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Deep Learning-Based Carbon Emission Forecasting and Peak Carbon Pathways in China's Logistics Industry

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Abstract: As a major energy-consuming industry, energy conservation and emission reduction in the logistics industry are critical to China's timely achievement of its dual-carbon goals of "carbon peaking" by 2030 and "carbon neutrality" by 2060. Based on deep learning, Random Forest (RF) was used to screen out the key factors affecting carbon emissions in the logistics industry, and the Whale Algorithm-optimized Radial Basis Function Neural Network (WOA-RBF) was proposed. The Monte Carlo simulation predicted the future evolution trends of each key factor under the three scenarios of baseline scenario (BAU), policy regulation scenario (PR), and technological breakthrough scenario (TB) and accurately predicted the carbon emission trends of the logistics industry from 2023 to 2035 by using the most probable future values of each influencing factor as inputs to the WOA-RBF prediction model. The results of the study demonstrate that fixed asset investment (LFI), population (P), total energy consumption (E), energy consumption per unit of value added of the logistics industry (EIL), share of oil consumption (OR), and share of railway freight turnover (RTR) are the key factors influencing the logistics industry's carbon emissions. Monte Carlo simulations can effectively reflect the uncertainty of future changes in these key factors. In comparison to the BAU and PR scenarios, the TB scenario, with the combined incentives of national policy regulation and technology innovation, is the most likely for the logistics industry to meet the "Peak Carbon" goal baseline scenario.

Keywords: China's logistics industry; carbon peak pathway; random forest; WOA-RBF; Monte Carlo simulation

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1. Introduction

The logistics industry has grown in importance as a strategic, fundamental, and pioneering industry for the growth of the national economy, and demand for logistics has increased. With the increase in logistics scale and geographical agglomeration, the logistics industry offers substantial support for numerous industries while using a lot of energy and emitting a lot of carbon dioxide (CO_2). At the same time, rising carbon dioxide and other greenhouse gas emissions have intensified climate change, resulting in irreparable losses to the world economy, society, and ecology [1]. As the largest developing nation and energy consumer in the world, China is proactively taking on the responsibility of energy conservation and emission reduction to counteract the warming trend. The country has committed to achieving "carbon peaking" by 2030 and "carbon neutrality" by 2060. Additionally, the implementation of the "dual-carbon" policy is having an impact on the growth of China's logistics industry [2]. However, China's logistics industry has traditionally demonstrated high input, high energy consumption, and poor output as harsh development characteristics [3]. The logistics industry's technology level and energy structure have not fundamentally changed; oil-based fossil fuels continue to dominate the logistics industry's energy consumption, and the consumption is massive, making the logistics industry one of the most difficult industries to achieve the "dual-carbon" goal [4,5]. Will China's logistics industry be able to meet the "peak carbon" goal by 2030 in the context of the "dual-carbon" policy? What are the factors influencing changes in carbon emissions in the logistics industry? How can the future trend of carbon emissions be predicted in uncertain situations, and when will the "peak carbon" goal be reached? The answers to these concerns are extremely important in terms of developing suitable emission reduction strategies, advancing the development of green logistics, reducing global warming, and fostering sustainable economic growth.

Existing research on carbon emissions from the logistics sector focuses mostly on the investigation of carbon emission-affecting variables and prediction methods. The key influencing elements determining the change in carbon emissions include the economy, population, energy consumption, energy intensity, energy structure, and so on [6–9]. Many studies have been conducted in recent years to investigate the influence of various macro-factors on carbon emissions, utilizing methodologies like the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. Wang et al. (2021) combined the system dynamics theory study to conclude that the economic scale consisting of infrastructure investment, tertiary sector value-added, and environmental investment is the core factor influencing carbon emissions in the transport sector [10]. Oladunni et al. (2022) examined the significant effect of population size, energy intensity, urbanization, economic level, energy consumption, and freight turnover on freight carbon emissions in South Africa [11]. Sporkmann et al. (2023) extended the classic STIRPAT model to explore the direct effects and spatial spillovers of infrastructure investment, energy intensity, transport intensity, and transport structure on carbon emissions from land transport in Europe [12].

Scholars have offered qualitative approaches such as scenario analysis and quantitative methods such as statistical analysis models, gray prediction models, machine learning, and deep learning models for prediction models. Both Asim et al. (2022) [13] and Wang et al. (2022) [14] used scenario analysis to predict the future trends of overall energy consumption and greenhouse gas (GHG) emissions in the transport sector under different scenarios. An Autoregressive Integrated Moving Average (ARIMA) model was employed by Yang and Connell (2020) to forecast the aviation sector's carbon emissions between 2017 and 2021 [15]. Saisirirat et al. (2022) predicted the carbon emissions of the transport industry in Ghana from 2020–2036 by constructing baseline, alternative, and extreme scenarios [16]. Li et al. (2023) analyzed the link between input variables such as demographic, economic, technological, and equipment structure and carbon emissions by partial least squares and used scenario analysis to calculate the carbon emissions of the transport industry from 2019 to 2035 [17]. However, the above models demand a large number of sample inputs and a large amount of raw data and have low prediction accuracy.

The gray model (GM) suggested by Deng (1982) [18] can successfully solve the uncertainty problem of small sample sizes. This model and various variants are also widely used for carbon emission prediction in the transportation field, such as the adaptive gray model with buffered rolling mechanism (BR-AGM (1, 1)) model proposed by Xu et al. (2019) [19] combining the grey model with the buffering rolling method, the classical gray prediction model (GM (1, 1)) model used by Kazancoglu et al. (2021) [20], and the accumulative time-delay multivariate gray prediction model (ATGM (1, N)) proposed by Ye et al. (2021) [21], as well as the Improved discrete gray prediction model (DGM (1, N)) proposed by Javed et al. (2022) [22]. These improved models, to some extent, overcome the problem of underfitting in traditional models and improve prediction accuracy.

As AI technology has advanced and the demand for prediction accuracy has increased, so has the number of available data samples on carbon emissions and their drivers. Because of their enhanced learning capabilities, robustness, and high nonlinear fitting performance, machine learning and deep learning methods have become increasingly utilized in the prediction of carbon emissions. Ghalandari et al. (2021) predicted carbon emission trends in the transport sector in the UK, Germany, Italy, and France using two types of Artificial Neural Networks (ANNs), the grouped data processing approach and the multilayer perceptron [23]. Ağbulut (2022) compared the effectiveness of three algorithms, Artificial

Neural Network (ANN), Support Vector Machines (SVMs), and deep learning (DL), in forecasting, and the results showed that compared to the DL algorithms, ANN and SVM algorithms were more effective in predicting carbon emissions and energy demand in the transport sector [24].

Meanwhile, scholars have suggested several hybrid algorithms to better capture the nonlinear connection of data samples and increase prediction performance. Sahraei and Çodur (2022) empirically analyzed the carbon emissions of the transport sector in Turkey from 1975 to 2019 by three hybrid algorithms, namely, ANN-Genetic Algorithm (ANN-GA), ANN-Simulated Annealing (ANN-SA), and ANN-Particle Swarm Optimization (ANN-PSO), respectively [25]. Tang et al. (2023) combined the Sparrow Search Algorithm Optimized Long Short-Term Memory Network (SSA-LSTM) and scenario analysis to predict the carbon emissions of the transport sector in 2036 [26]. Yang et al. (2023) predicted aviation carbon emissions in 2050 using the BP neural network, Monte Carlo simulation, and scenario analysis and quantified the carbon emission pathways [27]. Emami Javanmard et al. (2023) integrated the outputs of machine learning algorithms such as Autoregressive (AR), ARIMA, Autoregressive fractional integrated Moving Average (ARFIMA), Seasonal ARIMA (SARIMA), SVR, Mixed-Data Sampling (MIDAS), GM, and Generalized Autoregressive conditional heteroskedasticity (GARCH) and constructed a new framework of multi-objective optimization model, which was solved by the Whale Optimization Algorithm (WOA), which effectively predicts the energy demand and carbon emissions of the Canadian transport sector from 2019 to 2048 [28].

In summary, a huge number of results have emerged from studies on carbon emission-affecting variables and prediction in the field of transportation; however, several research gaps remain. On the one hand, most studies in the screening of carbon emission influencing variables employ the STIRPAT framework to uncover common factors in historical literature or use the least absolute shrinkage and selection operator (LASSO) regression, the Delphi method, and other methods to screen carbon emission influencing factors. Random Forest (RF), on the other hand, may examine the complex aspects of interactions to identify the influencing elements that can appropriately depict the prediction outcomes [29]. However, while most studies discuss carbon emission pathways by combining algorithms such as machine learning and deep learning with scenario analyses, the rate of change of each influencing factor is fixed, which may affect the final carbon emission forecast's accuracy and realism. As a result, the technique of Monte Carlo simulation can address the uncertainty of future carbon emission-impacting factors [30,31]. Based on previous literature analysis and the current state of China's logistics industry, this study investigates a machine learning method, Random Forest (RF), to screen the key factors impacting its carbon emissions and combines Radial Basis Neural Networks (RBF) and Whale Optimization Algorithm (WOA) to propose a WOA-RBF prediction model, which predicts the trend of China's logistics industry's carbon emissions from 2023 to 2035 and employs Monte Carlo simulation to account for the uncertainty of future changes in the variables, so that it can provide feasible policy recommendations for the logistics industry to achieve the goal of "peak carbon emissions".

