to 2060. This comprehensive approach aims to provide a reasonable estimation for achieving future energy-saving and emission-reduction targets and subsequently proposes policy recommendations to achieve the "dual carbon" goals.

2. Construction and analysis of the indicator system

2.1. Construction of the Indicator System

Carbon emission prediction involves a dynamic and complex system encompassing various factors such as the economy, population, and energy. Strictly following the principles of scientificity, comprehensiveness, and comparability, this paper establishes the indicator system shown in Table 1 below. This indicator system scientifically and objectively reflects the status of the economy, population, and energy consumption. This index system systematically captures key variables and ensures a thorough evaluation of the factors influencing carbon emissions in the region. It serves as the foundation for the subsequent analysis and prediction of carbon emission levels.

Table 1. Index system for factors influencing carbon emissions

Category	Variable name	Unit
Economic factors	GDP	Billion yuan
	Per capita GDP	Yuan/Person
	Value added of primary industry	Billion yuan
	Value added of secondary industry	Billion yuan
	Value added of tertiary industry	Billion yuan
Population	Permanent resident population	Ten thousand people
	Number of births	Ten thousand people
	Number of deaths	Ten thousand people
	Urbanization rate	%
Energy factors	Total energy consumption	Ten thousand tons of standard coal
	Energy consumption in the energy supply sector	Ten thousand tons of standard coal
	Energy consumption in the agriculture and forestry sector	Ten thousand tons of standard coal
	Energy consumption in the industrial sector	Ten thousand tons of standard coal
	Energy consumption in the transportation sector	Ten thousand tons of standard coal
	Energy consumption in the construction sector	Ten thousand tons of standard coal
	Energy consumption in the residential sector	Ten thousand tons of standard coal
	Proportion of non-fossil energy consumption	%

2.2. Data Source and Processing

The energy consumption in various sectors includes primary energy and secondary energy. Specifically, primary energy consumption comprises fossil energy consumption and non-fossil energy consumption, where fossil energy encompasses coal, oil, and natural gas. Secondary energy consumption includes thermal and electrical consumption. Given that the energy supply sector generates secondary energy, it solely includes fossil energy and non-fossil energy consumption. The relationship between various energy types is illustrated in the diagram below (Figure 1).
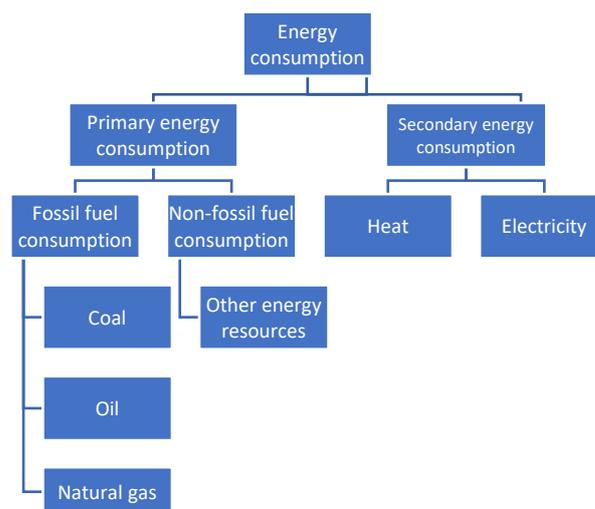

Figure 1. Varieties of energy consumption

The data for energy consumption in various sectors are sourced from the "China Energy Statistical Yearbook", specifically the terminal energy consumption section of the energy balance table. The selected time series spans from 2010 to 2020. Additionally, economy and population indicators are derived from official sources such as the "Jiangsu Statistical Yearbook" and the National Bureau of Statistics. Urbanization rate data are obtained from the "Statistical Bulletin of National Economic and Social Development of Jiangsu Province". All historical value data are transformed to constant 2010 prices, and standardization is applied to eliminate dimensionality effects. For missing data points, linear interpolation is employed for data completion.

