Scenario prediction of carbon peaking in China's logistics industry based on SVR

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Abstract. As a strategic, basic and leading industry for the development of China's national economy, the logistics industry shoulders the important mission of implementing the national "dual carbon" goal. It is urgent to keep up with the pace of the times and accelerate the green and low-carbon process of the logistics industry. Based on the relevant data from 1998 to 2020, this paper selects 8 indicators such as fixed asset investment in the logistics industry, freight turnover, passenger turnover, freight volume, the number of trucks, PM2.5 concentration and per capita GDP. The scenario analysis method is combined with the SSA-SVR model to establish a scenario prediction model for China's logistics industry's carbon peaking. The research results show that: under the baseline scenario, the carbon emissions of China's logistics industry will peak in 2047; under the low-carbon scenario, carbon emissions will peak in 2038; under the enhanced low-carbon scenario, carbon emissions will peak in 2029. 55.94 million tons. Combined with the trend analysis results under different scenarios, China should continue to strengthen the construction of the carbon trading market, optimize the industrial structure, and accelerate the progress of carbon peaking.

Keywords: support vector regression, sparrow search optimization algorithm, logistics industry, carbon peaking, scenario analysis.

1. Introduction

In recent years, with the accelerating pace of global industrialization, the phenomenon of increasing greenhouse gas emissions and excessive energy consumption has become increasingly serious. As a responsible and responsible big country, China actively promotes global climate governance. It has repeatedly proposed and emphasized China's "3060" dual-carbon goal, and has successively issued a series of policy documents to address climate issues. The "14th Five-Year Plan Outline" in 2021 more clearly proposes a low-carbon development path of "reducing carbon emission intensity and formulating an action plan for carbon emission compliance before 2030". The scale of China's logistics industry is large, and the ratio of total logistics cost to GDP in the whole society in 2020 is about 18.6%. Therefore, scientifically predict the carbon peaking situation of the logistics industry, and propose feasible emission reduction measures and peaking paths to promote China's "dual carbon" goal. Development is important.

By studying the previous literature on carbon emissions by domestic and foreign scholars, it is found that there are few studies on the issue of carbon peaking in the logistics industry, and most of the studies focus on influencing factors and carbon emission efficiency analysis. Qi Yu applied LMDI factor decomposition method to study the method of restraining the increase of carbon emission[1]. Jiang Leping applied the LMDI factor decomposition method to measure the carbon emissions of the logistics industry in Anhui Province from 2005 to 2019, and put forward suggestions from the energy structure and other aspects[2].Xu Weigan uses the Super-PEMB model and the global reference Malmquist index model to evaluate the efficiency of China's provincial logistics industry carbon emissions[3].Wu Zhenjia uses the super-efficiency BCC-DEA model to calculate the total factor carbon emission efficiency of the logistics industry in 17 provinces along the “Belt and Road”. Improving efficiency is of great significance to energy conservation and emission reduction[4]. At the same time, a small number of scholars conduct research from the perspective of scenario changes. Xu Xiangyang introduced various influencing factors of China's paper industry into scenario analysis, constructed a STIRPAT model, and predicted that its carbon peak time would be about 2029[5]. Taking Zhejiang Province as an example, Zhao Ci established a revised STIRPAT model and set three scenarios to predict carbon emissions[6]. Hu Maofeng set up 18 scenarios to study the peak forecast of transportation carbon emissions in Hubei Province[7].Based on the data from 2000 to 2018, Zhang Jinliang used prediction models to predict the carbon emissions of China's thermal power industry from 2021 to 2050 under four different scenarios including industrial optimization[8].Although the above references have analyzed the peaking scenarios, most of their research directions are focused on other industries or regions, and have not studied the carbon peaking scenarios of China's logistics industry.

In summary, in order to investigate the accessibility of the logistics industry's carbon peak target by 2030, this paper firstly constructs a carbon emission impact indicator system for China's logistics industry from previous research literature; secondly, it analyzes the carbon emission development trend of China's logistics industry under the baseline scenario, low-carbon scenario and enhanced scenario by combining algorithmic model and scenario analysis, in order to make accurate prediction of the carbon peak time and carbon emission in the logistics industry, and make corresponding emission reduction suggestions. The second is to analyze the carbon emission trends of China's logistics industry under the baseline scenario, low-carbon scenario and enhanced scenario.