2. Methodology

2.1. Random Forest

Random Forest (RF) is an integrated machine learning algorithm, i.e., it randomizes the use of variables and data to generate and aggregate the results of multiple classification trees [32]. Random forest has good robustness to missing data and unbalanced data, has fast learning speed, is widely used to solve regression, classification, and other problems, but can also be used for high-dimensional data feature selection [33].

Regarding the feature selection of RF, the Gini index is usually used to measure the importance of features; if there are M features, i.e., $X_1,\ X_2,\ X_3 \ldots X_m$, then the importance of each feature X_j needs to be calculated. The specific steps are as follows:

(1) From the original training dataset, K new sample sets are randomly selected by the bootstrapping method, and K classification regression trees are constructed. The unselected samples constitute K out-of-bag (OOB) data.

(2) Assuming that there are n features, m_{try} features ($m_{try} \leq n$) are randomly extracted at each node of each tree as a randomly generated feature subset. By calculating the information contained in each feature subset, the features with the strongest classification ability are selected among the m_{try} features for node splitting, thus making the decision tree more diverse.

(3) Use the Gini coefficient to score $VIM_J^{(Gini)}$ and calculate the importance of features.

VIM denotes variable importance, GI denotes Gini index, and $VIM_J^{(Gini)}$ denotes the Gini index of each feature X_j. The formula for the Gini index is as follows:

$$GI_m = \sum_{k=1}^{|K|} \sum_{k' \neq k} p_{mk} p_{mk'} = 1 - \sum_{k=1}^{|K|} p_{mk}^2 \tag{1}$$

where p_{mk} denotes the percentage of category k in node m. The importance of the feature X_j in node m is calculated as follows:

$$VIM_{jm}^{(Gini)} = GI_m - GI_l - GI_r \tag{2}$$

GI_l and GI_r represent the Gini index of two new nodes after branching. If the node of the feature X_j in the decision tree i belongs to set M, the importance of the feature X_j in the decision tree i is calculated as follows:

$$VIM_j^{(Gini)} = \sum_{m \in M} VIM_{jm}^{(Gini)} \tag{3}$$

Suppose there are n trees in the RF:

$$VIM_j^{(Gini)} = \sum_{i=1}^{n} VIM_{ij}^{(Gini)} \tag{4}$$

2.2. Radial Basis Function Neural Networks

Radial basis function neural network (RBF) is a locally responsive forward neural network that consists of input, hidden, and output layers [34]. Compared with BP neural networks, which tend to fall into local optimum, it has the characteristics of simple structure, fast training speed, and strong global approximation ability [35]. The structure of the RBF neural network is shown in Figure 1.

The basic idea of using the RBF neural network for prediction is as follows: the value of each influencing factor as input is mapped to the hidden layer through the RBF function, the network weight vector is determined through the training algorithm, and its output model can be expressed by a linear equation as follows:

$$y(x) = \sum_{i=1}^{I} \omega_{ij} \varphi_j (\|x_n - c_i\|) \tag{5}$$

where y(x) is the output of the neural network, $\|\cdot\|$ is the Euclidean paradigm, x_n is the nth input sample, ω_{ij} is the weights from the hidden layer to the output layer, i = 1, 2, . . ., I, j = 1, 2, . . ., J, and there are a total of i input nodes and j output nodes in the hidden layer; and c_i is the center of the radial basis function.

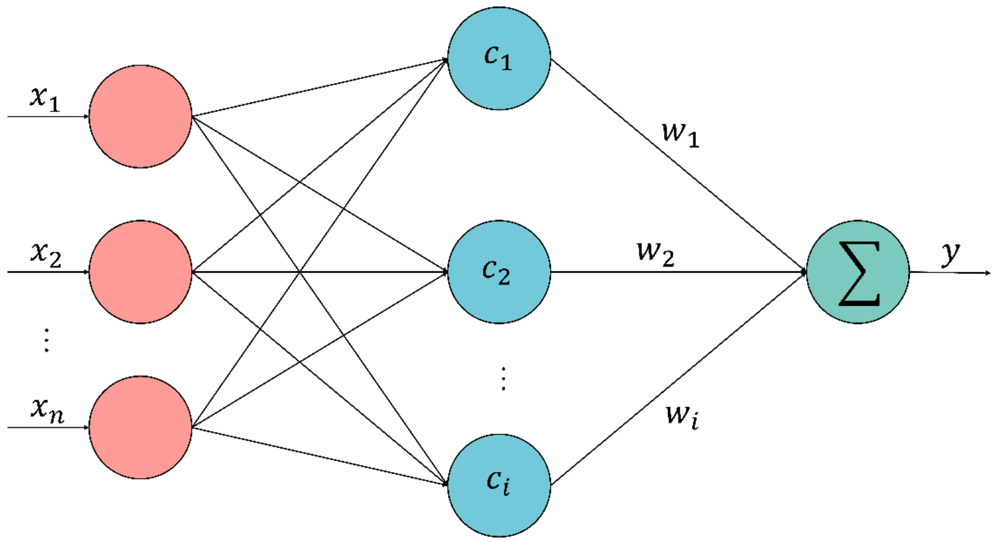


Figure 1. Structure of the RBF neural network.

The learning process of the RBF neural network is divided into two phases: self-organized learning and supervised learning, and the parameters of each part are learned quickly to improve the training speed. In the RBF neural network training process, the main radial basis functions are center c_i, variance σ, and network weights ω_{ij}. The most commonly used radial basis function is the Gaussian radial basis function. The formula is as follows:

$$\varphi_j(\|x_n - c_i\|) = exp\left(\frac{-\|x_n - c_i\|^2}{2\sigma^2}\right) \tag{6}$$

Typically, K-mean clustering is used to select the radial basis function center c_i located in the hidden layer, which in turn solves for the variance σ. The formula is as follows:

$$\sigma_i = \frac{c_{max}}{\sqrt{2I}} \tag{7}$$

Finally, the network weights ω can be calculated using the least squares method. The formula is as follows:

$$\omega = exp\left(\frac{1}{c_{max}^2}\|x_n - c_i\|^2\right) \tag{8}$$

2.3. Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA), proposed by Mirjalili and Lewis (2016) [36], is a population intelligence optimization algorithm that mimics the feeding behavior of whales in nature. It achieves the optimization purpose by simulating the behaviors of humpback whale groups, such as searching, encircling, pursuing, and attacking the prey, etc. It has the advantages of simple operation, fewer adjustment parameters, and a strong ability to jump out of the local optimal solution, and it can deal with the problems of image cutting, scheduling optimization, feature selection, and prediction. WOA consists of three main processes: surrounding prey, capturing prey, and searching for prey [36].

(1) Surrounding prey

Humpback whales can recognize prey locations and encircle them. Since the location of the optimal solution is unknown, the WOA assumes that the position of the optimal whale in the current population, i.e., the position of the goal prey, approaches the prey in various ways. Meanwhile, the other whales update their positions by using Equation (9) to move closer to the optimal individual.

$$X_i^{t+1} = X_{best}^t - A \cdot D_1 \tag{9}$$

$$D_1 = \left| C \cdot X_{best}^t - X_i^t \right| \tag{10}$$

where X_{best}^t is the position of the individual whale within the population that achieves the globally optimal solution when searching up to generation t, X_i^t is the position of individual i at the t th iteration, D_1 denotes the encircling step size, and A and C are coefficient vectors, which are calculated as follows:

$$A = 2a \cdot r - a \tag{11}$$

$$C = 2 \cdot r \tag{12}$$

$$a = 2 - 2\frac{t}{T} \tag{13}$$

where T is the maximum number of iterations and r is a random number between [0, 1].

(2) Capturing prey

To effectively model the way whales spit out bubble nets along the helix and approach their prey, Equation (14) was used to update the position of individual whales.

$$X_i^{t+1} = X_{best}^t + D_2 \cdot e^{bl} \cdot cos(2\pi l) \tag{14}$$

where $D_2 = \left| X_{best}^t - X_i^t \right|$ denotes the distance from the whale to the prey, b is a constant controlling the logarithmic spiral shape, and l is a random number between [−1, 1].

