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Evaluation of Influencing Factors of China's Energy Consumption and Carbon Emissions

Yunqing Ji[1,2], Zhonglin Sheng[3*], Jiongming Zhang[1], Xiaoliang Li[2]
[1] School of Metallurgical & Ecological Engineering, University of Science & Technology Beijing, Beijing, China
[2]Chinese Academy of Environmental Planning, Ministry of Ecological Environment, Beijing, China
[3]School of Economics & Management, University of Science & Technology Beijing, Beijing, China
*Corresponding Author.

Abstract:

Energy systems are the largest source of carbon emissions in a country or region. As the reform started, Chinese increasing economic growth has also brought about a vigorous increase in energy consumption and total carbon emissions. As a developing country, Chinese government has always acted the important part of a responsible major country, and has carried out fruitful work in promoting international emission reduction cooperation and controlling domestic emission intensity. This paper wants to figure out that industrial energy activities are the main source of emissions in the energy system. Hence, studying the carbon emissions caused by industrial combustion of energy is of great significance for using to formulate policies to reduce emissions policies. The conclusions indicate that the growth of total economic output, low energy utilization efficiency and coal-based energy consumption structure are the primary reasons for the substantial growth in carbon emissions in China. Accelerating technological progress, adjusting industrial and energy structure, and developing clean energy power generation to improve energy utilization efficiency and transform energy consumption structure can effectively reduce industrial carbon emissions.

Keywords*: Carbon emission, Energy consumption.*

I. INTRODUCTION

The influencing factors of Chinese CO_2 emissions are mainly which has to do with primary energy consumption structure, industrial structure and technical management level of energy consumption. Lots of researchers have done relevant research on the relationship between domestic energy consumption and carbon emissions. Zhang Lei [1], through the comparison of the long-term development of developed and developing countries, believed that the diversification of economic structure and the diversification of energy consumption structure will lead to national development. In the transition from high-carbon fuels to low-carbon fuels, slow primary energy consumption structure changes are the key to effectively controlling the growth of regional carbon emissions; Wang Zhongying and Wang Limao [2] thought that the economic growth mode that relied too much on investment and industry-based economic growth. The economic structure of China is to a large extent the main reason for the increase of greenhouse gas

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emissions; Jiang Yihong and Wang Zheng [3] believed that the indirect impact of technological progress and human capital could bring about the reduction of CO_2 emissions.

The existing evaluation methods are mostly AHP, fuzzy evaluation and factor analysis, but these methods are too subjective to determine the weight or the calculation process is too complicated. Catastrophe theory [4-5] mainly studies potential functions and classifies critical points according to potential functions. It does not involve any special intrinsic mechanism when dealing with discontinuous features, which makes it particularly suitable for studying systems whose internal effects are not known. Because this method takes into consideration the relative importance of each evaluation index, and combines qualitative and quantitative, so as to reduce subjectivity without losing rationality, and the calculation is simple and serious [6].

During the "Tenth Five-Year Plan" period and the first two years of the "Eleventh Five-Year Plan" plan, there was a slight decrease, mainly due to the growth in the proportion of carbon energy consumption in the primary energy consumption structure. Compared with the “10th Five-Year Plan” period, the overall CO_2 emission reduction in the first two years of the “11th Five-Year Plan” also showed a slight downward trend. Although the energy consumption technology management level has increased significantly in the first two years of the “11th Five-Year Plan” plan However, the reliance on carbon energy consumption in the primary energy consumption structure has been further strengthened, and the proportion of industry in the industrial structure has also increased compared with the "10th Five-Year Plan" period.

II. MATERIALS AND METHODS

2.1 Materials and Methodology

The elementary catastrophe theory has 7 basic models. The most common catastrophe system types are the cusp catastrophe system, the swallowtail catastrophe system, the butterfly catastrophe system, and the potential functions of the three catastrophe system models are:

Cusp catastrophe system model [7] ： $\mathrm{f(x)} = \mathrm{x}^4 + a\mathrm{x}^2 + bx$

Swallowtail catastrophe system model： $\mathrm{f(x)} = \frac{1}{5}\mathrm{x}^5 + \frac{1}{3}\,a\mathrm{x}^3 + \frac{1}{2}b\mathrm{x}^2 + cx$

Butterfly mutation system model： $\mathrm{f(x)} = \frac{1}{6}\mathrm{x}^6 + \frac{1}{4}\,a\mathrm{x}^4 + \frac{1}{3}b\mathrm{x}^3 + \frac{1}{2}cx^2 + \mathrm{dx}$

