Carbon neutrality planning based on time series analysis and hybrid supervision

Weihao Hong

School of Software, Heilongjiang University, Harbin, Heilongjiang,150080, China

1411737600@qq.com

Abstract. With the rapid development of industrialization and urbanization, the problem of climate change is becoming increasingly serious, and it has become crucial for China, to reduce greenhouse gas emissions and achieve carbon neutrality as an important contributor to global climate change. First, the ARIMA model was used to predict the energy consumption structure of each province in the coming years. The model predicted the energy consumption structure and obtained significant prediction accuracy with an average R-squared value of 0.83, which was better than the control group methods such as LSTM, BP, and RNN. Second, this study established a low-carbon situation evaluation system based on the AHP-TOPSIS evaluation method. Using the AHP-TOPSIS method enabled the quantification of regional low-carbon efforts by assigning weights to renewable and non-renewable energy sources, with coal having the highest weight at 48.264% and the lowest weight being wind energy at only 4.245%. Then, this study predicted the trend of carbon emission, assessed the carbon emission, and proposed a low-carbon optimization strategy. Through these methods and strategies, this study provided a scientific basis and decision support for China's carbon neutrality pathway planning. This study provides theoretical and practical support for China to achieve its carbon neutrality goal, but it still needs to be continuously improved. It is believed that with the joint efforts of all parties, China's carbon neutrality pathway planning will become more scientific and effective and contribute to the solution of global climate change.

Keywords: ARIMA model, AHP-TOPSIS evaluation method, Carbon Neutrality Pathway.

1 Introduction

1.1 Background

With the rapid development of industrialization and urbanization, China is becoming an important contributor to global climate change. Therefore, reducing greenhouse gas emissions and achieving carbon neutrality[1] are becoming a high priority. Therefore, this study needs to research China's carbon neutrality pathway planning deeply and proposes scientific and reasonable strategies to deal with the current climate change challenges.

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1.2 Restatement Problem Analysis

First, to achieve this goal, this study uses data from 2003 to 2020 as a training set to train an energy consumption prediction model to predict the future energy consumption structure of each province, to learn about the trend of energy consumption, and to provide data support for the development of a carbon neutrality pathway planning.

Second, the weights of different factors are quantified, and the scores of each factor are synthesized to derive the low carbon[2] scores of each region. An evaluation system for the low carbon situation is constructed.

Finally, this study proposes a series of low-carbon optimization strategies based on the above prediction model and evaluation system.

2 Materials and Methods

2.1 Datasets

The data covered the structure of energy consumption in 30 provinces and regions across the country for the period from 2003 to 2020. These energy consumptions included the consumption of raw coal, coke, crude oil, gasoline, natural gas, and electric energy. To verify the accuracy and generalization ability of the prediction model, this paper used the data of the first 13 years as the training set and used the data of the last five years as the test set. The data from the training set was used to train the energy consumption forecasting model. The ARIMA model[3] was chosen as the forecasting model.

2.2 Data pre-processing

To facilitate the construction of the subsequent evaluation system, it was necessary to unify the data outline processing, eliminating the role of numerical values in influencing the weights. At the same time, it was also necessary to unify the directionality of the data, to ensure that the role of each feature was in the same direction for the evaluation system to maintain consistency.

2.3 Modeling and Solution

Forecasting energy consumption structure. First, the ARIMA model[3] was used in the paper to predict the energy consumption structure of each province in the coming years, and its prediction in a short time in small samples had a good effect. The same models with predictive time series data such as LSTM[4], BP, and RNN were used in this paper for comparative experiments to test the efficiency of the ARIMA model in short-term data prediction. To verify the performance of model prediction, RMSE, MAE, and R-squared were used in this paper for validation of model effectiveness.