It is worth noting that the whale shrinks towards the prey through the spiral shape while also shrinking the envelope. Therefore, it is assumed that there exists a probability p_i to choose the shrinking envelope mechanism and a probability $1 - p_i$ to choose the spiral model to update the whale position as follows:

$$X_i^{t+1} = \begin{cases} X_{best}^t - A \cdot D_1 \\ X_{best}^t + D_2 \cdot e^{bl} \cdot cos(2\pi l) \end{cases} \tag{15}$$

(3) Searching for prey

In the prey search phase, individual whales no longer target the optimal individual for position updates but instead target a random individual in the current group for position updates. The equation in this phase is as follows:

$$X_i^{t+1} = X_{rand}^t - A \cdot D_3 \tag{16}$$

$$D_3 = \left| C \cdot X_{rand}^t - X_i^t \right| \tag{17}$$

where X_{rand}^t represents the exact position of a single whale chosen at random throughout the population at generation t. Meanwhile, when $A \geq 1$, a search agent is randomly selected to update the position of other whales with the position of the randomly selected whale as the goal, forcing whales to move away from the prey and then search for a more suitable prey to expand the search range and discover the best solution while preserving the population's variety. The flowchart for WOA is shown in Figure 2.

2.4. Uncertainty Analysis Based on Monte Carlo Simulation

The WOA-optimized RBF model can forecast the trend of carbon emissions in China's logistics industry going forward, but the yearly growth rate of each indicator is set because it is based on classical scenario analysis. In actuality, though, there are many uncertainties regarding the future evolution trend of carbon emissions as well as additional factors; therefore, the probable rate of change needs to be a range rather than an exact value [37]. Monte Carlo simulation, as a method of analyzing uncertainty problems, can simulate the actual physical processes with its flexibility and comprehensiveness, so that the solution results can be consistent with the actual situation [38]. The advantage of Monte Carlo simulation over other methods of uncertainty analysis is that it can not only set the probability of the occurrence of different variables but also set values based on existing research and policy [39]. Based on this, this study introduces Monte Carlo simulation to dynamically analyze the potential evolution of carbon emissions in China's logistics industry under different scenarios in the context of the "dual-carbon" goal. Before conducting the Monte Carlo analysis, the distribution of key variables in the model must be assumed, which has a significant impact on the prediction results [37]. The results of Monte Carlo simulation depend on the selection of probability distributions for the potential rates of change of the factors, and there are usually discrete, normal, and triangular distributions for the selection of the distributions. When the possible outcomes of the variables and the value intervals are known but the probability distribution is unknown, the triangular distribution is more suitable for variable selection [39]. Therefore, in this study, the triangular distribution is chosen to randomly generate the variables.

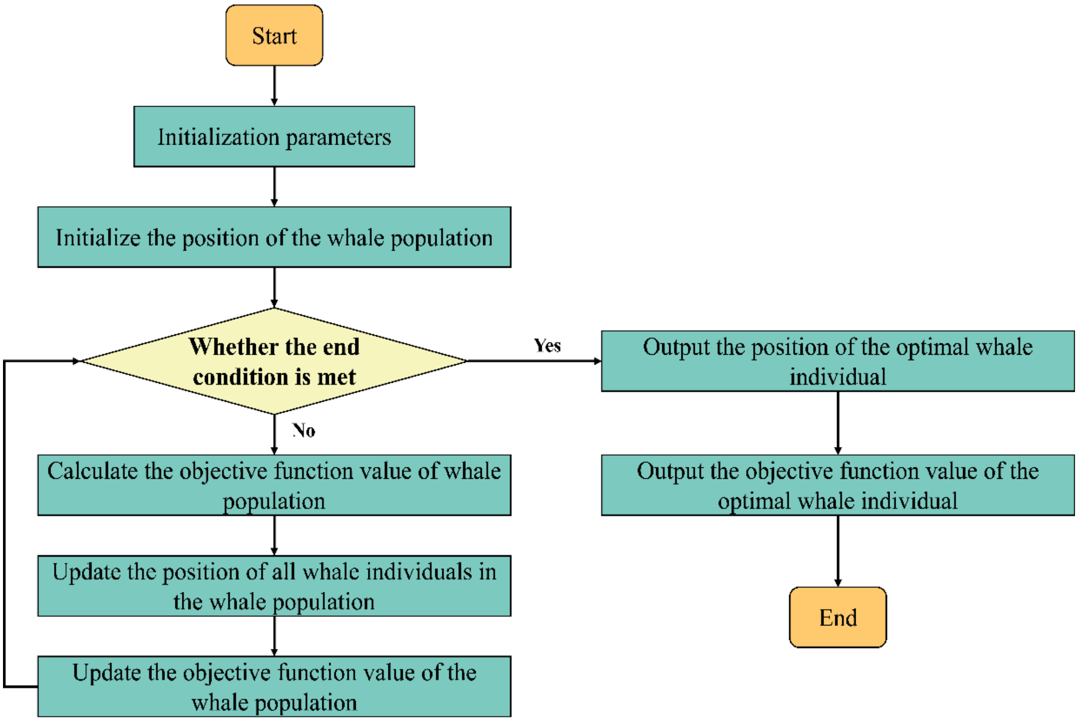


Figure 2. Flowchart of the Whale Optimization Algorithm.

2.5. Research Process

Combining RF, WOA, RBF, and Monte Carlo simulation to establish the carbon emission prediction model of the logistics industry. Firstly, based on the STIRPAT theory, to find potential influencing factors, RF is used to measure and rank the importance of each variable, and the most important influencing factors are screened out to simplify the prediction model. Second, the RBF neural network model under WOA optimization is constructed as well as proving the superiority of the model. Third, Monte Carlo simulation is used to reflect the uncertainty of the future changes of the influencing factors under the three scenarios, and then the WOA-RBF model is used to predict the trend of carbon emissions in China's logistics industry and to judge the realistic path of carbon emission reduction in the logistics industry.

3. RF-WOA-RBF for Forecasting Carbon Emissions

3.1. STIRPAT Model

The STIRPAT model, which is improved by Dletz and Rosa [40] based on the IPAT model, serves as the primary basis for choosing the potential influencing factors of carbon emissions in the logistics industry in this study. This model can be used to reveal the effects and influences of population, economic and social development, and science and technology on the environment, and its specific equations are as follows:

$$\mathrm{I} = \alpha P^{\beta} A^{\theta} T^{\gamma} \varepsilon \tag{18}$$

where I denotes environmental impact, P denotes population, A denotes affluence, and T is the level of technology; α represents the coefficient for constructing the model; ε represents the error in constructing the model; and the parameters of the STIRPAT model corresponding to the driving forces are denoted by β, θ, and γ, respectively. Taking logarithms on each side of the equal sign of Equation (19) can be obtained as follows:

$$lnI = ln\alpha + \beta lnP + \theta lnA + \gamma lnT + ln \tag{19}$$

The model is deformed to get the following:

$$lnI = \alpha + blnP + clnA + dlnT + \varepsilon \tag{20}$$

In this study, the model is improved and extended based on the traditional STIRPAT theory, and the extended model is as follows:

$$lnI = \alpha + blnP + clnA + dlnEC + elnEI + flnES + glnTS + \varepsilon \tag{21}$$

where I denotes carbon emissions, P is population, A is economic level, EC is total energy consumption, EI is energy intensity, ES is energy structure, and TS is transport structure; b, c, d, e, f, and g represent the coefficients of each factor.

3.2. Data Collection and Processing

In this study, based on six parameters, 14 potential factors influencing carbon emissions in the logistics industry were chosen. At the same time, data on the 14 potential factors and carbon emission data from 1980 to 2022 were collected from the "China Statistical Yearbook", "China Energy Statistical Yearbook", "China Logistics Yearbook", etc., which did not include carbon emission data in the information reviewed. The consumption of raw coal, gasoline, paraffin, diesel fuel, fuel oil, natural gas, liquefied petroleum gas, thermal energy, and electricity consumed by the "transport, storage, and postal industry" are the items chosen for this study's measurement of carbon emissions in the logistics industry. The carbon emission coefficients and the conversion factor of standard coal for each type of energy are derived from the "2006 IPCC Guidelines for National Greenhouse Gas Inventories". Therefore, combined with the estimation methods provided by IPCC, this study adopts a "top-down" approach to measure the carbon emissions of the logistics industry [41]. The formula is as follows:

$$TCE = \sum_{i} TCE_i = \sum_{i} E_i \times \alpha_i \times \delta_i \times \frac{44}{12} \tag{22}$$

where E_i denotes the actual consumption of energy class i, α_i denotes the standard coal conversion factor of energy class, and δ_i denotes the carbon emission factor of energy class. The particular coefficients are displayed in Table 1.

3.3. Importance of Potential Influences on Logistics Carbon Emissions

Carbon emissions in the logistics industry in real-life activities are subject to a variety of influencing factors, and this study summarizes 14 influencing factors. However, if all the influencing factors are used as input variables in the WOA-RBF prediction model, the model will be too complex, thus increasing the training time [29]. As a consequence, this study uses RF to evaluate the significance of 14 influencing factors and chooses the most accurate and representative influencing factors to measure the outcomes of the carbon emission projection. The specific influencing factors are displayed in Table 2.

Table 1. Standard coal factor and carbon emission factor for various energy sources.

Energy Type	Standard Coal Conversion Coefficients	Carbon Emission Coefficient	Energy Type	Standard Coal Conversion Coefficients	Carbon Emission Coefficient
Raw coal	0.7143	0.7599	Natural gas	1.2721	0.4483
Gasoline	1.4714	0.5538	Liquefied petroleum gas	1.7143	0.5042
Kerosene	1.4714	0.5714	Heating power	0.0341	0.2520
Diesel oil	1.4571	0.5921	Power	0.1229	0.7140
Fuel oil	1.4286	0.6185			

Source: 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

Table 2. Potential influences on logistics carbon emissions.