The catastrophe progression method is based on catastrophe theory, and the total evaluation index is divided into multiple levels of primary and secondary contradictory decomposition or grouping, arranging into a tree-like target hierarchy and gradually decomposed from the overall evaluation index to the next sub-index. Therefore, the control variables of a state variable of a common catastrophe system are not more than 4, and accordingly, the number of indicators at each level is generally not more than 4. In the above model, x is a state variable in the catastrophe system, f(x) is the potential function of the state

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variable x, and a, b, c, and d are all control variables of the state variable. The primary control variables were written at the front, and the secondary variable is behind. If an indicator can be decomposed into 2 sub-indicators, the system can be regarded as a cusp catastrophe system; similarly, if it can be decomposed into 3 sub-indicators or 4 sub-indicators, the system can be regarded as a swallowtail catastrophe system or a butterfly catastrophe system [8].

The normalization formula can be derived from the divergent set equation of the catastrophe system model. The normalization formula unifies the control variable into the mass state represented by the state variable. The bifurcation point set equation indicates that when the control variables satisfy this equation, the system will mutate. For example, for the cusp catastrophe system, its phase space is three-dimensional, and f'(x)=0, that is, the equilibrium surface V is given by 4x^3+2ax+b=0, and the singularity set satisfies the equation 12x^2+ A subset of V where 2a=0. Eliminate x from the two equations, get $8a^3+27b^3=0$, find the set of bifurcation points, and its decomposition form is:

$a=-6x^2$， $b=8x^3$. Transformed into a mutation fuzzy membership function, the following normalization formula can be obtained:

$$x_a = a^{1/2}，\ x_b = b^{1/3} \tag{1}$$

In the formula, x_a represents the x value corresponding to a; $x_b$represents the x value according to b. To be similar, the decomposition form of the swallowtail catastrophe system is: $a=-6x^2$, $b=8x^3$, $c=-3x^4$; its normalization formula is:

$$x_a = a^{1/2}，\ x_b = b^{1/3}，\ x_c = c^{1/4} \tag{2}$$

The decomposition form of the butterfly mutation system is:a=-10x2，b=20x3，c=-15 x4，d= 4x5，its normalization formula is：

$$x_a = a^{1/2}，\ x_b = b^{1/3}，\ x_c = c^{1/4}，\ x_d = d^{1/5} \tag{3}$$

Using the normalized formula for comprehensive evaluation, the calculated value of each control variable corresponds to a state variable can be based on three different evaluation criteria: (1) Non-complementary criterion: if the functions of the control variables of the system cannot be replaced with each other, take the value according to the principle of “large, middle and small”; (2) Complementary criterion: if the control variables of the system make up for the opponent's shortcomings, take the value according to their mean value; (3) Complementary principle over threshold: all control variables A certain threshold must be reached to complement each other.

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2.2 Selection of Evaluation Indicators

Primary energy consumption structure, industrial structure and technical management level of energy consumption are the main factors affecting CO_2 emission reduction in China. Therefore, reducing the proportion of humidity in the industry and increasing the proportion of the tertiary industry to adjust the industrial structure will also help to reduce carbon emissions. The improvement of the technical management level of energy consumption depends on the improvement of energy itself. On the other hand, since the overall labor productivity is a comprehensive performance of the industry's production technology level, management level, employees' technical proficiency and labor enthusiasm, the labor productivity growth of the three industries reflects the improvement of energy use efficiency.

The mutation series method is used to evaluate specific indicators. Among the indicators of the same attribute and the same level, the relatively important indicators are ranked in the front, and the relatively minor indicators are ranked in the back. Since the entropy method is a relatively accurate method of objective weight [10], in order to overcome the subjectivity of sorting, the weight of each index can be calculated according to the entropy method to sort them, so as to ensure the ordering of each index. and corresponding importance. The entropy value method is used to determine the weight calculation formula of each indicator as follows, where Zij represents the i-th sample of the j-th indicator, which are all standardized data. Firstly, proportion t_{ij} of the i-th sample of the j-th indicator:

$$t_{ij} = Zij/\sum_{i=1}^{m} zij \quad (i= 1,2,\dots,m;\ j = 1,2,\dots,n) \tag{4}$$

Secondly, the entropy value ej of the j-th index:

$$e_j=-\frac{1}{\ln(m)}\sum_{i=1}^{m} tij\, lntij \quad (j=1,2,\dots,n) \tag{5}$$

Finally, calculate the utility value of the indicator dj=1-ej, and the weight of the j-th indicator is:

$$W_j=d_j/\sum_{j=1}^{n} dj \tag{6}$$

For the evaluation index of the multi-layer structure, according to the additivity of entropy, the utility value of the index of the lower structure is summed to obtain the utility value of various indexes of the upper layer, which is denoted as D_k (k=1,2,…,s), we get The weight of the corresponding upper-level indicator:

$$Tk = Dk /\sum_{k=1}^{s} Dk \tag{7}$$

According to the data from 1991 to 2014 in the “China Statistical Yearbook 2014”, the ranking of

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indicators at all levels is as follows: first-level indicators (M1, M3, M2); second-level indicators (Z3, Z4, Z1, Z2); (Z8, Z7)); (Z6, Z5).