2. Model Fundamentals

2.1. Support vector regression

Support Vector Regression (SVR) is an application of support vector machine to solve regression problems.Assume that the ith input sample of the regression model is xi.. The corresponding real output is yi. The model output is f(xi). It is transformed into the solution with constraints to minimize the objective function and the penalty factor is introduced to fuse the constraints into the objective function:

$$\min \ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}(\xi_i + \hat{\xi}_i) \tag{1}$$

$$S.T. \begin{cases} f(x_i) - y_i \le \varepsilon + \xi_i \\ y_i - f(x_i) \le \varepsilon + \hat{\xi}_i \\ \xi_i \ge 0, \hat{\xi}_i \ge 0. i = 1, 2, \cdots, m \end{cases} \tag{2}$$

$$f(x) = \sum_{i=1}^{m}(\hat{\alpha}_i - \alpha_i) \cdot x_i + b \tag{3}$$

SVR performs very well on a variety of datasets. The important parameters of SVR are the regularization parameter C and the kernel parameter g. The regularization parameter C affects the complexity and stability of the model. The larger C is, the model will pay attention to outliers and cause overfitting, otherwise, it will be underfitting.

2.2. Sparrow Search Algorithm

SSA is a biological heuristic algorithm mainly inspired by the foraging behavior and anti-predation behavior of sparrows. It has the advantages of strong optimization ability and fast convergence speed. In this model population, sparrows are divided into predators, joiners and watchmen. The position of each sparrow represents a solution. The renewal strategy of sparrow population is as follows:

Let the solution space dimension be D, the number of sparrow population population, the ith individual's position in the solution space, the finder with better fitness value in SSA will get food first in the search process.

Discoverer's update strategy is as follows:

$$X_{i,d}^{t+1}\begin{cases} X_{i,d}^{t}\cdot\exp(-\dfrac{i}{\alpha\times iter_{\max}}) & if\ R_2 < ST \\ X_{i,d}^{t}+Q\cdot L & if\ R_2 \geq ST \end{cases} \tag{4}$$

In equation (4),t is the number of current iterations. itermax represents the maximum number of iterations,α is a random number on [0,1],R2∈[0,1] represents the alert value, ST∈[0.5,1] represents the security threshold, Q is a random number subject to normal distribution, and L is an all-one matrix of 1*D.

The update strategy of the subscriber is as follows:

$$X_{i,d}^{t+1}\begin{cases} Q\cdot\exp(\dfrac{X_{worst}-X_{i,d}^{t}}{i^2}) & if\ i>\dfrac{N}{2} \\ X_P^t+\left|X_{i,d}^{t}-X_p^t\right|\cdot A^{+}\cdot \mathrm{L} & \text{otherwise} \end{cases} \tag{5}$$

In Equation (5), A^+ represents a 1*D matrix whose principal elements are randomly composed of 1 or -1,X_p^t represents the best position occupied by the current discoverer, and X_{worst} represents the current global worst position

The vigilance update strategy is as follows:

$$X_{i,d}^{t+1}\begin{cases} X_{best}^{t}+\beta\cdot\left|X_{i,d}^{t}-X_{best}^{t}\right| & if\ f_i < f_g \\ X_{i,d}^{t}+K\cdot(\dfrac{\left|X_{i,d}^{t}-X_{worst}^{t}\right|}{(f_i-f_w)+\varepsilon}) & if\ f_i = f_g \end{cases} \tag{6}$$

In Equation (6),X_{best}^t is the current global optimal individual position, K is a random number following normal distribution,β is a random number on [-1,1],K is a random number on [-1,1],ε is a small constant, avoid the denominator of 0, f_i is the current individual fitness value, f_w and f_g is the current worst and best fitness value.

2.3. SSA - SVR model

Aiming at the optimization problem of SVR parameters, this paper combines SSA with SVR to further solve the problems such as too small step size, long running time of the model, inability to find a set of parameters quickly and accurately, and insufficient prediction accuracy of the improved model. The flow chart of SSA-SVR algorithm is shown in Figure 1.

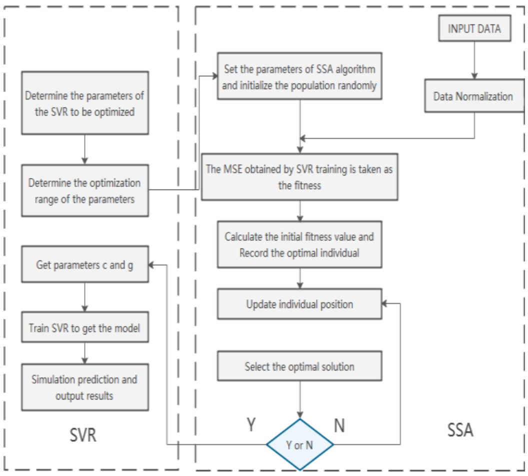

Fig.1 Flowchart of SSA-SVR model construction

3. Empirical Analysis

3.1. Data sources and initial indicator system construction

This paper selects eight indicators by researching the previous literature. The data are mainly from the "China Fixed Asset Investment Statistical Yearbook", "Logistics Statistical Yearbook", "China Statistical Yearbook", and the carbon dioxide emission data comes from the "China Statistical Yearbook" by the University of Washington. Measured data of global surface PM2.5 concentrations by the Atmospheric Composition Analysis Group". Based on this, the initial prediction index system of China's logistics industry is constructed as shown in Table 1.