Dimension	Factor	Abbreviation	Unit	Reference
Economy (E)	Gross Domestic product	GDP	CNY 10^8	[7]
	Fixed asset investment in logistics	LFI	CNY 10^8	[6]
	Value added to the logistics	LVA	CNY 10^8	[10]
Population (P)	Total population at the end of the year	P	person	[11]
	Urbanization rate	UR	percent	[11]
Energy consumption (EC)	Total energy consumption of the logistics	E	million tons	[6,28]
Energy intensity (EI)	Energy consumption per unit of GDP	EIG	tons of standard coal/CNY 10^4	[11]
	Energy consumption per unit of value added in the logistics industry	EIL	tons of standard coal/CNY 10^4	This study
	Energy consumption per unit turnover of goods	EIT	tons of standard coal/10^4 tons kilometers	[42]
Energy structure (ES)	The percentage of fossil fuels in total energy consumption	FR	percent	[29]
	The percentage of oil in total energy consumption	OR	percent	[29]
	The percentage of clean energy in total energy consumption (natural gas, electricity, and heat)	CR	percent	[26]
Transportation structure (TS)	The percentage of railway freight volume in total freight volume	RFR	percent	[12,43]
	The percentage of railway freight turnover in total freight turnover	RTR	percent	This study

Source: Authors.

The normalized raw data are used as input to the RF to generate several decision times to calculate the importance of the 14 variables. To ensure the stability and reliability of the measurement results, the importance degree of each variable of the 40 outputs was averaged after 40 consecutive runs through the RF, and the results are shown in Figure 3.

To balance the comprehensiveness of variable dimensions with the importance of individual variables, this study screens the key influences through the following two steps: First, variables with an importance level greater than or equal to 0.3 are retained. Second, among the retained variables, the optimal variables for each dimension are selected according to the dimensions to which the variables belong in Table 2. Six key variables were finally screened, namely *LFI*, *P*, *E*, *EIL*, *OR*, and *RTR*. Their importance degrees are shown in Table 3.

3.4. Model Test Results

To test the accuracy of the WOA-RBF prediction model, this study selects 80% of the samples (1980–2013) as the training set and 20% of the samples (2014–2022) as the test set to predict the total carbon emissions from China's logistics industry. The WOA algorithm is used to optimize the expansion speed parameter of RBF, the number of whale searches in WOA is set to 5, the maximum number of iterations is set to 40, and MATLAB 2023a is used to implement the general steps of WOA-RBF. At the same time, the optimized RBF algorithm is compared with the particle swarm algorithm optimized under the back propagation neural network (PSO-BPNN), support vector machine (SVM), and extreme learning machine (ELM) tuned to the optimal parameter. The comparison of the carbon emission prediction results in the period 2014–2022 with the actual values is displayed in Figure 4, and the results of the calculation of the error indicators are displayed in Table 4.

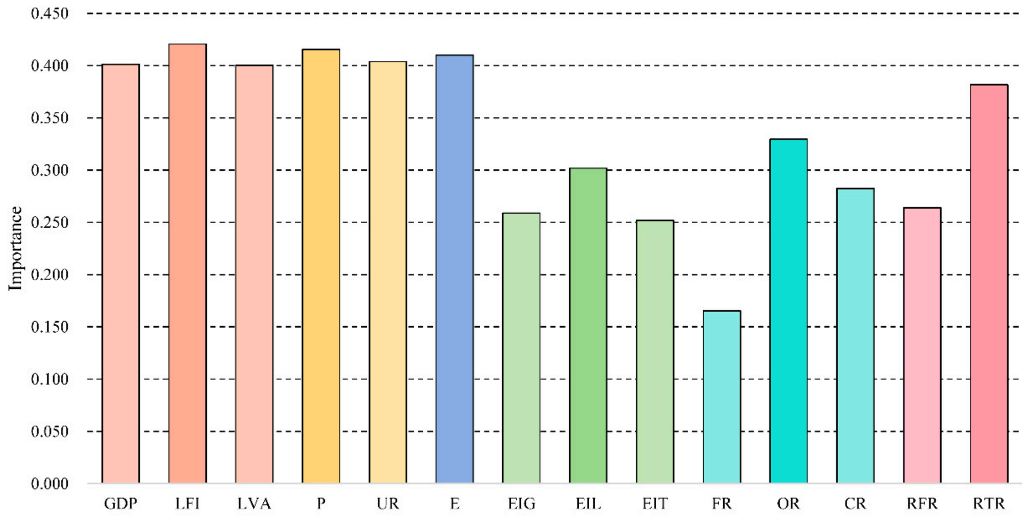


Figure 3. Importance of potential impact factors.

Table 3. Importance of key influencing factors.

Importance Degree (Note: Retain Three Decimal Places)					
LFI	***P***	***E***	***EIL***	***OR***	***RTR***
0.421	0.415	0.410	0.302	0.329	0.382

Table 4. Calculation of error metrics for each algorithm.

Error Index	PSO-BPNN	ELM	SVM	WOA-RBF
R^2	0.921	0.980	0.989	0.999
RMSE	11.325	6.003	4.528	1.397
MAPE, %	1.266	0.685	0.466	0.138
MAE	10.024	5.436	3.660	1.101

Source: Authors.

As demonstrated by Table 4, the R^2 of the carbon emission forecasts for the logistics sector varies between 0.921 and 0.999. R^2 is the most commonly used metric when discussing the degree of success of the forecast results about the actual data, and it gives an idea of how the forecast curve follows the forecast curve of the actual data [24]. The values of R^2 show that all four algorithms have values greater than 0.9, which is a strong fit overall. The remaining three indicators, such as RMSE, MAPE, and MAE, are also important metrics in the prediction process, all of which indicate that the lower the value of the indicator, the higher the prediction accuracy. Based on this, by comparing multiple error indicators, WOA-RBF has the smallest error in doing carbon emission prediction in the logistics industry, and the prediction accuracy of each algorithm is ranked as WOA-RBF > SVM > ELM > PSO-BPNN. PSO-BPNN has the worst prediction performance. The main reason may be that the prediction result of BPNN relies on the repeated training of large sample data, and the number of hidden layers affects the prediction result, so it is easy to fall into the local optimal solution even if the parameters are optimized by the PSO algorithm, which affects the prediction result. Overall, the RBF neural network is more advantageous than SVM, ELM, and PSO-BPNN in terms of approximation ability and learning speed, and it can achieve better prediction results even in the face of datasets in terms of years and with smaller sample data sizes. Therefore, the hybrid WOA-RBF algorithm is better suited for carbon emission prediction in China's logistics industry, provided that the parameters are adjusted using the whale optimization technique.

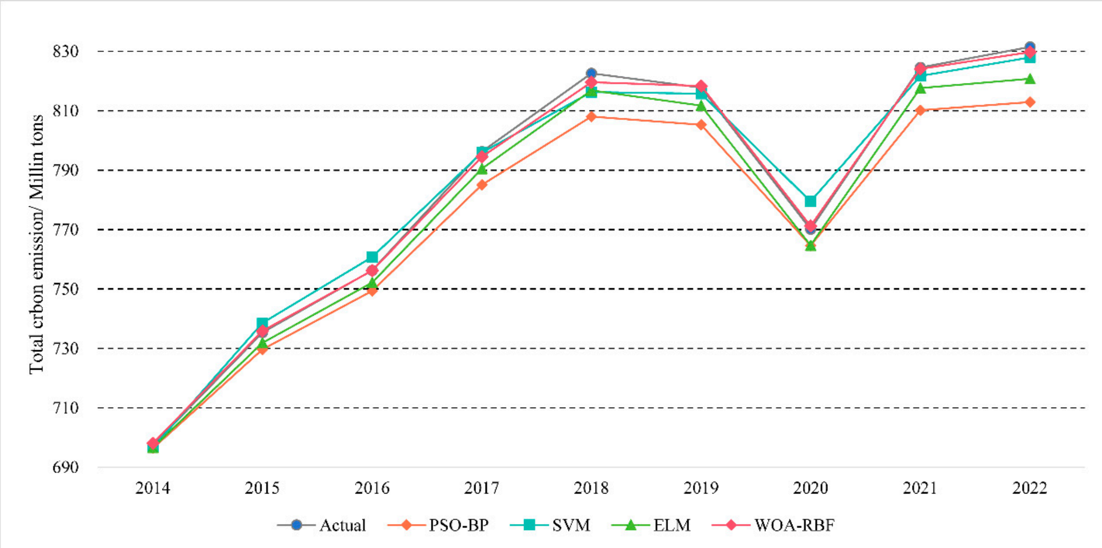


Figure 4. Comparison of the carbon emission prediction results for the logistics industry.