2.3. Carbon Emission Estimation and Current Situation Analysis

Given the absence of direct monitoring data for carbon emissions in China, scholars commonly utilize the carbon emission coefficient calculation method outlined in the "IPCC Guidelines for National Greenhouse Gas Inventories". This method relies on energy consumption data and carbon emission coefficients to estimate carbon emissions. In this study, we adopt the IPCC carbon emission coefficient method, employing the energy-related carbon source estimation approach to calculate and consolidate carbon emissions. The specific formula is as follows:

$$T = \sum_{i=1}^{n} E_i * H_i * F_i$$

(1)

In the formula, T represents the total carbon emissions; E_i is the energy consumption; H_i is the conversion coefficient to standard coal; F_i is the carbon emission coefficient. The conversion coefficients of various energy

types to standard coal are referenced from the "China Energy Statistical Yearbook", as detailed in Table 2:

Table 2. Carbon emission coefficients for various energy sources

Energy types	Conversion coefficient to standard coal	Carbon emission coefficient
Coal	0.71	0.76
Washed coal	0.90	0.76
Coke	0.97	0.86
Shaped coal	0.60	0.76
Crude oil	1.43	0.59
Gasoline	1.47	0.55
Diesel	1.46	0.59
Fuel oil	1.43	0.62
Liquefied gas	1.71	0.50
Natural gas	1.33	0.45
Refined coal	0.80	0.76
Electricity	1.23	3.15
Heat	0.03	9.46

We have calculated the carbon emissions for various sectors in Jiangsu Province, and Figure 2 illustrates their changing trends. It is evident from the graph that, relative to other sectors, the industrial consumption sector and the energy supply sector contribute significantly to the overall emissions. In comparison to the year 2010, there is an overall increase in carbon emissions during both the Twelfth Five-Year Plan (2011－2015) and the Thirteenth Five-Year Plan (2016－2020) periods. However, there is a notable difference between the two periods: during the Twelfth Five-Year Plan, the carbon emissions show a substantial fluctuation, reaching a peak in 2012, while during the Thirteenth Five-Year Plan, the emissions exhibit a gradual increase. With the introduction of the dual carbon policy in 2020, there is a subsequent decline in carbon emissions. Generally, the carbon emissions in this region demonstrate a fluctuating trend with a growth rate resembling an "S" shape.
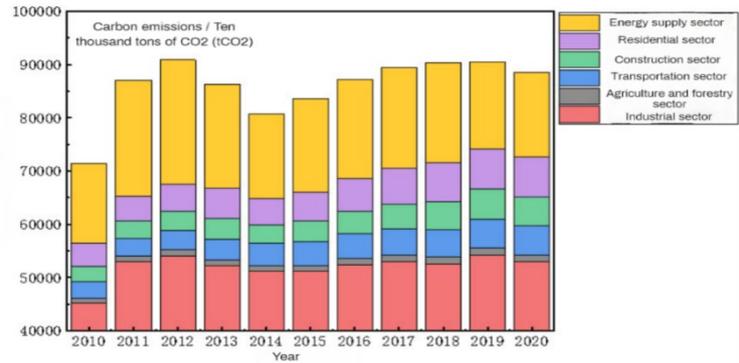

Figure 2. Carbon emissions from different sectors

2.4. Carbon Emission Factors Analysis

Indicator Correlation Analysis

Before conducting correlation analysis, it is essential to assess whether the indicators adhere to a normal distribution. Due to the relatively small sample size in this study, the Shapiro-Wilk test is employed, and the result indicates that the data does not follow a normal distribution. Therefore, this study chooses the Spearman correlation coefficient for correlation analysis. The results are presented in Table 3. There exists a significant correlation among the four major indicators, implying a close mutual influence. Energy, economy, population, and carbon emissions exhibit a positive correlation, indicating that as energy consumption increases and society and the economy develop, carbon emissions will also correspondingly increase.

Table 3. Spearman correlation coefficients between variables

	Carbon emission	Energy	Economy	Population
Carbon emission	1	0.909 (0.000***)	0.9 (0.000***)	0.9 (0.000***)
Energy		1	0.991 (0.000***)	0.991 (0.000***)
Economy			1	1 (0.000***)
Population				1

