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Research on the Factors Affecting Carbon Emissions Based on Multivariate Regression Models

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Abstract: Carbon peak and carbon neutrality are two new terms that are being mentioned more frequently, and the measurement of carbon emissions has become an important research topic. Based on relevant data, this paper studies the relationship and evolution law of the driving factors of carbon emissions from energy structure and industrial structure as well as the result factors of carbon emissions from energy consumption, and then establishes corresponding mathematical models. The driving factors, result factors, and relationship attributes that are difficult to measure in the carbon emissions from energy structure and industrial structure are analyzed to fathom the evolution law of carbon emissions and absorption. Based on the results, phased and global suggestions for carbon neutrality have been suggested, taking into account the characteristics of different industries and regions.

Keywords: Carbon emissions; Energy structure; Industrial structure; Multivariate regression model

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1. Introduction

In recent years, with the industrialization in China, carbon emissions are increasing. China contributes 39% while consuming 70% energy, resulting in 80% of carbon emissions, of which fossil energy consumption accounts for 70%. Therefore, at the 75th United Nations Conference, it was emphasized that China will strive to hit carbon peak by 2030 and attain carbon neutrality by 2060. The goal of carbon neutrality is to minimize or even offset carbon emissions through natural processes and man-made means, thus ultimately achieving zero carbon emissions. Hitting carbon peaks and attaining carbon neutrality are being mentioned more frequently, and the measurement of carbon emissions has become an important research topic. Therefore, in China, where carbon consumption is high, optimizing structural industries through energy supply, consumption, and anthropogenic carbon sequestration has become an important issue to be considered to fulfill the ideal goal.

2. Research methods

In regard to the factors affecting carbon emissions, this study quantitatively analyzes the relationship and evolution law of the driving factors of carbon emissions from energy structure and industrial structure as well as the result factors of carbon emissions from energy consumption, and then establishes corresponding mathematical models. The driving factors, result factors, and relationship attributes that are difficult to measure in the carbon emissions from energy structure and industrial structure are analyzed to fathom the evolution law of carbon emissions and absorption. Based on the results and the characteristics of different industries and regions, phased and overall recommendations for carbon neutrality have been suggested.

Through the official data of the National Statistical Yearbook, three main driving factors affecting carbon emissions from our energy structure and industrial structure have been determined: the number of China's social population, N; China's gross domestic product (GDP), G; the number of effective patents published in China, L. Amid the energy structure and industrial structure, the main sources of carbon emissions are primary energy, secondary energy, and energy consumption in major industries.

A series of data information regarding the components of energy structure and industrial structure that can generate carbon emissions, the factors that can contribute to or influence their carbon emissions, and the carbon emissions of energy consumption generated from these driving factors are collected. By organizing the data, the measurable main driving factors are transferred into MATLAB, and the images of the relationship between the main driving factors and the energy and industrial structures are formed, respectively. The statistical analysis software SPSS (Statistical Product and Service Solutions) is used to build a series of corresponding multivariate linear regression models [1] and derive the corresponding evolution law equations. For those factors that are difficult to measure and are unpredictable, the approximate results and relational attributes are sorted out, and the influence and evolution law of carbon emissions and carbon absorption are analyzed.

3. Establishing research models based on multivariate regression models for factors affecting carbon emissions

Firstly, the three main driving factors affecting carbon emissions are analyzed [2]: the number of China's social population, N; China's gross domestic product (GDP), G; and the number of effective patents published in China, L. In accordance with the data of the National Statistical Yearbook, the data of N, G, and L each year from 2010 to 2020, and the annual primary energy consumption, secondary energy consumption, as well as industrial consumption from 2010 to 2020 are sorted out to acquire the formula for energy carbon emission [3].

$$\mathrm{M} = \Sigma(\mathrm{F} \cdot \mathrm{R} \cdot \mathrm{C}) \tag{1}$$

M refers to the carbon emissions from energy consumption, F denotes the energy emission factor, and C represents the energy consumption. From that, the annual primary energy consumption carbon emissions, secondary energy consumption carbon emissions, and industrial structure consumption carbon emissions from 2010 to 2020 can be obtained.

3.1. Data fitting and establishing a mathematical model for primary energy consumption carbon emissions

According to the 10-year primary energy consumption carbon emission data, a mathematical model of primary energy consumption carbon emissions is fitted using SPSS [4-9], as shown in **Table 1** and **Table 2**.