2.3 Factor Decomposition of Carbon Emission from Industrial Energy Activities

Index decomposition analysis is a widely accepted method in international energy and environmental policy formulation [11]. We can divide different decomposition ways into three categories: Laspeyres exponential mean, simple average decomposition mean, and adaptive weight decomposition mean.

E. Laspeyres of Germany propose the Laspeyres index in 1864. It is a weighted comprehensive index with the quantitative index of the base period as the weight, and the same measurement factors are fixed in the base period. In specific applications, if the contribution of a certain variable factor needs to be examined, it is only necessary to keep other variables unchanged. At the same time, researchers also used this method to do research on the energy consumption of the United States and some other OECD (Organization for Economic Cooperation and Development) countries [12]. Later, some scholars in developing countries applied the Laspeyres index method to study energy problems [13].

The simple average decomposition method generally uses a certain average value of the corresponding parameters of the first year and the last year as the factor weight, and can be divided into many types according to the different methods of calculating the average value. The decomposition method [14] uses the average value of the energy consumption in the first and last years as the weight, and uses the logarithmic way to calculate the increment of the corresponding factor. This way is most widely used, although computational problems arise when there exist zeros in the data; the decomposition method proposed. On this basis, the Logarithmic Mean Weight Division Index method (LMDI) is proposed. He uses a logarithmic mean formula:

$$\mathrm{L}(E_{i,\ T},\ E_{i,\ 0}) = (E_{i,\ T} - E_{i,\ 0}) / \ln(E_{i,\ T} \,/\, E_{i,\ 0}) \tag{8}$$

Replaces the simple arithmetic mean weights of his last proposed forms. The favor of this mothed is that does not generate residual values and allows zeros in the data, and he used this method to conduct empirical analysis on three countries including China; Korean scholars Chung and Rhee [15]proposed an average growth rate The rate index method (mean rate-of-change index (MRCI)), their method of determining the weight is to introduce the average value of the average increasing rate of all coefficients as an essential part of the weight factor, allowing a free residual value, and important The difference with the LMDI method is that the data can have negative values. They believe that this method is more scientific and reasonable than the method proposed. It's just that the input-output coefficient is introduced into his carbon emission calculation formula. According to the different ideas of the Laspeyres index method and the above four SAD methods, we can express the energy consumption increment caused by all the output value, industrial structure and energy consumption intensity as the form of the following table.

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TABLE I. Expressions of different decomposition methods

METHODS	**OUTPUT VARIABLE / ΔE_{pdn}**	**STRUCTURE VARIABLE / ΔE_{str}**	**INTENSITY VARIABLE / ΔE_{int}**
LASPEYRES	$\sum_i Y_T S_{i,0} I_{i,0} - E_0$	$\sum_i Y_0 S_{i,T} I_{i,0} - E_0$	$\sum_i Y_0 S_{i,0} I_{i,T} - E_0$
SAD1	$0.5\sum_i (E_{i,T} + E_{i,0}) \ln (Y_T / Y_0)$	$0.5\sum_i (E_{i,T}+E_{i,0}) \ln (S_{i,T}/S_{i,0})$	$0.5\sum_i (E_{i,T} + E_{i,0}) \ln (I_{i,T} / I_{i,0})$
SAD2	$0.5(I_0 + I_T)(Y_T - Y_0)$	$0.5\sum_i (I_{i,0}Y_0 + I_{i,T}Y_T)(S_{i,T} - S_{i,0})$	$0.5\sum_i (S_{i,0}Y_0 + S_{i,T}Y_T)(I_{i,T} - I_{i,}$
LMDI	$\sum_i L(E_{i,T}, E_{i,0}) \ln (Y_T / Y_0)$	$\sum_i L(E_{i,T}, E_{i,0}) \ln (S_{i,T} / S_{i,0})$	$\sum_i L(E_{i,T}, E_{i,0}) \ln (I_{i,T} / I_{i,0})$
MIRCI	$\sum_{ij} M_{ij}(*)(1/\bar{y})(y_t - y_0)$	$\sum_{ij} M_{ij}(*)(1/\bar{S_j})(S_{i,T} - S_{i,0})$	$\sum_{ij} M_{ij}(*)(1/\bar{I_j})(I_{i,T} - I_{i,0})$

III. RESULTS

After the indicators at all levels are sorted, the original data from 1991 to 2014re converted into mutation fuzzy membership function values [16]. For the positive index, the bigger the better, the maximum value in the sample is used as the benchmark, and the mutation fuzzy membership function value is taken as 1.0; for the reverse index, the smaller the better, the minimum value in the sample is used as the benchmark, and the mutation fuzzy membership function value is taken as 1.0. The degree function value is acted as 1.0, and the mutation fuzzy membership function value of each evaluation index from 1991 to 2014 shown in TABLE II.