Note: ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

Contribution Analysis

This study employs the Grey Relational Analysis method to determine the contribution of each factor. Grey relational coefficients reflect the degree of similarity between two sequences, ranging from 0 to 1, with values closer to 1 indicating greater similarity. Initially, considering carbon emissions as the main sequence and energy, economy, and population as the feature sequences, with a resolution coefficient set at 0.5, the grey relational coefficients between

the main and feature sequences are calculated. Subsequently, the grey relational degree values are obtained, representing the average of the grey relational coefficients. Finally, the grey relational degree values are ranked, as shown in Table 4. It is evident that the population has the highest relational degree, followed by energy, and the economy exhibits the lowest degree. Additionally, following the same procedure, this study conducts grey relational degree analysis for various sub-indicators. The results indicate that indicators such as total energy consumption, energy consumption in the energy supply sector, energy consumption in the industrial sector, and permanent population contribute significantly. Their trends align closely with the variations in carbon emissions, emphasizing their crucial role as influential factors affecting carbon emissions. The contribution of added value in the tertiary industry is relatively low, indicating that its trend of change is not closely aligned with the trend of carbon emissions.

Table 4. Grey relational degree

Evaluation item	Relational degree	Ranking
Population	0.965	1
Energy	0.918	2
Economy	0.553	3

3. Prediction Model Construction and Optimization

3.1. Extended STIRPAT Model for Carbon Emission

In this study, we adopt the STIRPAT model and integrate the Environmental Kuznets Curve theory. Additionally, we introduce the quadratic term of economic factors into this model. Simultaneously, we treat energy as an independent key factor, resulting in the extended STIRPAT model for carbon emissions as follows:

$$lnCE = lna + blnP + clnA + dlnA^2 + dlnE + lnf \quad (2)$$

Where CE represents the carbon emission, P represents population factors, A represents economic factors, and E represents energy factors.

To assess the presence of multicollinearity, a variance inflation factor (VIF) test is conducted. The result indicates that the VIF value significantly exceeds 10, suggesting strong collinearity among these variables, which could lead to the issue of spurious regression. Principal component regression analysis and ridge regression analysis are two commonly used methods to overcome multicollinearity. Following the approach of [18], ridge regression is applied to analyze the STIRPAT model. Through regularization of the data, which reduces the correlation among independent variables, the model's predictive accuracy is enhanced. The

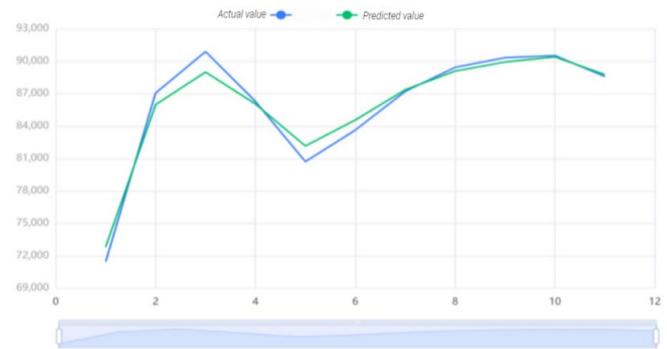fitted curve is depicted in Figure 3, demonstrating a satisfactory fit for this model.

Figure 3. The fitted curves

3.2. Construction of Population Prediction Model

The long-term trend of regional population does not exhibit exponential or linear growth but often follows a trend line with an asymptotic point as a limit. In terms of graphical changes, it shows an upward concave rise followed by a downward concave rise, resembling the shape of the letter "S". This long-term population fluctuation is analogous to the growth process of a biological population. To predict the changing trend of population growth in the region, we analyzed mainstream population growth models and their applicability conditions. We found that the GM (1,1) grey model is more suitable for short-term time series forecasting. The Logistic model combines known population status with the regularities of population change and proposes various assumptions affecting the process of population development, allowing us to infer future trends in population development. Considering the characteristics of the data, we ultimately chose the Logistic population prediction model.

3.3. Construction of Economic Prediction Model

The ARIMA model is a model that transforms a non-stationary time series into a stationary time series and is a commonly used model to predict the economy. Using ARIMA for forecasting requires only endogenous variables, without the need for external variables, making it applied for long-term predictions. Therefore, we use this method to predict per capita GDP from 2021 to 2060. ADF test results show that when the differencing order is 0, the significance p-value is 0.019, rejecting the null hypothesis, and indicating that the time series is stationary. When the differencing order is 1, the significance p-value is 0.956, failing to reject the null hypothesis, indicating non-stationarity. When the differencing order is 2, the significance p-value is 0.999, also indicating non-

stationarity. Using the AIC criterion, we find the optimal parameters, and the model result shows an ARIMA model (0,1,0). Considering variables such as Gross Domestic Product (GDP), Q-statistics analysis reveals that Q6 is not significant horizontally, thus failing to reject the hypothesis that the model residuals are a white noise sequence. Additionally, the model's goodness of fit (R^2) reached 0.998, as shown in Figure 4, demonstrating excellent predictive performance and meeting the model's requirements.