Table 1. Data fitting of primary energy consumption carbon emissions

Model abstract[b]					
Model	**R**	**R^2**	**Adjusted R-square**	**Error in standard estimation**	**Durbin-Watson**
1	.999[a]	.999	.998	130.1111186	2.066

Note: [a]Predictor variables: (constant), number of effective invention patents (pcs), number of people (10,000), GDP (100 million); [b]Dependent variable: carbon emissions from primary energy consumption

Table 2. Coefficient fitting of the mathematical model of carbon emissions from primary energy consumption

Coefficient[a]					
Model 1	**Unstandardized coefficients, B**	**Standard error**	**Standardized coefficients, Beta**	***t***	**Significance**
(Constant)	-88754.606	20740.911		-4.279	.004
Number of people (10,000)	.787	.159	.611	4.958	.002
GDP (100 million yuan)	.022	.002	1.526	9.957	.000
Number of effective invention patents (pcs)	-.008	.001	-1.151	-9.151	.000

Note: [a]Dependent variable: carbon emissions from primary energy consumption

The meanings and explanations of the parameters in **Table 1** and **Table 2** are as follows: $R^2 = 0.999$ means that N, G, and L can explain 99.9% of the variation of C1; N refers to the number of social population; G refers to China's gross domestic product (GDP); L refers to the driving role of China's scientific and social development level; Durbin-Watson ≈ 2 means that the samples are independent of each other among the variables; a significance of less than 0.05 means that the change of the variable significantly affects the change of the dependent variable.

Based on the above analysis, the fitting formula of carbon emissions from primary energy consumption can be obtained as follows:

$$C_1 = 0.787N + 0.022G - 0.008L - 88754.606 \tag{2}$$

3.2. Data fitting and establishing a mathematical model for secondary energy consumption carbon emissions

According to the 10-year secondary energy consumption carbon emissions data, a mathematical model of carbon emissions from secondary energy consumption is fitted using SPSS [4-9], as shown in **Table 3** and **Table 4**.

Table 3. Data fitting of secondary energy consumption carbon emissions

Model abstract[b]					
Model	**R**	**R^2**	**Adjusted R-square**	**Error in standard estimation**	**Durbin-Watson**
1	.994[a]	.989	.984	167.3742428	2.696

Note: [a]Predictor variables: (constant), number of effective invention patents (pcs), number of people (10,000), GDP (100 million); [b]Dependent variable: carbon emissions from secondary energy consumption

Table 4. Coefficient fitting of the mathematical model of carbon emissions from secondary energy consumption

Coefficient[a]					
Model 1	**Unstandardized coefficients, B**	**Standard error**	**Standardized coefficients, Beta**	***t***	**Significance**
(Constant)	-102299.980	26680.996		-3.834	.006
Number of people (10,000)	.798	.204	1.360	3.909	.006
GDP (100 million yuan)	.008	.003	1.154	2.666	.032
Number of effective invention patents (pcs)	-.005	.001	-1.542	-4.345	.003

Similar to the previous section, the fitting formula of carbon emissions from secondary energy consumption is as follows:

$$C_2 = 0.798N + 0.008G - 0.005L - 102299.98 \tag{3}$$

3.3. Data fitting and establishing a mathematical model for industrial structure consumption carbon emissions

According to the 10-year industrial energy consumption carbon emission data, a mathematical model of carbon emissions from industrial energy consumption is fitted using SPSS [4-9], as shown in **Table 5** and **Table 6**.

Table 5. Data fitting of industrial energy consumption carbon emissions

Model abstract[b]					
Model	**R**	**R^2**	**Adjusted R-square**	**Error in standard estimation**	**Durbin-Watson**
1	.984[a]	.967	.953	912.9892017	2.165

Note: [a]Predictor variables: (constant), number of effective invention patents (pcs), number of people (10,000), GDP (100 million); [b]Dependent variable: carbon emissions from industrial structure energy consumption

Table 6. Coefficient fitting of the mathematical model of carbon emissions from secondary energy consumption

Coefficient[a]					
Model 1	**Unstandardized coefficients, B**	**Standard error**	**Standardized coefficients, Beta**	***t***	**Significance**
(Constant)	-285143.614	145538.890		-1.959	.091
Number of people (10,000)	2.237	1.113	1.203	2.010	.084
GDP (100 million yuan)	.026	.015	1.251	1.681	.137
Number of effective invention patents (pcs)	-.015	.006	-1.492	-2.443	.045

Note: [a]Dependent variable: carbon emissions from industrial structure energy consumption

Similar to the previous section, the fitting formula of carbon emissions from industrial energy consumption is as follows:

$$C_{ind} = 2.237N + 0.026G - 0.015L - 285143.614 \quad (4)$$

Based on the three fitting formulas obtained, the corresponding C_1, C_2, and C_{ind} data are obtained. MATLAB is used to visualize the data to obtain the fitting curve, as shown in **Figure 1**.