Table 1. Construction of the initial indicator system

indicator	meaning	unit	references
Fixed asset investment in logistics industry	Construction and acquisition of fixed assets for the logistics industry and changes in costs associated therewith	billion	[9]
Freight turnover	The product of the quantity of goods to be transported and the distance to be transported	billion ton kilometers	[10]
Passenger turnover	The number of passengers transported within a certain period of time	million person kilometers	[11]
Freight volume	The quantity of goods transported or required to be transported in the transport of goods	billion tons	[12]
The number of trucks	The number of vehicles in the locally registered car that function as a cargo carrier	ten thousand	[13]
Employment in the logistics industry	Population engaged in labor or business in the logistics industry and earning income	ten thousand	[14]
PM2.5 concentration	The diameter of fine particles in the air is less than or equal to 2.5 microns perm³	$\mu g/m^3$	[15]
GDP	Gross Domestic Product	dollars	[16]

3.1.1. Model parameter construction

In this paper, the SSA-SVR model is used to study the carbon emissions of the logistics industry. Let N be the number of populations, imax is the maximum number of iterations, and ST is the safety threshold. The constructed model parameters are shown in Table 2.

Table 2. SSA-SVR model parameter

NAME	N	imax	vigilant ratio	ST	upper bound	the Nether	discoverer ratio
NUMBER	20	300	0.1	0.8	[100,1]	[1,0.01]	0.2

3.1.2. Model comparison evaluation

In order to evaluate the performance of the model, three regression evaluation indicators commonly used in machine learning are introduced: mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). The specific results are shown in Table 3.

Table 3. Comparison of evaluation indicators of each model

Evaluation standard	SVR	GREY	SSA-SVR	BP	LSTM
MAE	1332515	9756675.52	341378	2429491	1106563
MAPE	0.043	0.42	0.021	0.121	0.052
RMSE	2618910	11786120.3	378897.2	2759167	1825048

From the evaluation of the prediction accuracy of the model, the MAE, MAPE, and RMSE values of the SSA-SSR model all reach the lowest among several types of comparative models. The above results show that the optimization algorithm has better search ability than the traditional fixed search step size network search algorithm , the SSA-SVR model can train a model with higher prediction accuracy by obtaining better parameters.

3.2. Scenario settings

According to the "Implementation Opinions on Completely, Accurately and Comprehensively Implementing the New Development Concept and Doing a Good Job in Carbon Peaking and Carbon Neutralization", "Science and Technology Supporting Carbon Reaching and Carbon Neutralization Implementation Plan (2022-2030)" and other relevant policy documents, this paper establishes a benchmark., low-carbon and intensified low-carbon scenarios.

Among them, benchmark means continuous development according to the existing situation, low carbon means the development situation that may be caused by certain interventions compared with the benchmark situation, and strengthening low carbon means that compared with the low carbon situation, the degree of development is deeper. The development of the intervention to quickly reach the carbon neutralization target, the specific numerical settings are shown in Table 4.

Table 4. THE Rate of change of indicators in 2022-2050 under three scenarios

		2022-2025	2026-2030	2031-2035	2036-2040	2041-2045	2046-2050
Fixed asset investment in logistics industry	standard	5.50%	4.50%	3.50%	2.50%	1.50%	0.50%
	low	4.50%	3.50%	2.50%	2.00%	1.00%	0.30%
	strengthen	3.50%	2.50%	1.50%	1.50%	0.50%	0.10%
Freight turnover	standard	2.60%	2.40%	2.20%	1.80%	1.50%	1.30%
	low	2.30%	2.10%	1.90%	1.50%	1.20%	1.00%
	strengthen	2.00%	1.80%	1.60%	1.20%	0.90%	0.70%
Passenger turnover	standard	4.30%	3.80%	3.30%	2.80%	2.30%	1.80%
	low	3.90%	3.30%	2.80%	2.30%	1.80%	1.30%
	strengthen	5.20%	2.80%	2.30%	1.80%	1.30%	0.80%
Freight volume	standard	2.70%	2.30%	1.90%	1.50%	1.10%	0.70%
	low	2.40%	2.00%	1.60%	1.20%	0.80%	0.40%
	strengthen	2.10%	1.70%	1.30%	0.80%	0.50%	0.10%
The number of trucks	standard	4.32%	3.25%	2.02%	1.05%	1.00%	0.50%
	low	2.10%	1.10%	-0.80%	-1.00%	-1.50%	-1.80%
	strengthen	2.00%	1.00%	-0.75%	-1.25%	-1.50%	-1.75%
Employment in the logistics industry	standard	3.21%	2.03%	1.00%	0.50%	0.30%	0.20%
	low	2.00%	1.50%	1.20%	0.50%	0.30%	0.10%
	strengthen	1.00%	0.80%	0.60%	0.40%	0.30%	0.20%
PM2.5 concentration	standard	6.17%	4.02%	2.86%	2.00%	1.50%	1.20%
	low	3.50%	2.50%	1.50%	1.00%	-1.00%	-1.50%
	strengthen	3.00%	2.00%	1.00%	0.50%	-0.50%	-1.00%
GDP	standard	4.50%	3.50%	2.50%	2.00%	1.50%	1.00%
	low	2.40%	2.00%	1.20%	1.00%	0.50%	0.30%
	strengthen	1.80%	1.50%	0.70%	0.50%	0.30%	0.20%