Figure 4. Time series plot

3.4. Establishment of Neural Network Model

Multilayer Perceptron (MLP) is a type of deep learning network based on a feed-forward neural network. Each layer comprises multiple neurons, and each neuron is fully connected to the neurons in the preceding layer. MLPs, even with a single hidden layer, can capture complex interactions between inputs using hidden neurons. These neurons depend on the values of each input. Given a sufficient number of neurons and correct weights, MLPs can model any function. They possess strong generalization and expressive capabilities, making them suitable for handling high-dimensional data and nonlinear problems. The backpropagation algorithm trainLM (train-Levenberg-Marquardt) is employed in this study to train the neural network. We utilize a single-hidden-layer MLP, a three-layer perceptron, for training and predicting data. The structure comprises an input layer, a hidden layer, and an output layer, as illustrated in Figure 5.
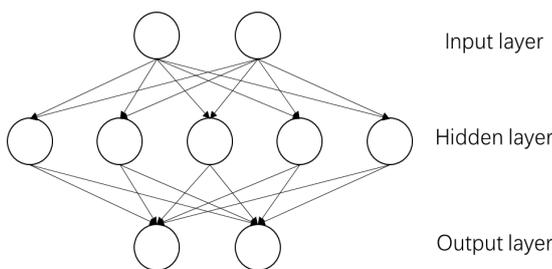

Figure 5. Structure of the multilayer perceptron

According to the requirements of the problem-related indicators, the input data is categorized based on the indicators. The output data represents the predicted results. The number of neurons (N) in the intermediate hidden layer is a hyperparameter determined through training. This single-hidden-layer multilayer perceptron consists of N hidden units. In this study, the hyperbolic tangent function is employed as the activation function, replacing the conventional ReLU activation function. The expression for the activation function is provided below:

$$f(x) = \frac{2}{1 + e^{-2x}} - 1 \qquad (3)$$

3.5. Construction of Energy Consumption Prediction Model

The process of the energy consumption prediction model is illustrated in Figure 6. Firstly, based on the population prediction model and the economic change model, specific data for population and economy from 2021 to 2060 are forecasted. Secondly, existing real data from 2010 to 2020 are used to train the MLP model, and the Mean Squared Error (MSE) loss value is calculated to determine whether to proceed with backpropagation and optimize weight parameters, selecting the optimal weights and biases. Then, an optimal model for predicting energy consumption is obtained. Finally, using the trained model, energy consumption from 2021 to 2060 is predicted. The MLP prediction model for energy consumption is illustrated in Figure 7, where the input layer consists of two parameters (population and economic indicators), and the hidden layer contains 30 neurons.
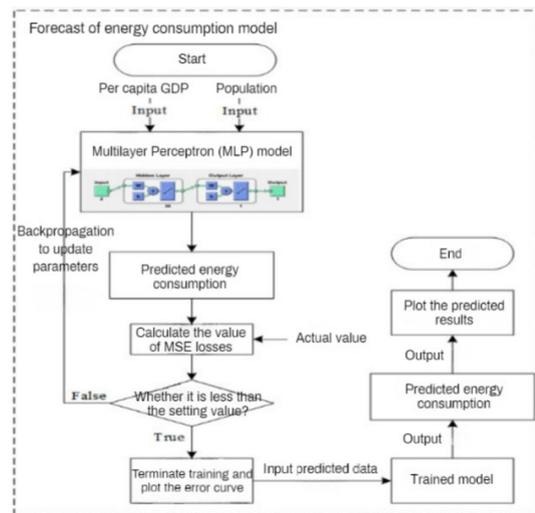

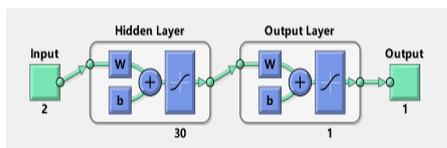**Figure 6.** The process of the energy consumption prediction model

