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Original Research

Cluster Analysis of CO_2 Emissions by the Chinese Power Industry

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Abstract

The power industry is a major fossil fuel consumer in China, with large amounts of CO_2 emissions released from the production process of the power industry. To decrease CO_2 emissions, it is practical to start by analyzing its influencing factors in the power industry. This paper identified five influencing factors of CO_2 emissions through the extended STIRPAT model, including GDP, urbanization level, electric power structure, industrialization level, and power-consumption efficiency. According to the projection pursuit model, 30 provinces in China were divided into 4 categories based on the average of all the best projection values. Results indicate that there were positive correlations between the five influencing factors and CO_2 emissions – especially per capita GDP, power-consumption efficiency, and urbanization level. The impact of industrialization level and electric power structure on CO_2 emissions fluctuated greatly. The regional features of the each type were analyzed and policy implications proposed.

Keywords: CO_2 emissions, influencing factors, STIRPAT model, projection pursuit model, power industry

Introduction

Climate change has drawn widespread concern all over the world, and it remains one of the most complex challenges. China is in a crucial period of rapid development of urbanization and industrialization. The power industry is a major industry in China. With the rapid development of China's economy, the power industry is growing, and the production and consumption of electricity are also increasing. The power generation industry, which is dominated by thermal power generation, is also expanding its scale and increasing the output of electricity, which means that there will be more CO_2 emissions. Therefore, in order to complete China's energy-saving emission reduction targets, we should pay more attention to the CO_2 emissions reduction of the power industry in China. Recently there has been extensive research on CO_2 emissions. These studies are mainly focused on the following two aspects: on the one hand, some scholars from the perspective of influencing factors studied and analyzed CO_2 emissions in China. On the other hand, other scholars have studied CO_2 emissions from the perspective of regional differences.

Muangthai [1] decomposed the CO_2 emissions from power industry in Thailand into the level of economic growth, power intensity, CO_2 emissions coefficient, and

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fuel intensity. Moutinho et al. [2] introduced renewable energy consumption into the study and proposed that energy integration was one of the major drivers of reducing CO_2 emissions. Furthermore, Can and Gozgor [3] pointed out that the industrial structure had a significant contribution to CO_2 emissions in France. Liu [4] studied the basic trend of carbon intensity change in the power industry. Employing the exponential decomposition method, combined with the relevant carbon intensity factor decomposition technology, the carbon intensity of the power industry was decomposed into energy carbon emission coefficient, power generation structure, power generation intensity, power generation ratio, power consumption intensity, and industrial structure. The results showed that the power consumption intensity was the dominant factor affecting the carbon intensity change in the power industry, and the decline of carbon intensity in power industry was the result of the interaction of various factors. Zhu [5] pointed out that electricity consumption was the main factor leading to the growth of China's power system CO_2 emissions from 2007 to 2012, resulting in a positive contribution of about 96% of carbon dioxide emissions, while the negative contribution of CO_2 emissions increments in China's power system were mainly from the power generation technology and thermal power factor during this period. Zhang [6] found the factors affecting the change of CO_2 emissions in power production through introducing the status of carbon emissions in power production, namely emission factors, energy structure, power structure, economic scale, industrial structure, living consumption, population size, and so on. And it was proposed to reduce carbon emissions by reducing energy consumption and energy waste.

Wang et al. [7] analyzed the factors influencing energy carbon emissions in Xinjing in 1997 from the regional perspective based on the input-output theory and structure decomposition (SDA) model. The results showed that from 1997 to 2007, energy-related carbon emissions of Xinjiang increased from 20.7 million tons to 40.34 million tons, showing an overall increase of 94.88% over 11 years. And per capita GDP, final demand structure, production structure, and population size change were the main factors leading to carbon growth, while carbon intensity was a factor curbing carbon emissions. Economic and population growth was not matched by optimization in economic structure and improvements in production techniques, leading to the rapid growth of carbon emissions in Xinjiang. Employing the logarithmic mean differentiation index (LMDI) based on the extended Kaya identity, Wang et al. [8] discussed the main driving factors of economic and energy-related carbon emissions from the regional perspective in Guangdong Province from 1990 to 2014. The results showed that the impacts of various factors were different at different development stages. Dietz and Rosz [9] constructed the STIRPAT model, which was the random form of the IPAT equation, and tried to introduce more relevant factors and study the impact of human factors on the natural environment. York et al. [10] analyzed the relationship between IPAT identity, ImPACT identity, and STIRPAT, and explored the relationship between CO_2 emissions and population employing the extended STIRPAT model. Hubacek et al. [11] found that population growth had no significant effect on China's CO_2 emissions. The growing economy was the main driver of China's CO_2 emissions growth. Song et al. [12] constructed the STIRPAT model to study the impact of population scale, population structure, consumption structure, and energy intensity on CO_2 emissions in China. Using the STIRPAT model, Zhu and Zhang [13] studied the relationship between population, urbanization, per capita GDP, and CO_2 emissions in Beijing. They proposed the necessary measures for carbon reduction in Beijing and provided a reference for Beijing to achieve high-quality economic development in the future. All of the above studies demonstrated that STIRPAT is an effective model for decomposing the influencing factors of CO_2 emissions. Wang et al. [14] studied the main driving factors of energy-related carbon emissions in Xinjiang based on the extended STIRPAT model at the three stage of "reform and opening up," "after the reform and opening up," and "Western development" (1952-2012). The results showed that before reform and opening up, carbon intensity and population were two main factors of carbon emissions increases. After reform and opening up, economic growth and population are the two main factors of carbon increment, while during the western development period, fixed assets investment and economic growth are two factors in the increase in carbon emissions, and in the latter two stages, carbon intensity played an inhibitory role in carbon emissions.