4. Scenario Analyses for Forecasting Carbon Emissions

4.1. Scenario Setting

This study sets the future scenarios into a baseline scenario, a policy regulation scenario, and a technological breakthrough scenario based on the distributional characteristics, change trends, and emission reduction potentials of the key influencing factors of carbon emissions in the past. It then uses Monte Carlo simulation to explore the evolutionary trends of the influencing factors from 2023 to 2035 in order to predict the trend of carbon emissions in China's logistics industry and determine a reasonable carbon emission reduction path.

According to the STIRPAT theory, one of the major variables influencing carbon emissions is population. According to the data in the "Forecast of Medium- and Long-Term Trends in China's Population Changes (2021–2050)", the country's population will peak in 2022 and then slowly decline, which is in high agreement with the trend of actual population data recorded by the National Bureau of Statistics (NBS). According to predictions, China's population will fall to 1.382 billion in 2035, with a −0.16 percent yearly change compared to 2022. As a result, the median value of the average annual rate of population change is anticipated to be −0.16 percent for the three scenarios, with the minimum and maximum values established by floating up and down by 0.05 percentage points from the median value. The future rates of change concerning demographic factors are displayed in Table 5.

Table 5. Annual rates of change in demographic factors (unit: %).

Variable	2023–2035		
	Min	**Middle**	**Max**
P	−0.21	−0.16	−0.11

Source: Authors.

(1) Baseline scenario (BAU)

Based on past industrial development characteristics, the baseline scenario assumes that the trend of carbon emissions follows the "inertia characteristics" of industrial development and that future economic conditions, technological advancements, policy direction, and other factors have not changed [44]. Existing research indicates that the presence of "inertia characteristics" in economic and industrial development makes the baseline scenario highly relevant [37], especially given that China's economic development trend since the beginning of the 21st century has had a profound impact on economic and industrial development in the coming period.

This study combines the research of Lin and Ouyang (2014) [44] and the cyclical features of China's "Five-Year Plan" for development to set the minimum, median, and maximum values of the potential annual average rates of change of each influential factor in the baseline scenario for the period 2023–2035. The three values are set concerning the average annual rates of change in 2001–2005, 2006–2010, 2011–2015, and 2016–2020. Specifically, the minimum and maximum values correspond to the minimum and maximum of the average annual rates of change in the past four cycles, respectively. For the two average annual rates of change in the middle, the average annual rate of change closer to the current period is selected as the middle value, considering that the closer the time between the cycles, the less different the future situation will be. The rates of change of the factors for the baseline scenario are displayed in Table 6.

Table 6. Annual rates of change of the impact factors in the baseline scenario (unit: %).

Variable	2023–2035		
	Min	**Middle**	**Max**
LFI	5.44	14.84	25.46
E	0.58	6.71	13.42
EIL	−4.45	−1.85	1.61
OR	−1.37	−0.44	0.44
RTR	−8.30	−5.76	3.99

Source: Authors.

(2) Policy Regulation Scenarios (PR)

As a result of the "dual-carbon" goal, the government will implement a series of policy initiatives to hasten the green and low-carbon transformation of the logistics industry. The State Council's 2021 publication, "The Action Plan for Carbon Dioxide Peaking Before 2030", states that in order to reach the goal of peak carbon dioxide emissions, the logistics industry must boost the share of renewable energy consumption and enhance energy efficiency; meanwhile, the State Council's 2022 publication, "14th Five-Year Plan for the Development of a Modern Comprehensive Transportation System" and "14th Five-Year Plan for the Development of Modern Logistics", both propose initiatives such as developing multimodal transport and increasing the percentage of rail and waterway transport. Under the policy regulation scenario, the rates of change of each factor based on the historical data of the National Bureau of Statistics and relevant policies are displayed in Table 7.

Table 7. Annual rates of change of the impact factors in the policy regulation scenarios (unit: %).

Variable	2023–2025			2026–2030			2031–2035		
	Min	**Middle**	**Max**	**Min**	**Middle**	**Max**	**Min**	**Middle**	**Max**
LFI	4.00	5.00	6.00	3.50	4.50	5.50	3.00	4.00	5.00
E	3.00	4.00	5.00	2.00	3.00	4.00	1.00	2.00	3.00
EIL	−3.92	−2.92	−1.92	−4.42	−3.42	−2.42	−4.92	−3.92	−2.92
OR	−1.60	−1.40	−1.20	−1.80	−1.60	−1.40	−2.00	−1.80	−1.60
RTR	4.30	4.80	5.30	4.50	5.00	5.50	4.70	5.20	5.70

Source: Authors.

In terms of the economy, to achieve the "carbon peak" goal of the logistics industry as soon as possible, the government will take more measures to curb excessive investment and improve investment efficiency. Considering the average annual growth of fixed asset investment in the logistics industry since the "13th Five-Year Plan" and the resumption of work and production after the liberalization of the epidemic in China at the end of 2022, fixed asset investment will maintain steady growth in the next few years. The fixed asset investment growth rate is expected to remain at around 5% per year on average between 2023 and 2025. The growth rate is expected to decrease during the "15th Five-Year Plan" and "16th Five-Year Plan" periods. In summary, the logistics industry expects the annual average change rate of fixed assets investment (LFI) to be 5% (2023–2025), 4.5% (2026–2030), and 4% (2031–2035). This value is taken as the middle value, and the minimum and maximum values are set by floating up and down by one percentage point.

In terms of energy consumption, according to the "Energy Supply and Consumption Revolution Strategy (2016–2030)", the overall energy consumption should be kept under 6 billion tons of standard coal by 2030. In 2021, the logistics industry consumed 8.4% of the nation's energy, and by 2030, that percentage is predicted to rise to almost 12%. This means that the logistics industry's overall energy consumption should be kept under control at 720 million tons, which calls for a 4% annual growth rate. Therefore, the average annual change rate of energy consumption (E) in the logistics industry will decrease by 0.5 percentage points, with median values of 4% (2023–2025), 3% (2026–2030), and 2% (2031–2035). Correspondingly, the minimum and maximum values will be set by a fluctuation of one percentage point.

In terms of energy intensity, the "14th Five-Year Plan for Modern Energy System" proposes a cumulative decrease of 13.5% in energy consumption per unit of GDP by 2025, which can be inferred as an average annual decrease of 2.92% during the period 2021–2025. Due to the similar downward trend between energy consumption per unit of value added in the logistics industry and energy consumption per unit of GDP and considering the continuous maturity of industries such as smart logistics and new energy technologies driven by future policies, the growth rate of value added in logistics will accelerate year by year, while the energy consumption growth in the logistics industry will slow down year by year. Therefore, it is inferred that the annual average change in energy intensity during the periods 2026–2030 and 2031–2035 will further increase. Therefore, it is expected that the average annual change rate of energy consumption per unit of value added (EIL) in the logistics industry will be -2.92% (2023–2025), -3.92% (2026–2030), and -4.92% (2031–2035), with corresponding fluctuations of one percentage point to set the minimum and maximum values.

In terms of transportation structure, the "14th Five-Year Plan for the Development of Comprehensive Transportation Services" proposes to increase the percentage of railway freight turnover to 17% by 2025, compared to 15.5% in 2022. To achieve the 2025 goal, the average annual change rate of the percentage of railway freight turnover from 2023 to 2025 is at least 4.8%. At the same time, with the maturity of technologies such as high-speed rail express and the continuous promotion of multimodal transportation policies, the percentage of railway freight turnover will continue to accelerate. Therefore, this article predicts that the average annual change rates of the percentage of railway freight turnover (RTR) are 4.8%, 5%, and 5.2%, with a fluctuation of 0.5 percentage points to set the minimum and maximum values.

(3) Technology Breakthrough Scenario (TB)

Technological innovation and progress are necessary pathways for energy conservation and emission reduction, which can effectively adjust the energy structure of the logistics industry, increase the percentage of nonfossil energy use, optimize the transportation structure of the logistics industry, increase the percentage of railway, waterway, and other transportation, and carry out multimodal transportation, thus achieving the goal of "energy conservation and emission reduction" in the logistics industry. "14th Five-Year Plan for the Development of Modern Logistics" proposes to promote the development of green logistics, including strengthening the application of new energy equipment, using circular packaging, accelerating the promotion of standardized logistics turnover boxes, establishing reverse logistics information systems, and other technical measures, relying on technological innovation to achieve the upgrading and upgrading of the logistics industry. At the same time, in the scenario of a technological breakthrough, the focus of investment in fixed assets in the logistics industry has gradually shifted from traditional productive investment to investment in energy-saving and emission-reduction technologies such as green packaging and new energy logistics vehicles, and fixed asset investment still maintains steady growth. Therefore, compared with the policy regulation scenario, the change rate of LFI in the logistics industry remains unchanged, and the relevant parameters of E, OR, EIL, and RTR in the logistics industry are adjusted. The change rates of various factors in the technology breakthrough scenario are displayed in Table 8.