Figure 7. The MLP prediction model for energy consumption

Figure 8 illustrates the disparity between the predicted and actual energy consumption values from 2010 to 2020. The small gap between predicted and actual values attests to the effectiveness of the energy consumption prediction model constructed based on MLP. The forecast for energy consumption from 2021 to 2060 indicates a significant increase from 2021 to 2025, followed by a noticeable downward trend from 2056 to 2060. These predictions align well with the trends toward achieving carbon peaking by 2030 and carbon neutrality by 2060.
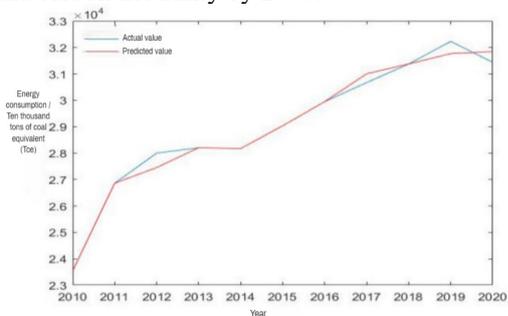

Figure 8. Fitted curve of energy consumption

3.6. Construction of Carbon Emission Prediction Model

Initially, the input layer encompasses parameters such as population, GDP, GDP^2, total energy consumption, energy consumption in the industrial sector, energy consumption in the construction sector, energy consumption in the transportation sector, energy consumption in the residential sector, energy consumption in agricultural and forestry sector, energy consumption in the energy supply sector, and the proportion of non-fossil energy consumption and the output layer is the carbon emissions. Subsequently, real data from 2010 to 2020 is utilized to train the MLP model for regional carbon emission prediction, as illustrated in Figure 9. After inputting the data indicators, the MLP model predicts carbon emissions, and the Mean Squared Error (MSE) is calculated to determine whether it is below the setting threshold. If not, the process continues with backpropagation to optimize weight updates; if yes, the optimal carbon emission prediction model is obtained. Finally, the optimal MLP carbon emission prediction model, as depicted in Figure 10 with 100 neurons in the hidden layer, is obtained. The comparison between predicted and actual carbon emission values, shown in Figure 11, indicates a satisfactory prediction performance.
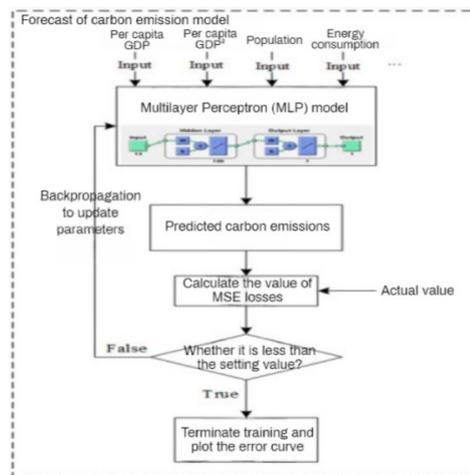

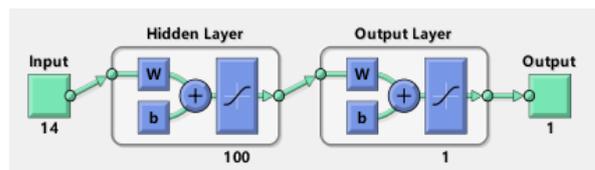**Figure 9.** The process of the carbon emission prediction model

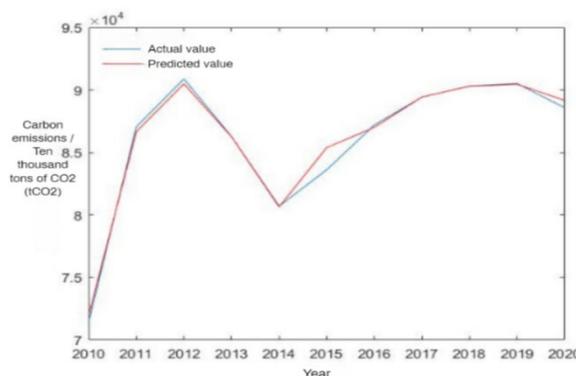**Figure 10.** The MLP prediction model for carbon emission

Figure 11. Fitted curve of carbon emission

4. Scenario Simulation and Results Analysis

4.1. Scenario Settings

Scenario analysis is a method that establishes future scenarios through analysis, assumptions, and predictions. In comparison to other forecasting methods, scenario analysis not only considers singular trends but also predicts the possible developments of various factors based on comprehensive quantitative and qualitative methods, comprehensively and systematically capturing changing trends. This study employs three scenarios: natural scenario, baseline scenario, and human intervention scenario. The scenario without human intervention is the natural scenario, achieving carbon peaking and carbon neutrality targets on time according to the dual-carbon goals constitutes the baseline scenario, and achieving carbon peaking and carbon neutrality targets before or after the setting time according to the dual-carbon goals is the human intervention scenario.