Yue and Zhu et al. [15] divided the carbon emission types of 30 provinces other than Tibet into four regions based on two indicators, such as emissions and discharge efficiencies, by employing the cluster analysis method. Yao Yi and Ni Qin [16] constructed a projection pursuit model of comprehensive evaluation of carbon reduction capacity. By comparing the best projection values, the carbon reduction capacity and potential of each region in China from 1996 to 2008 were analyzed. The results showed that the level of economic development, opening up level, and energy consumption levels had a greater impact on carbon reduction. According to the research results, the corresponding suggestions are put forward for carbon reduction. Based on the accelerated genetic algorithm, Zhang [17] carried out the cluster analysis of carbon emissions in each province in China employing the Projection Pursuit model. The optimal projection direction was determined and the best projection value of the low carbon economy development level in each province was obtained. And carbon emissions in China were divided into four categories. Long Jia Yong [18] established a low-carbon economic development level evaluation index system for the economy, society, technology, environment, and industry. And by using the projection pursuit model, the influence degree of each factor on carbon emissions in provinces was determined, which was compared with the weight value of each index

Table 1. The meaning of each variable.

Variable	Definition	Variable	Definition
a	Intercept term	B	Elasticities of environmental impact with P
P	Size of the population	C	Elasticities of environmental impact with A
A	Country's affluence	D	Elasticities of environmental impact with T
T	Technological progress	ξ	Random disturbance

obtained by the analytic hierarchy process. Chen Chao [19] analyzed the influencing factors of carbon emissions in Jiangsu Province from 2002 to 2011 by employing the projection pursuit model. The results show that economic growth was an important factor affecting carbon emissions reduction capacity. The economic development level is different and the carbon emissions reduction capacity will be different. Therefore, the carbon emissions reduction targets in Jiangsu Province should be achieved sub-regionally.

In contrast to the wealth of studies mainly exploring the influencing factors of carbon emissions in China's power industry, there has been less research looking at the relative indicators in power industry such as power consumption efficiency and electric power structure. To fill these gaps, through the extended STIRPAT model, the influencing factors of carbon emissions were decomposed into GDP, urbanization level, industrialization level, power consumption efficiency, and electric power structure. Through the projection pursuit model and the optimal projection value, 30 provinces in China could be divided into four groups, and the spatial distribution pattern was analyzed. According to the research results, this study proposed the corresponding policy measures and suggestions.

Methodologies

Carbon Emission Calculation Method

Since China has not yet announced CO_2 emissions in the power sector, it is necessary to estimate CO_2 emissions. Based on various data of energy consumption in the power industry, and CO_2 emissions factors of each energy from the 2006 IPCC reports [20], we calculated the power industry's CO_2 emissions from 2000 to 2014. So calculating CO_2 emissions may be conducted as follows:

$$C = \sum_i E_i \cdot K_i \cdot \varepsilon_i \cdot \eta_i \times 44/12 \tag{2-1}$$

…where C represents the power industry's CO_2 emissions; i is the energy type; E refers to energy consumption; K denotes the average low calorific value; ε is the carbon content of the energy; and η represents the carbon oxidation factor, which is usually replaced by constant 1.

Extended STIRPAT Model

The STIRPAT model, proposed by Dietz and Rosa in 1997 [9], is usually employed to decompose contaminant emissions factors:

$$I_t = aP_t^{\,b} A_t^{\,c} T_t^{\,d} \xi_t \tag{2-2}$$

The meanings of each variable are shown in Table 1. Eq. (2-2) may be converted to logarithmic form as:

$$\ln I_{it} = \ln a + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \xi_{it} \tag{2-3}$$

In order to explore CO_2 emission influencing factors of the power industry in China, Eq. (2-3) could be rewritten as:

$$\ln CO_2 = a + b \ln POP + c \ln GDP + d \ln ENE \tag{2-4}$$

Each abbreviation is defined in Table 2.