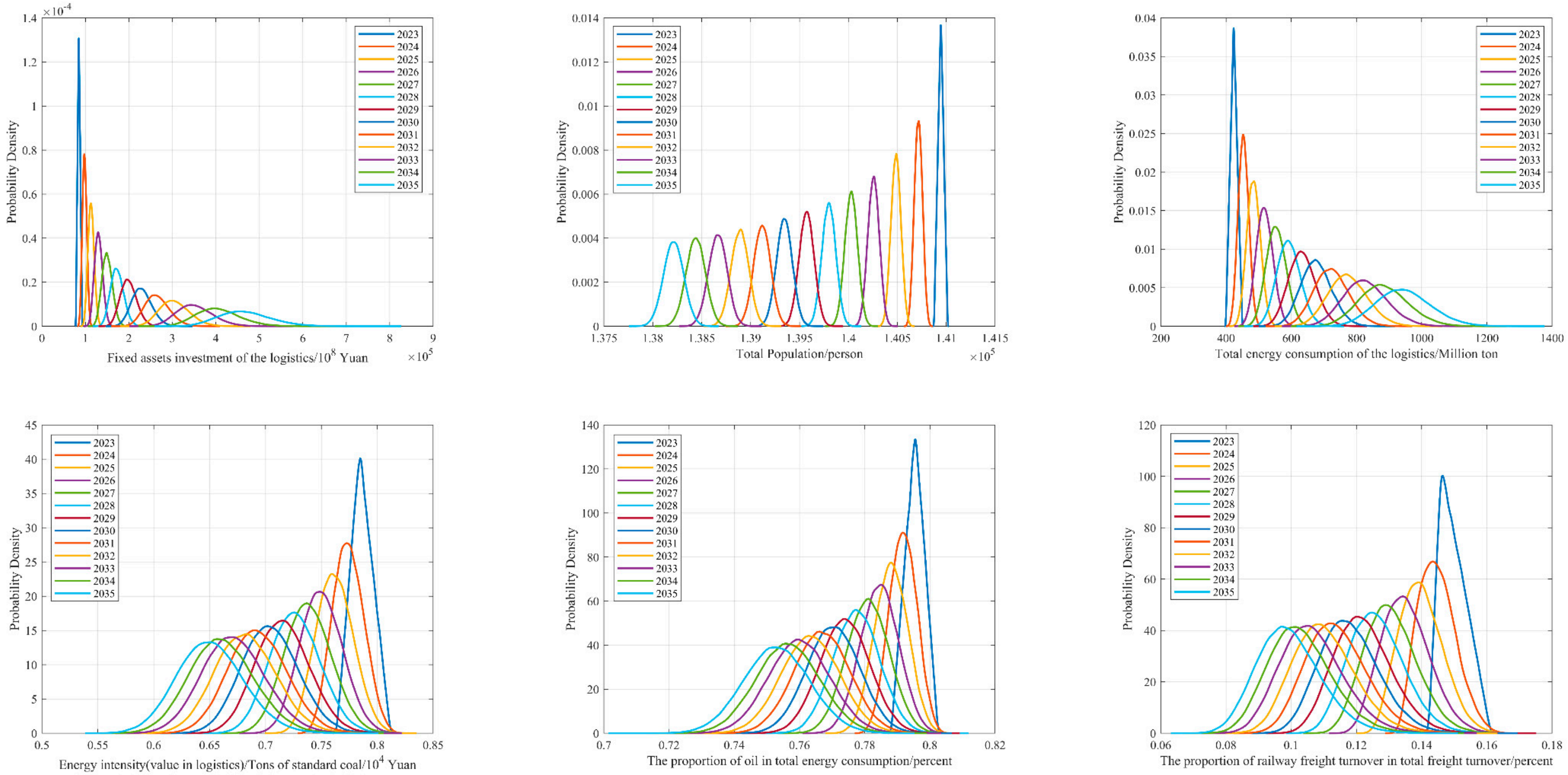
Table 8. Annual rates of change of the impact factors in the technology breakthrough scenarios (unit: %).

Variable	2023–2025			2026–2030			2031–2035		
	Min	Middle	Max	Min	Middle	Max	Min	Middle	Max
LFI	4.00	5.00	6.00	3.50	4.50	5.50	3.00	4.00	5.00
E	2.00	3.00	4.00	0.50	1.50	2.50	−1.00	0.00	1.00
EIL	−3.92	−2.92	−1.92	−4.92	−3.92	−2.92	−5.92	−4.92	−3.92
OR	−1.60	−1.40	−1.20	−2.00	−1.80	−1.60	−2.40	−2.20	−2.00
RTR	4.30	4.80	5.30	4.70	5.20	5.70	5.10	5.60	6.10

Source: Authors.

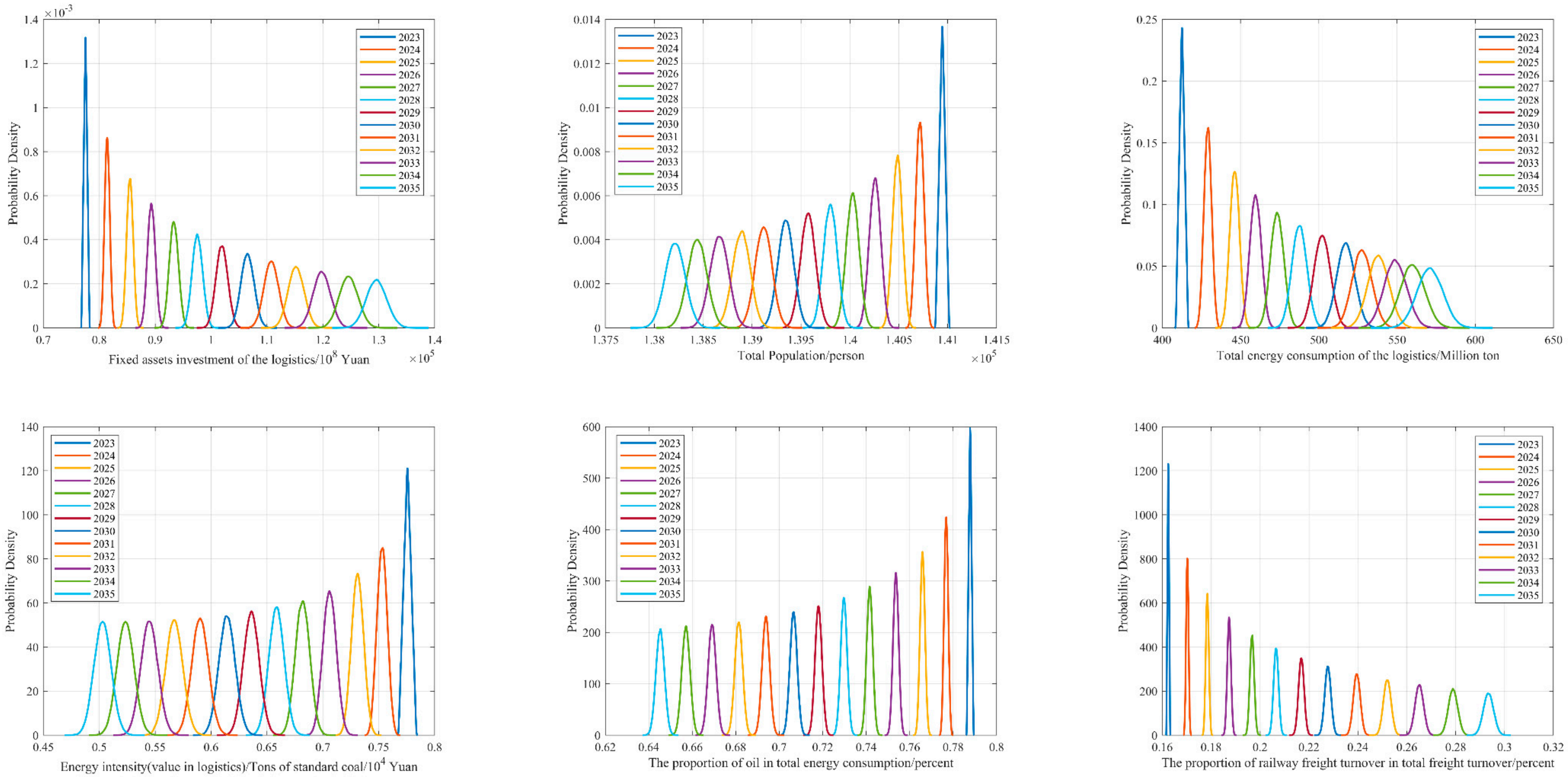
4.2. Monte Carlo Simulation Ideas

Through Monte Carlo simulation, the range of values and probable values of each influencing factor from 2023 to 2035 under various scenarios are determined based on the change rates of each factor in the three scenarios mentioned above and their respective occurrence probabilities. This article establishes the probability distribution relationship between the minimum, median, and maximum potential change rates of each variable through a triangular distribution and uses MATLAB 2023a to simulate 100,000 potential change rates in benchmark scenarios, policy regulation scenarios, and technological breakthrough scenarios, thereby presenting the value range and most likely values of each variable. The evolution trend of various influencing factors is displayed in Figure 5.