Development of an evaluation system for the low-carbon situation. In this study, the evaluation system of low-carbon situations was constructed based on the AHP[5]-

TOPSIS[6] evaluation method. By comprehensively analyzing the degree of energy consumption in each region each year, the low carbon score of each region was derived. First, the AHP method[5] was used to assign weights to each feature. The relative importance of each feature was determined through comparative analysis. Electricity, as a modern low-carbon energy source, was assigned a greater weight. Since the use of coal would emit many harmful gases, a lower weight value was given to coal. After determining the weights of each feature, several indicators were selected for TOPSIS evaluation[6]. These indicators included the consumption of various types of fuel, the degree of energy consumption, and the decarbonization index of the energy consumption structure. These indicators were all factors that must be considered when evaluating the low-carbon situation of a region. The calculation of the decarbonization index considered factors such as the consumption of various types of fuel and the energy consumption structure. After establishing this low-carbon situation evaluation system based on AHP-TOPSIS, this study also combined the ARIMA model. Through the ARIMA model, the decarbonization index of each city in the coming years was predicted.

Low-Carbon Optimization Strategies. This paper not only predicted the trend of carbon emission in different places and evaluated the amount of carbon emission but also proposed a low carbon optimization strategy. First, the evaluation indicators of each city were clustered based on the K-means[7] clustering method, and the cities were divided into two major categories: high-carbon and low-carbon. To visualize the results, PCA[8] was used to downscale the raw data, and three principal components were extracted for subsequent visualization operations. For each cluster type, several cities with low evaluation scores were selected for intervention treatments to reduce local carbon emissions. The methodology used is shown in formula 1:

$$S = -\sum(\alpha + \beta) \cdot \omega + \sum \gamma \cdot \omega + \sum \theta \cdot x - \sum(\rho + \sigma) \cdot x \quad (1)$$

S represents the current net benefit of urban energy use (the difference between the energy produced by an energy source and the cost of consuming that energy source). ω is the amount of old resources used. α is the price of old resources. β is a hazard from the depletion of old resources (such as harmful gases). γ is the energy produced by the old resource unit. x , ρ , σ , and θ are the amount of the new resource used, the price, the hazards and the energy produced per unit, respectively. Information on the amount and value of each resource used needed to be determined according to the financial situation of the local government. This was because different cities had different resource profiles and financial capabilities, and these factors needed to be considered to develop a more reasonable optimization strategy. In this paper, the optimization of the model was achieved based on a genetic algorithm to achieve the maximum S-value and promoted the local low carbon level.

3 Results & Discussion

3.1 Results

The following Table 1 gives an Analytic Hierarchy Process Matrix

Table 1. Analytic Hierarchy Process Matrix

indicator	Wind energy	electrical energy	nuclear energy	crude oil	coal
Wind energy	1	0.5	0.25	0.167	0.125
electrical energy	2	1	0.5	0.25	0.167
nuclear energy	4	2	1	0.167	0.125
crude oil	6	4	6	1	0.5
coal	8	6	6	2	1

The weights of each indicator are shown in Table 2:

Table 2. Weights of indicators

Hierarchical analysis results				
term	eigenvector	weights(%)	Maximum characteristic root	CI-value
Wind energy	0.212	4.245		
electrical energy	0.358	7.156		
nuclear energy	0.514	10.277	5.275	0.069
crude oil	1.503	30.058		
coal	2.413	48.264		

Table 3 indicates that the given matrix passes the consistency test.

Table 3. Results of the consistency test

Maximum characteristic root	CI-value	RI-value	CR-value	Results of consistency tests
5.275	0.069	1.11	0.062	Passed

Table 4 shows the results of predicting the test set with the ARIMA model and the control group model, and the results include RMSE, MAE, and R-squared values.

Table 4. Prediction results of ARIMA and control group model

	ARIMA	LSTM	BP	RNN
RMSE	**241.53±65.41**	1083.94±247.16	543.47±146.37	344.81±102.34
MAE	**131.33±43.31**	496.81±179.66	273.46±89.69	176.96±76.39
R-Squared	**0.83±0.09**	0.42±0.15	0.53±0.13	0.69±0.17

Based on the K-means clustering method, the evaluation indexes of each city were clustered and divided into two major categories: high-carbon cities and low-carbon cities. To visualize the results, this paper adopted Principal Component Analysis to downscale the original data and extracted three principal components for subsequent visualization. The visualization results are shown in Figure 1.