To further explore the influencing factors of CO_2 emissions from the power industry, the STIRPAT model is extended by introducing per capita GDP, industrialization level, urbanization level, power-consumption efficiency, and electric power structure. The extended STIRPAT model can be established as:

$$\ln CO_{2it} = a + \beta_1 \ln GDP_{it} + \beta_2 \ln URB_{it} + \beta_3 \ln IND_{it} + + \beta_4 \ln PCE_{it} + \beta_5 \ln EPS_{it} + \xi_{it} \tag{2-5}$$

Table 2. The definition of each abbreviation.

Variable	Definition
CO_2	CO_2 emissions from power industry in China
POP	Population scale
GDP	The level of economic development
ENE	Energy production input divided by its physical output

…where CO_2 represents CO_2 emissions from the power industry in China (10^4 tons). GDP denotes the per capita GDP, representing the economic growth level; IND represents the industrialization level; URB denotes urbanization level (%); PCE represents the power-consumption efficiency; and EPS indicates the electric power structure.

Projection Pursuit

The projection pursuit model, proposed by Kruskal [21], is a multi-data processing method projecting high-dimensional data into low-dimensional space by numerical optimization calculation, so as to find the optimal projection reflecting the data structure characteristics. The model, a robust high-dimensional data processing method, has no special requirements for data and sample size, and could ignore the effects of variables that are not related to the structure and features of the data, and could effectively solve various practical problems [21]. The specific steps are as follows:

Step 1: Normalizing the evaluation index. The normalization process can eliminate the dimensions of the index and unify the range of the evaluation index.

Normalizing the forward indicator as follows:

$$x_{(i,j)} = \frac{x^{*}{}_{(i,j)} - x_{\min(j)}}{x_{\max(j)} - x_{\min(j)}} \tag{2-6}$$

Normalizing the negative indicator as follows:

$$x_{(i,j)} = \frac{x_{\max(i,j)} - x^{*}{}_{(i,j)}}{x_{\max(j)} - x_{\min(j)}} \tag{2-7}$$

…where $\{x^{*}_{(i,j)}|i = 1,2...n,\ j = 1,2...p\}$, the sample set of each evaluation index, is the index j of sample i; n and P respectively refer to the sample size and number of indicators; $x_{max(j)}$ and $x_{min(j)}$ respectively denote the maximum and minimum values of index j; and $x_{(i,j)}$ is the normalized sequence of indicators.

Step 2: Constructing a projection function $Q_{(a)}$. The p-dimensional data, $\{x^{*}_{(i,j)}|i = 1,2...n,\ j = 1,2...p\}$, is synthesized into $Z_{(i)}$, one-dimensional projection value with the projection direction $a = \{a_{(1)}, a_{(2)},...a_{(p)}\}$, which is the unit vector in the projection pursuit model.

Where,

$$Z_{(i)} = \sum_{j=1}^{p} a_{(j)} x_{(i,j)}, i = 1,2,\ldots,n \tag{2-8}$$

When $Z_{(i)}$ is integrated, the distribution of the projection value is as follows: the local projection point is as dense as possible; it is better to gather into several points; the whole projection point is scattered as much as possible. Therefore, the projection function may be denoted as follows:

$$Q_{(a)} = S_z D_z \tag{2-9}$$

Where,

$$S_z = \sqrt{\frac{\sum_{i=1}^{n}\left(Z_{(i)} - E_{(z)}\right)^2}{n-1}} \tag{2-10}$$

$$D_z = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(R - r_{(i,j)}\right)\cdot u\left(R - r_{(i,j)}\right) \tag{2-11}$$

Where,

$$r_{(i,j)} = \left|Z_{(i)} - Z_{(j)}\right| \tag{2-12}$$

$$u_{(t)} = \begin{cases} 1 & t \geq 0 \\ 0 & t < 0 \end{cases} \tag{2-13}$$

Here S_z denotes the standard deviation of $Z_{(i)}$; D_z denotes the local density of $Z_{(i)}$; $E_{(z)}$ denotes the average of the sequence; R denotes the window radius of D_z; $r_{(i,j)}$ denotes the distance between the samples; and $u_{(t)}$ denotes the unit step function.

Step 3: Optimizing the projection index function. When the sample set of each index is gained, the projection function varies only with the projection direction. Therefore, the optimal projection direction may be calculated by solving the maximum problem of the projection function as follows:

$$\begin{gathered} Max: Q_{(a)} = S_z D_z \\ s.t. \sum_{j=1}^{p} a^2{}_{(j)} = 1 \end{gathered} \tag{2-14}$$

Step 4: The project value of each sample point could be obtained by substituting the best projection direction $\vec{a}$ obtained by step 3 to $Z(i) = \sum_{j=1}^{p} a(j)x(i,j)$. Since the projection index of the projection pursuit model is based on the clustering of projection eigenvalues, the most significant results of cluster analysis are obtained.