4.2. Scenario Simulation and Analysis

The simulation results under the natural scenario, as shown in Figure 12, indicate that the region's carbon emissions are predicted to peak in 2035 and achieve carbon neutrality after 2060. The natural scenario assumes that future development is primarily influenced by market and natural factors, with limited government intervention. This may result in a relatively slow pace of change, as the driving forces of market and natural factors may not necessarily align with carbon reduction targets. In this case, more policy interventions are needed to guide sustainable development.

The simulation results under the baseline scenario, as depicted in Figure 13, show that the region will reach carbon peaking around 2030 and achieve carbon neutrality in 2060. The baseline scenario reflects the continuation of current policies and practices, with the population gradually increasing and the economy steadily developing. Although the proportion of non-fossil energy is increasing, it may not be sufficient to support the dual-carbon goals. This implies that more efforts are needed to accelerate sustainable development for the smooth achievement of carbon reduction targets.

The simulation results under the human intervention scenario, as illustrated in Figure 14, reveal that the region achieves the carbon peaking target around 2035 and attains carbon neutrality in 2060. In the human intervention scenario, the government and stakeholders adopt proactive policy measures to accelerate the realization of dual-carbon goals. This may include promoting clean energy development, improving energy efficiency, reducing carbon emissions, and encouraging sustainable economic growth. While the human intervention scenario may lead to faster changes in indicators, the specific policy interventions will determine the direction and magnitude of the changes.
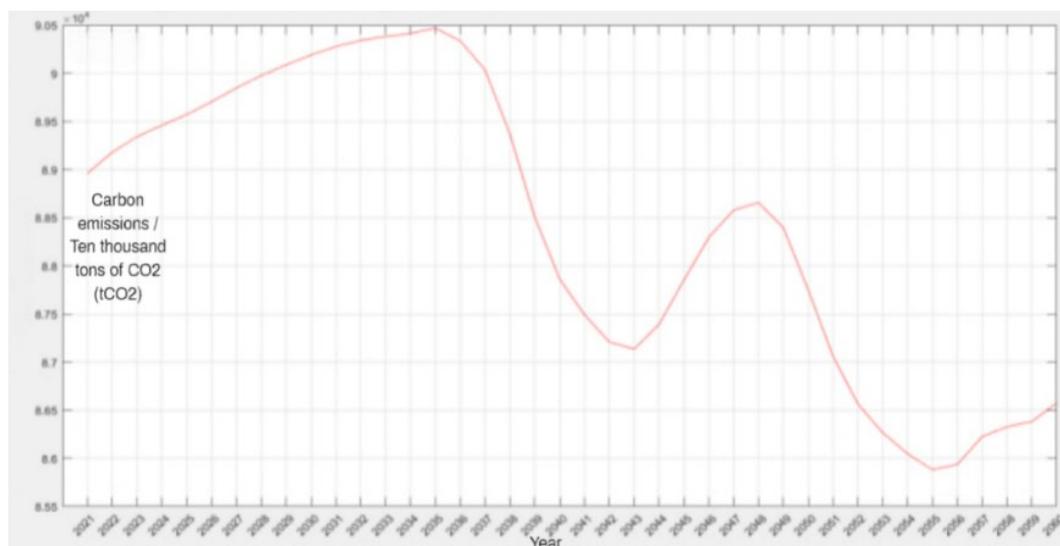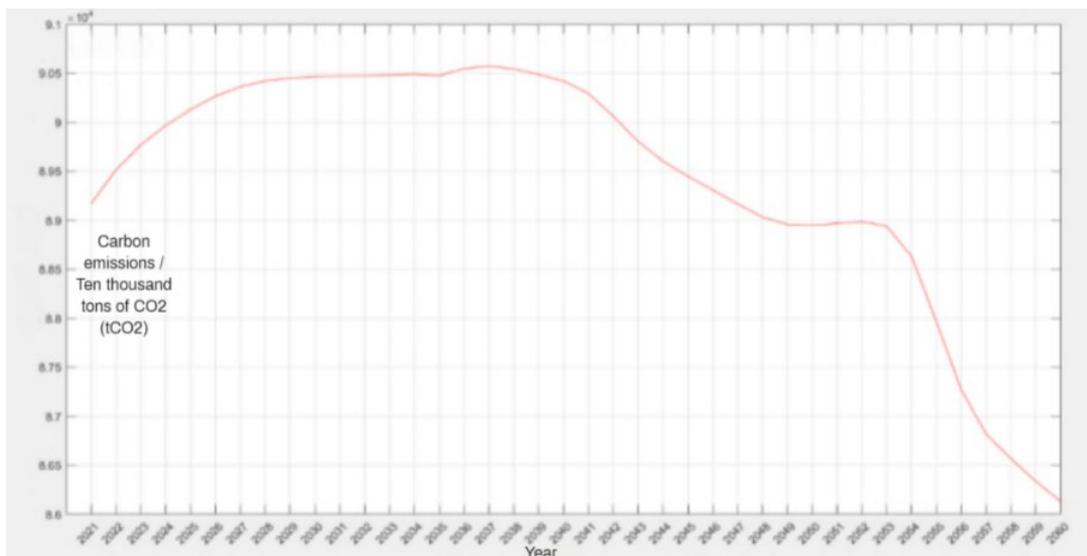