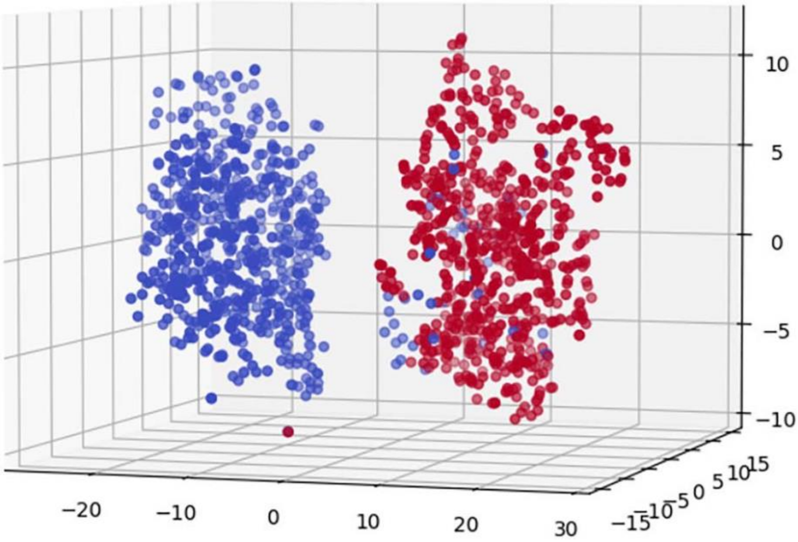

Fig. 1. Visualization results

3.2 Discussion

The ARIMA model accurately predicts trends in energy consumption, with results indicating a shift towards cleaner energy use. The AHP-TOPSIS assessment quantified regional low-carbon development, revealing significant differences between regions. For example, the weighting of coal in the low carbon score was as high as 48.264%, suggesting that certain regions were heavily dependent on high-carbon energy sources and required policy intervention to decarbonize. Regions with low-carbon scores needed to prioritize the transition to renewable energy sources such as wind and solar, which had a lower carbon output. In contrast, regions with advanced low-carbon infrastructure could focus on optimizing existing sustainable practices. When discussing impacts on carbon neutrality, differences in energy consumption trends across regions informed strategic planning. Regions with projected increased in energy demand may need to step up investments in renewable energy to prevent a corresponding increase in carbon emissions, while regions with declining energy use could serve as models of low-carbon efficiency. In addition, categorizing cities into high-carbon and low-carbon categories based on scores could guide targeted measures. High-carbon cities could benefit from optimizing their energy mix and improving efficiency, while low-carbon cities could focus on maintaining their position through improved green technologies.

4 Conclusions

First, this paper used energy consumption data from 2003 to 2020 as a way to observe the trend of energy consumption, which provided essential data support for the development of carbon neutrality pathway planning. Secondly, the ARIMA model was used for prediction. The ARIMA model could accurately predict the future energy consumption structure, which helped us to understand the changing trend of energy consumption in the future. After that, a low-carbon scoring system was constructed through the AHP-TOPSIS method to quantify the weights of each factor and made a comprehensive score, which gave a scientific and objective way of evaluating the low-carbon situation. Finally, based on the prediction model and evaluation system, a series of low-carbon optimization strategies were proposed, such as improving energy efficiency, promoting clean energy, optimizing energy structure, and so on. It proposes a concrete action plan for achieving China's carbon neutrality goal. Overall, the model of the paper has the advantages of high accuracy, flexibility, objectivity, and practicality. Based on the prediction model and evaluation system, the proposed optimization strategies are specific and feasible, which helps achieve China's goal of carbon neutrality.

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