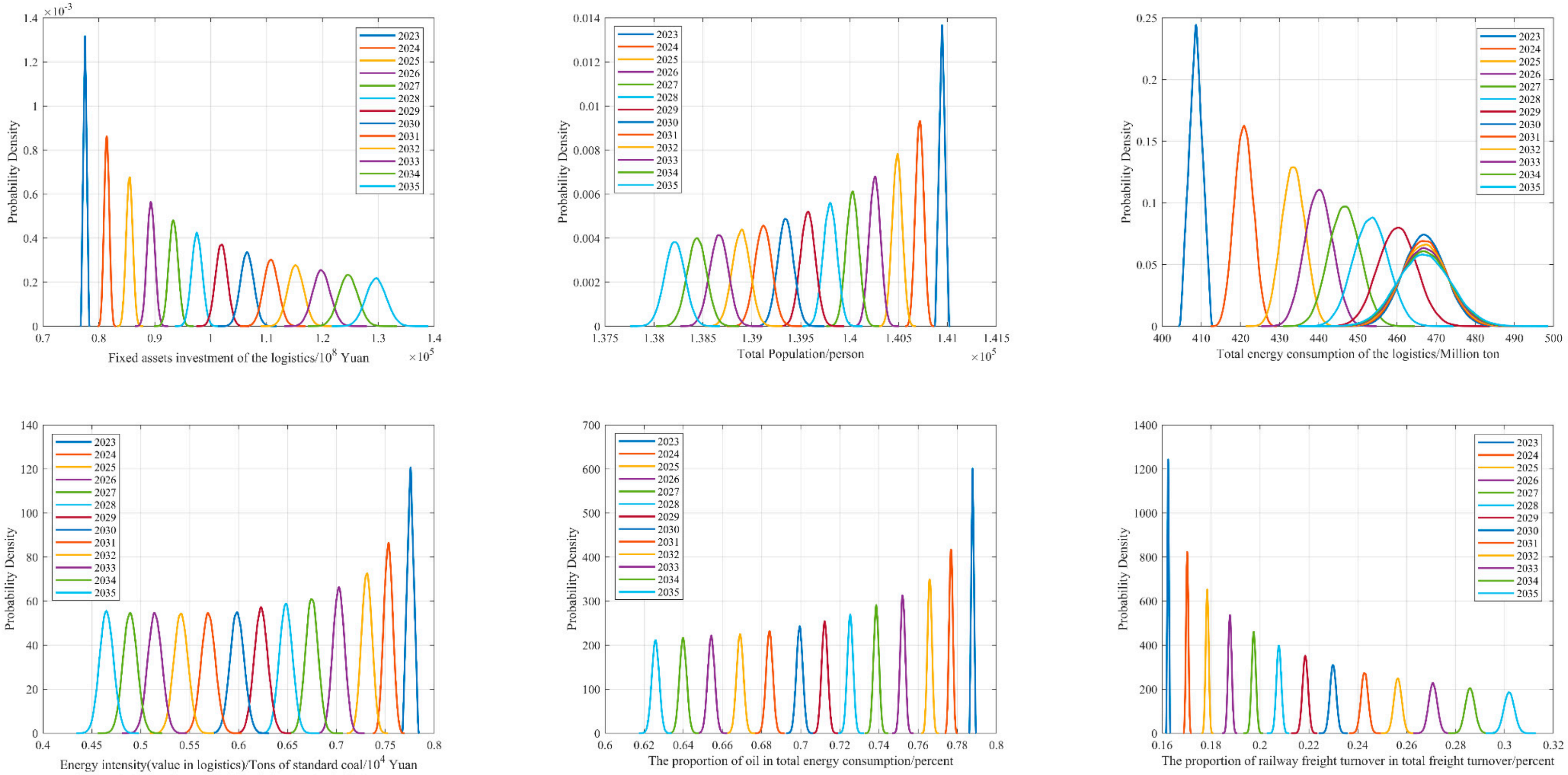
(a)

Figure 5. *Cont*.



(**b**)

Figure 5. *Cont*.



(**c**)

Figure 5. (**a**) Evolution trend under the baseline scenario. (**b**) Evolution trend under the policy regulation scenario. (**c**) Evolution trend under the technological breakthrough scenario.

5. Results of Carbon Emissions in the Logistics Industry Forecasting

Through scenario analysis and Monte Carlo simulation, this study obtained the range of the predicted values of each influential factor from 2023 to 2035 and used the most likely values of each variable and historical data as inputs to the WOA-RBF neural network model to predict the carbon emissions of China's logistics industry from 2023 to 2035 under the baseline scenario (BAU), the policy regulation scenario (PR), and the technological breakthrough scenario (TB). The results of the carbon emission predictions are displayed in Figure 6 and Table 9.

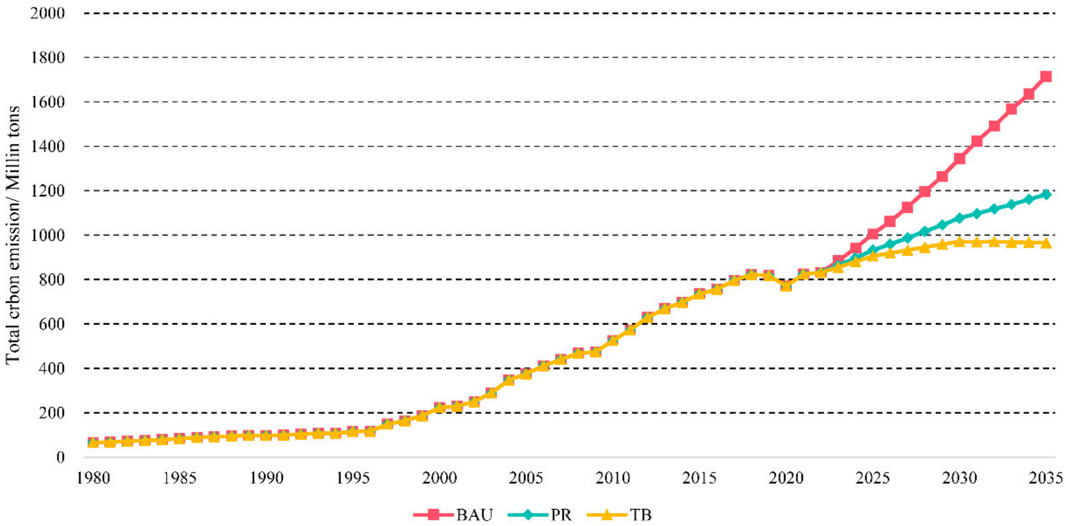


Figure 6. Prediction results of carbon emissions under BAU, PR, and TB conditions.

Table 9. Forecast results for 2025, 2030, and 2035 under BAU, PR, and TB conditions.

Year	TCE (Unit: Million Tons)		
	BAU	**PR**	**TB**
2025	1005.56	932.26	906.09
2030	1344.23	1076.93	971.03
2035	1715.22	1183.11	965.30

Source: Authors.

According to the BAU scenario, China's logistics industry would emit 1005.56 million tons of total carbon emissions (TCE) in 2025, 1344.23 million tons in 2030, and 1715.22 million tons in 2035. The average annual growth rate during the 2021–2025, 2026–2030, and 2031–3035 periods is estimated to be 5.09%, 6.09%, and 4.78%. During the period 2016–2020, carbon emissions from the logistics industry achieved negative growth for two consecutive years in 2019 and 2020 and gradually rebounded in 2021 and 2022. However, based on the baseline scenario, if the logistics industry continues to follow its previous extensive development model, this type of emission reduction will not be sustainable in the absence of more legislative involvement and more cutting-edge technology breakthroughs. With the orderly resumption of work and production in the post-epidemic era, as well as the expanding scale of the domestic logistics industry and the increasing number of consumption scenarios, the logistics industry in this scenario will result in even larger-scale carbon emissions. Therefore, government policy intervention and regulation are crucial for the logistics industry to achieve the goal of "peak carbon emissions".

According to the PR scenario, the TCE is 932.26 million tons in 2025, 1076.93 million tons in 2030, and 1183.11 million tons in 2035, compared with the BAU scenario, which achieves emission reductions of 73.3 million tons, 267.3 million tons, and 532.11 million tons, respectively, with emission reductions of about 7.29%, 19.88%, and 31.02%, with a significant decrease. Meanwhile, the average annual growth rates of 3.12%, 2.93%, and 1.91% during the 2021–2025, 2026–2030, and 2031–3035 periods are expected to slow down compared with the baseline scenario. The average annual growth rates during the "14th Five-Year Plan", the "15th Five-Year Plan", and the "16th Five-Year Plan" are 3.12 percent, 2.93 percent, and 1.91 percent, respectively, which are also slower than the base scenario. This shows that if the series of low-carbon policies and corresponding goals introduced by the government are strictly implemented, the asset investment, energy structure, and transport structure of the traditional logistics industry will be optimized, and the construction of green logistics and low-carbon supply chain systems will be accelerated, resulting in a significant reduction in energy consumption and overall carbon emissions in the logistics industry.