Figure 12. Natural scenario
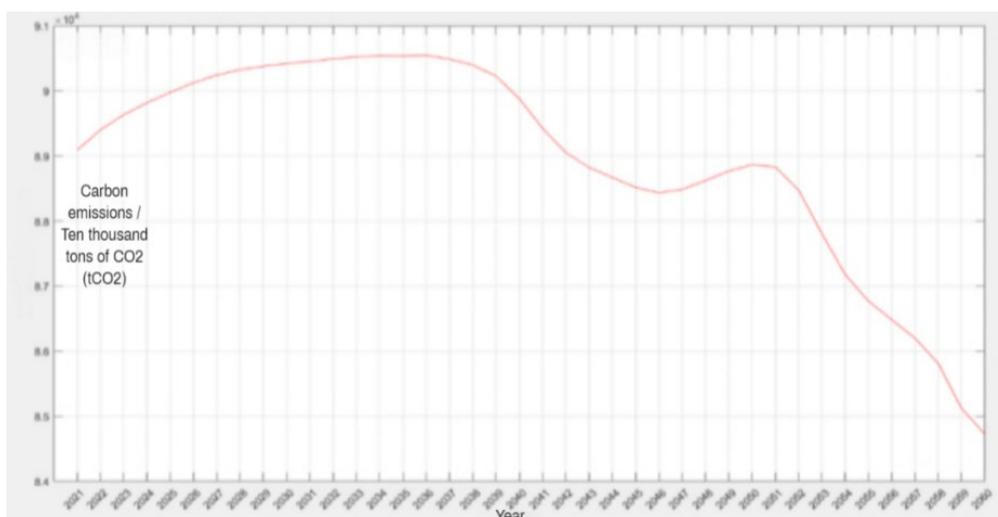
Figure 13. Baseline scenario

Figure 14. Human intervention scenario

When considering the achievement of the regional dual carbon target, Table 5 provides a strategic perspective under different scenarios. By setting three scenarios, the targets for population, per capita GDP, and increasing the share of non-fossil energy consumption are determined for each year (2025, 2030, 2035, 2050, 2060) to achieve these scenarios. Indicator data under the different scenarios can be used to assess the effectiveness of policy choices and interventions to ensure that future development is sustainable, low-carbon, and responsive to the climate change challenge. Policymakers need to formulate policies based on specific circumstances to actively promote the realization of dual carbon goals in practice.