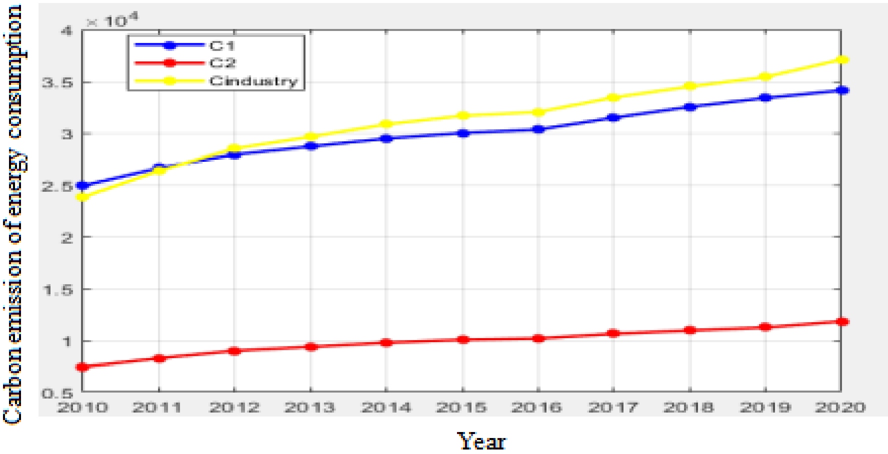

Figure 1. Visual fitting curve graph of C_1, C_2, and C_{ind}

From the fitted curve, it can be appreciated that the three dependent variables C_1, C_2, and C_{ind}; namely, the carbon emissions from energy consumption, all show a slow upward trend. The carbon emissions from primary energy consumption, C_1, are similar to those from industrial structure energy consumption C_{ind}. In recent years, the carbon emissions from industrial structure energy consumption have caught up with those from primary energy consumption, indicating that China's industrial production has developed rapidly, and it is positively related to the carbon emissions generated by primary energy consumption. The carbon emissions from secondary energy consumption are significantly lower than those from primary energy consumption and industrial structure energy consumption; however, the carbon emissions from secondary energy consumption are still rising slowly. This demonstrates that China's secondary energy consumption is developing, and energy utilization is progressing with social development. Based on the three mathematical models, an equation of energy consumption and carbon emissions is obtained by using MATLAB superposition fitting. The data of each year corresponding to the equation and the year are fitted again using MATLAB to obtain a quadratic equation of one variable. The mathematical model of carbon emissions is obtained by fitting.

$$M = -76.85T^2 + 312105.30T - 316802866 \ \text{(T refers to the year)} \quad (5)$$

It is predicted that by 2030, China's carbon emissions will hit a peak at 79,756.76 million tons, and by 2063, its emissions and carbon absorption will reach a balance – carbon neutrality.

4. Conclusion

The goal of China's carbon peak is to hit the peak of total carbon emissions by reducing carbon emission intensity. On the one hand, energy intensity must be reduced, while on the other hand, industrial structure and energy structure must be adjusted. In order to achieve carbon neutrality, there are generally two methods: (1) remove greenhouse gases through special means; (2) use renewable energy to reduce carbon emissions. Improving the integration of industrial structure and employment structure is conducive to the rational and adequate allocation of resources, reducing losses in the production process, improving energy efficiency, as well as reducing the energy consumption of a single product in the same resource field.

According to the Porter hypothesis, environmental regulation can motivate enterprises to further optimize the efficiency of resource allocation and improve the technical level, thereby stimulating the effect of "innovation compensation" [10]. Meanwhile, efforts and modest adjustments should be made to establish an environmental adjustment mechanism for industrial structures.

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Disclosure statement

The author declares no conflict of interest.

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