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TABLE II Factor decomposition of the carbon emission increment caused by China's industrial combustion of energy from 1992 to 2014 (%)

	TOTAL ENERGY CONSUMPTION	ENERGY STRUCTURE	TECHNOLOGY	MIDDLE PUT-IN	OUTPUT VALUE STRUCTURE	TOTAL PRODUCTION
1992-1997	34.09	-3.30	5.28	-65.93	-30.77	60.63
1997-2002	7.43	0.24	-13.74	-86.26	7.54	84.79
2002-2007	35.96	1.07	13.10	-100.00	2.84	47.03
2007-2014	45.78	2.03	14.02	-90.63	0.48	28.32

Similarly, the evaluation results of CO_2 emission reduction in other years can be computed in turn, as shown in the following table. [17]

From the three influencing factors of primary structure of energy consumption, energy technology management level and industrial structure, primary energy consumption structure plays a leading role in CO_2 emission reduction. This requires further strengthening the development and utilization of new energy, increasing the proportion of clean energy in the energy consumption structure, and reducing the use of conventional carbon energy [18]. From 1991 to 2007, Chinese energy processing and conversion efficiency and production management showed an obvious upward trend, indicating that technological progress has played an obvious direct and indirect role in the use of carbon energy. From the aspect of industrial structure, combining the two tables, the CO_2 emission reduction in the industrial structure in 2007-2014 showed a downward trend, and in 2002-2007, the CO_2 emission reduction increased slightly. The proportion of the tertiary industry has gone up [19], and the proportion of the tertiary industry has decreased. In 2007-2014, the proportion of the tertiary industry has increased, and the proportion of the industry has decreased, reflecting that the industrial structure adjustment will also play a certain role in promoting CO_2 emission reduction.

IV CONCLUSION

First, fluctuations in the economic growth cycle and the increase in industrial production are the major reasons for the prompt increase in emissions of carbon. From 1992 to 2005, the increment of carbon emissions caused by industrial combustion of energy in China increased rapidly, especially from 2002 to 2005. In 1992, Chinese industrial combustion energy emitted a total of 494 million t/c. It increased by 639 million t/c between 1992-2005, reaching 1.132 billion t/c in 2005. In terms of time period, the increase was

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the largest between 2002 and 2005, and the increase in only 3 years accounted for 2/3 of the total increase in 13 years.

Second, the insignificant increase in energy efficiency is a key factor in the increase in carbon emissions. If the total energy consumption also increases with the increase of the total production, it indicates that the energy consumption per unit of output value does not decrease significantly. Although the comparable energy consumption per unit of GDP in China dropped from 4.05t standard coal/10,000 yuan GDP in 1992 to 2.44t standard coal/10,000 yuan GDP in 2014, the increase in total energy consumption is still the direct cause of the increase in carbon emissions. This reflects Chinese basic national conditions of using coal as the main energy source, and also reflects the low efficiency of China's energy utilization.

Third, the overall lack of improvement in the overall energy structure is the fundamental reason for the rapid growth of carbon emissions. Because the carbon emission coefficients of various energy sources vary greatly, especially the carbon emission coefficients of cleaner energy such as hydropower, nuclear power, wind energy, and biomass energy are almost zero. Therefore, a radical change in the energy structure can fundamentally change the total carbon emissions of a country or region.

However, the change in the amount of intermediate inputs has an obvious inhibitory effect on carbon emission reduction. It may be manifested in the change of intermediate input structure and total input, which cannot be distinguished here due to the limitation of the formula itself and data.

In a word, the growth of total economic output, low energy utilization efficiency and coal-based energy consumption structure are the major reasons for the rapid increase in carbon emissions in China. However, changes in technology (proportion of intermediate inputs), industry output value structure, energy structure and other factors have little effect on carbon emission reduction. Therefore, accelerating technological progress, adjusting industrial structure and energy structure, and developing clean energy power generation to improve energy utilization efficiency and transform energy consumption structure can effectively reduce industrial carbon emissions. This is consistent with the conclusion of the aforementioned evaluation of the impact factors of energy consumption and carbon emissions.

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