3.3. Results and Analysis

The predicted values of influencing factors under the three scenarios of baseline, low-carbon and enhanced low-carbon are substituted into the SSA-SVR model, and the results are shown in Figure 2.

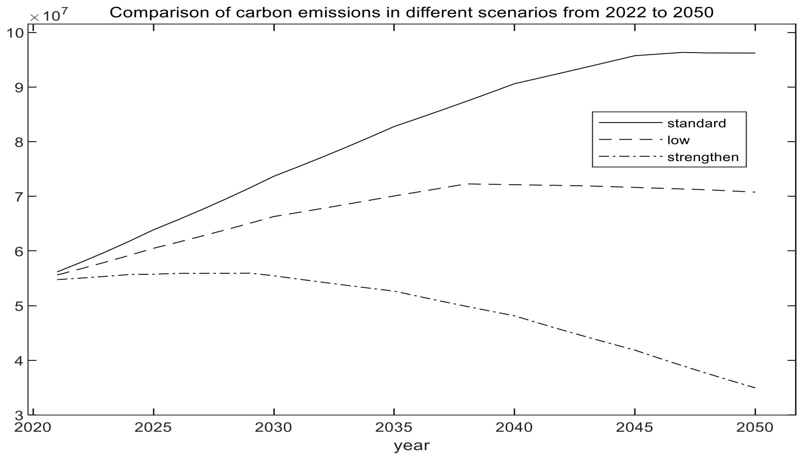

Fig.2 Comparison of carbon emissions in different scenarios from 2022 to 2050

Among them, under the baseline scenario, the carbon emission of China's logistics industry will peak in 2047, with a peak emission of 96.34 million tons. Under the low-carbon scenario, carbon emissions will peak in 2038, with a peak of 72.27 million tons. In the low-carbon scenario and the baseline scenario, although there is a peak, the trend is still smooth and there is no obvious downward trend, which shows that there is still a long way to go to achieve the next carbon neutrality goal. Under the enhanced low-carbon scenario, carbon emissions will peak in 2029, with a peak of 55.94 million tons. In the three scenarios, the enhanced low-carbon scenario peaked earlier than the other two scenarios. It shows that under the current environment, further policy restrictions and related incentive measures made by the government can accelerate the realization of the expected goals and promote the realization of China's "dual carbon" process.

4. Conclusion

The SSA-SVR model is used to predict, and the results show that the correlation coefficient between the predicted value of the model and the actual value is above 0.99, and the fitting and regression effect of the model is good. However, in the enhanced scenario, the peak time is 2030, which is basically in line with national policy goals. A social atmosphere in which the government, industry, and enterprises work together to promote green and low-carbon development has taken shape. This paper puts forward the following suggestions for energy saving and emission reduction in China's logistics industry:

(1) Strengthen the optimization of industrial structure and the impact of government intervention on reaching the carbon peak. A good industrial structure can improve the production efficiency of the logistics industry while promoting the development of the logistics industry. According to the results of the scenario analysis, it is necessary to strengthen policy restrictions to promote the earlier target of reaching the actual carbon peak. By implementing the concept of green and sustainable development, we can limit the consumption of fossil energy and increase the financial guarantee for the development of low-energy-consumption industries.

(2) To promote the use of new energy vehicles, the purpose of reducing emissions can be achieved by strengthening technical cooperation with foreign companies, exploring and developing new energy vehicle technologies. In its infancy, it needs higher and newer technologies to give it stronger market competitiveness to compete with traditional fossil energy vehicles, thereby increasing its market share.

(3) Focus on promoting the low carbonization of the logistics industry and related industries. Clear policy orientation, emission reduction is not a reduction in production, but should drive the industry to transition to low-carbon with advanced management concepts and high economic models, and guide consumers and enterprises in the industry to design low-carbon concepts, so as to improve policy effectiveness and accelerate Advance carbon peaking progress.

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