According to the TB scenario, the TCE are 906.09 million tons in 2025, 971.03 million tons in 2030, and 965.3 million tons in 2035, compared with the BAU scenario, which achieves emission reductions of 26.17 million tons, 105.9 million tons, and 217.81 million tons, respectively, with emission reductions of about 2.81%, 9.83%, and 18.41%; and compared with the BAU scenario, which achieves emission reductions of 99.47 million tons, 373.2 million tons, and 749.92 million tons, with emission reductions of about 9.89%, 27.76%, and 43.72%, and the emission reduction effect is further increased. Unlike the BAU and PR scenarios, the TCE predicted in the TB scenario will reach an inflection point in 2030 and maintain a downward trend in the following years. This indicates that with the increasing popularity of energy-saving logistics equipment such as new energy vehicles, the promotion of recycled logistics packaging, the improvement of green logistics standards, the maturity of multimodal transport equipment and business models, as well as the gradual diversification of logistics information systems and carbon emission monitoring mechanisms, the logistics industry is most likely to achieve the goal of "Peak Carbon" under the dual conditions of guidance from national policy and the driving force of logistics innovation.

6. Discussions

In order to represent the future development trend of the logistics industry and the state of emission reduction, the purpose of this study is to examine the possible rate of change of numerous major elements impacting carbon emissions in China's logistics industry under three very different scenarios:

(1) In the baseline scenario, the logistics industry continues to follow the traditional "investment-heavy, service-light" model, with a lack of policy guidance and energy-saving technology, as well as severe homogeneous competition and duplication of investment by logistics enterprises, making it difficult to meet the rapidly increasing demand for new retailing, cold chain, and bulk commodity consolidation in the post-pandemic era. At the same time, in this scenario, the logistics industry always adheres to an energy structure based mostly on fossil fuels like oil and a transport structure based mostly on road transportation, which will inevitably result in resource waste and environmental pollution, resulting in higher carbon emissions.

(2) In the policy regulation scenario, the government establishes several emission reduction goals and proposes and implements initiatives such as limiting excessive investment, increasing the percentage of non-fossil energy use, and implementing multimodal transportation such as "public-to-water transfer", "public-to-rail transfer", and "public-to-rail-to-water transfer". "Multimodal transport" and other initiatives in existing energy-saving technology will optimize the energy structure of the logistics industry and the transport structure, reduce logistics energy consumption and energy intensity, and achieve a more significant effect of emission reductions. However, many of the existing energy-saving technologies are not yet mature, the green logistics standard system is not yet perfect, and not forming large-scale energy-saving technologies in the short term may increase the cost pressure on the logistics industry. In addition, China's logistics enterprises are "small, scattered, and chaotic" in distribution, with large regional development gaps, especially for small and medium-sized enterprises (SMEs) and central and western regions

that can hardly bear the loss of economic costs brought about by low-carbon transformation, which also inhibits the promotion of energy-saving technologies among these enterprises and regions. Therefore, it is difficult for China's logistics industry to achieve the goal of reaching its peak under the scenario of policy regulation.

(3) In the scenario of technological breakthroughs, the Chinese government has always followed the policy guidelines of energy conservation, emission reduction, and logistics development planning, gradually integrating digital technologies such as the Internet of Things (IoT), big data, artificial intelligence, and other digital technologies into the logistics industry and deeply plowing into the emerging fields of smart logistics and green logistics. Simultaneously, the government, while suppressing traditional production-oriented investment, gradually shifted the focus of investment to intelligent platforms, new energy equipment, green packaging, and other areas, which will further improve the logistics industry's investment efficiency, accelerate the transformation of low-carbon logistics technology results, and facilitate equipment iteration to better meet the development needs of low-carbon logistics. In addition, technological breakthroughs can accelerate the large-scale production of software and hardware such as intelligent platforms, new energy equipment, green packaging, etc., reduce application costs, help many small and medium-sized logistics enterprises gradually achieve intensive digital and low-carbon transformation, and promote the popularity of green logistics technology in the central and western regions of China through the spillover effect of digital technology to optimize the energy structure of the logistics industry and the transport structure to a greater extent and lower the energy intensity, thus bringing more significant emission reduction. Therefore, under the scenario of technological breakthroughs, China's logistics industry has the potential to reach "peak carbon" by 2030.

7. Conclusions and Policy Implications

7.1. Conclusions

This study proposes an RF-WOA-RBF prediction model to accurately predict the future trend of carbon emissions in China's logistics industry and to provide a potential reference for low-carbon research in other areas under the "dual-carbon" context. The main findings of this study are as follows:

(1) Adopting RF for feature selection can effectively screen out key factors, reduce data redundancy, and improve forecasting efficiency and accuracy. It is also concluded that logistics fixed asset investment (LFI), population (P), total energy consumption of the logistics industry (E), energy consumption per unit of logistics value added (EIL), share of oil consumption (OR), and share of railway freight turnover (RTR) are the key factors affecting the carbon emissions of the logistics industry.

(2) Comparing with PSO-BPNN, ELM, and SVM algorithms, WOA-RBF has a lower error-index value and a higher prediction accuracy of carbon emissions in the logistics business.

(3) The accuracy of carbon emissions prediction under the WOA-RBF model can be increased by using Monte Carlo simulation to effectively reflect the uncertainty of future changes in the key factors affecting carbon emissions in the logistics industry and to determine the range of values and most likely values of each variable's potential rate of change.

(4) It is difficult for China's logistics industry to achieve the goal of a "carbon peak" in 2030 under the BAU and PR scenarios, while it is most likely to achieve the goal under the TB scenario. This also shows that energy savings and emission reduction in the logistics industry cannot be achieved without the dual incentives of national policy regulation and technological innovation.

In addition, this study still has some limitations: First, the selection of factors influencing the logistics industry's carbon emissions is mainly based on the econometric method of STIRPAT theory, and in the future, we can consider combining the factor decomposition method of LMDI and GDIM with machine learning algorithms for the feature selection of variables. Secondly, logistics policy and digital transformation, as important factors affecting carbon emissions, have not yet been considered in this study due to the lack of good quantitative mechanisms and data support, which can further expand the research on these areas in the future.

7.2. Policy Implications

(1) Promoting the low-carbon transformation of logistics and building a green logistics service system

The government should strengthen the layout and construction of infrastructure such as freight vehicle charging piles, accelerate the application of new energy batteries, hydrogen energy, natural gas, advanced biological liquid materials, etc. in the field of power and energy storage, and promote the application of new energy vehicles, forklifts, etc. in the field of transportation and warehousing. At the same time, we are accelerating the standardization and construction of green logistics packaging, popularizing circular packaging, reducing secondary packaging and excessive packaging in logistics activities, and promoting the research and development process of degradable and high-performance packaging. Furthermore, establishing a mature reverse logistics service system, cultivating a group of professional reverse logistics service enterprises around the national logistics hub, and carrying out circular utilization of resources such as product packaging, logistics equipment, new energy batteries, and materials. In addition, relying on third-party institutions such as industry associations to carry out green logistics carbon trading markets and monitoring the carbon footprint and emission reduction of logistics enterprises in real-time through public information platforms promotes the contract energy management model, thereby establishing a low-carbon management concept for enterprises.

(2) Strengthening the digital empowerment of logistics and carrying out emerging formats of smart logistics

The government should closely follow the development trend of low-carbon green logistics and fully play the role of policy guidance, legal constraints, standard specifications, and process supervision in the process of "new infrastructure" strategy and modern circulation system construction. While promoting internet construction and intelligent manufacturing, it should work with enterprises to apply the existing information infrastructure achievements to strengthen the layout of freight hub facilities, enhance the intensification and digitization level of logistics nodes, build a moderately high logistics resource-sharing platform, and other aspects that can better integrate technologies such as the Internet of Things, big data, and cloud computing with the logistics industry. In addition, strengthening the construction of a green logistics public information platform and jointly establishing a carbon emission monitoring and management system with leading enterprises will provide services such as carbon disclosure, quota trial calculation, carbon account management, and green finance to logistics enterprises, especially small and micro enterprises.

(3) Accelerating the diversified transformation of transportation and creating a competitive advantage in multimodal transportation

The government should increase efforts to control pollution from large diesel trucks, adjust transportation structures, and increase the percentage of railways and waterways. Firstly, promoting the "public to rail or water" transfer of bulk materials, encouraging grain, mining, and other related enterprises to use container transportation, and using railway and waterway transportation for medium to long distances, while new energy vehicles and ships are used for short distance transportation. Secondly, accelerating the research and application of standardized container, semi-trailer, pallet, and other transportation units, as well as new energy-heavy trucks, transport ships, aircraft, charging stations, and other technical equipment, and building a green and intelligent port and station hub. Thirdly, promoting information sharing among various intermodal transportation entities, that is, strengthening the integration of information systems and data sharing among departments such as railways, ports, shipping companies, and civil aviation, including information on cargo loading and unloading, vehicle arrival and departure times, and ship arrival and departure times, and carrying out joint scheduling of logistics operations to achieve monitoring and traceability throughout the transportation process.

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