Table 5. Strategic perspectives under different scenarios for achieving dual-carbon goals

Year	Scenario	Population	Per capita GDP	Increase the share of non-fossil energy consumption (%)
2025	baseline scenario	8980.2238	124247.4988	20%
	human intervention	8893.9590	125452.6061	>20% or <20%

	scenario			
	natural scenario	8766.4187	127277.7831	<20%
	baseline scenario	9513.0289	147567.0528	25%
2030	human intervention scenario	9331.1410	150443.5142	>25% or <25%
	natural scenario	9065.4407	154852.8842	<25%
	baseline scenario	10119.9938	175263.3678	34%
2035	human intervention scenario	9831.1461	180412.7604	>34% or <34%
	natural scenario	9414.2430	188402.2110	<34%
	baseline scenario	7778.3825	293627.2782	62%
2050	human intervention scenario	7340.6936	311134.8059	>62% or <62%
	natural scenario	6731.3103	339301.7383	<62%
	baseline scenario	6423.3674	414190.2748	80%
2060	human intervention scenario	5946.0218	447441.3959	>80% or <80%
	natural scenario	5297.1611	502249.4590	<80%

5. Conclusion, Policy Recommendation, and Discussion

5.1. Conclusion

Based on the statistical data of Jiangsu Province from 2010 to 2020, this study constructed a comprehensive indicator system incorporating economic, population, and energy dimensions for carbon emission influencing factors. Utilizing the Grey Relational Analysis method to analyze the contribution of relevant indicators and integrating the STIRPAT model, Logistic model, and ARIMA model, a Multilayer Perceptron (MLP) predictive model for carbon emissions was developed. Scenario analysis was employed to simulate carbon emissions in Jiangsu Province from 2021 to 2060. The following conclusions were drawn:

(i) The carbon emissions in Jiangsu Province from 2010 to 2020 exhibit an "S"-shaped trend. The industrial consumption sector and energy supply sector contributed significantly to carbon emissions compared to other sectors.

(ii) The correlation between economy, energy, population, and carbon emission strengthens successively. Among them, total energy consumption, energy consumption in the energy supply sector, energy consumption in the industrial sector, and permanent resident population contribute significantly, serving as crucial factors influencing carbon emission. Meanwhile, the contribution of added value in the tertiary industry is relatively low.

(iii) The Multi-Layer Perceptron (MLP) model exhibits higher accuracy in forecasting carbon emissions.

(iv) In the absence of human intervention, the attainment of carbon neutrality is an unattainable goal. However, through human intervention, specifically in the form of baseline and intervention scenarios, Jiangsu Province is forecasted to reach its carbon neutrality target as planned. Nevertheless, the realization of the peak carbon goal by 2030 presents a formidable challenge.

5.2. Policy Recommendation

To achieve the "peak carbon and carbon neutrality" goals in Jiangsu Province, the government must actively intervene. The following policy recommendations are proposed:

(i) The government should intensify efforts to adjust the industrial structure. It should eliminate outdated production capacity, prioritize the development of strategic emerging industries with low energy consumption and high added value, and incentivize the development of high-tech and environmental protection industries.

(ii) The government should advocate for residents to adopt low-carbon lifestyles. Active promotion and widespread dissemination are necessary to reinforce public awareness and behavioral habits of low-carbon living, encouraging residents to adopt low-carbon, frugal sustainable lifestyles, and transition towards a "low-carbon" consumption pattern.

(iii) It is necessary to incentivize enterprises to improve energy utilization efficiency. Enterprises should prioritize energy conservation and emission reduction efforts, aiming for green, circular, and low-carbon practices. They should intensify technological research, improve efficiency, and continuously reduce energy consumption per unit of GDP.

(iv) It is necessary to optimize the energy consumption structure. The government should strictly control the use of fossil fuels such as coal and oil, and increase the proportion of non-fossil energy in the energy consumption structure. Enterprises should develop new clean and renewable energy sources such as solar energy, wind energy, and biogas.

5.3. Discussion

Despite extending the research methods for carbon emission predictions, this study has limitations:

(i) Incomplete indicator system: Carbon emissions are influenced not only by economy, population, and energy factors but also by technological and environmental factors. Future research should further refine the indicator system.

(ii) Limited training data: Due to data availability constraints, the model did not have access to a large

dataset for training, affecting the accuracy of the prediction. Future studies should consider larger and more diverse datasets for model training.

(iii) Simplified model structure: The relationships among population growth, economic growth, energy consumption, and carbon emissions may not be linear and fully connected. The model in this study treated all data as input, neglecting the impact of noise. Future research should incorporate different data sources and consider the influence of noise on the model.

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