Data Resources

We chose data of 30 provinces from 2000 to 2014 as panel data. All the observations were selected from the China Statistical Yearbook. The CO_2 emissions from power industry were calculated by energy consumption, the average net calorific value of energy, and the CO_2 emissions factor, where the average net calorific of energy and the CO_2 emissions factor came from the IPCC Guidelines for National Greenhouse Gas Inventories [20]. This study chose five factors as influencing factors,

Table 3. Five influencing factors and CO_2 emissions.

Year	Per capita GDP	Urbanization level	Industrialization level	Power-consumption efficiency	Electric power structure	CO_2
2000	8286.6175	38.9977	34.5918	6.7850	74.5065	3900.1249
2001	8889.8575	40.1135	34.3774	6.9872	73.2678	4216.3773
2002	9604.1495	41.2015	34.3505	6.9911	76.6305	4756.6052
2003	10456.7697	42.3238	35.6516	6.8979	78.0850	5651.3252
2004	11376.8746	43.4665	36.9268	7.1844	77.0504	6414.1992
2005	12572.9778	44.6261	38.3439	7.6387	77.0713	7295.0768
2006	13959.8392	45.5937	39.7910	7.8284	77.8668	8435.5936
2007	15689.2676	46.5410	40.2284	8.2652	78.3267	9644.9869
2008	16922.3729	47.6136	40.7769	9.3343	73.6310	9632.4497
2009	18244.5749	48.5537	39.2104	9.5721	76.1248	9639.2888
2010	19837.6162	50.2175	40.7918	10.0541	75.0698	10514.4962
2011	21517.7690	51.4368	41.2652	10.8512	77.2404	11823.2119
2012	22994.5970	52.6949	40.2458	11.4583	74.8405	11630.2713
2013	24561.2553	53.6862	38.3854	11.7813	74.7833	13124.9735
2014	26167.0820	54.7178	37.4258	12.2696	72.5448	13110.6014

including GDP, urbanization level, industrialization level, power consumption efficiency, and electric power structure. Per capita GDP was obtained by GDP divided by the total population. URB represented urbanization level (%). The industrialization level was obtained by the share of the added value of the secondary industry in the gross product, where the added value of the secondary industry and the gross product came from the National Bureau of Statistics of China. Power consumption efficiency was obtained by the ratio of total GDP to power consumption. The electric power structure was obtained by the proportion of thermal power generated to total electricity capacity.

Results and Discussion

Decomposition of Carbon Emissions Factors

A total of 30 provinces in the power industry of China from 2000 to 2014 were explored by employing the STIRPAT model, as shown in Table 3. The development trend of per capita GDP, urbanization level, industrialization level, power-consumption efficiency, electric power structure, and CO_2 emissions from 2000 to 2014 are shown in Fig. 1, and the correlations between the five indicators and CO_2 emissions were analyzed through their development trends.

As indicated in Fig. 1, CO_2 emissions showed an upward trend on the whole. With the development of the national economy, the consumption of electricity was increasing, and the investment of the provinces in the power industry was also rising. Electricity is generated mainly through the consumption of coal, which would result in an increase in CO_2 emissions. The development of power industry in various provinces and municipalities are inseparable from energy consumption, which will undoubtedly increase CO_2 emissions.

Per capita GDP reflects the level of national economic development, and it has been increasing, which would cause an increase in CO_2 emissions. Per capita GDP is positively related to CO_2 emissions from the power industry. The increase in per capita GDP indicates that living standards have improved. In pursuit of a more convenient life, electricity consumption has been increasing, resulting in an increase in CO_2 emissions from the power industry. Therefore, China's policy of slowing economic growth is conducive to carbon control.

Industrial level was inverted "U" form. Industrialization level reflects the level of development of the secondary industry. This paper mainly studied the proportion of the electricity industry. A high industrialization level indicated that the second industry, including the power industry, has developed rapidly. Investment in the power industry in China continues to increase, whether from power generation or residential electricity consumption. This will increase CO_2 emissions.

The power structure curve is characterized by volatility. In 2007, 2011, and 2013, CO_2 emissions showed a downward trend, and the power generation structure also generally showed a downward trend, which indicated that the share of thermal power generation in China began to decline. The consumption of coal and other energy generated from thermal power generation was reduced, resulting in a reduction in CO_2 emissions. Thus, the power structure has great impact on CO_2 emissions.

Power consumption efficiency achieved rapid growth on the demand side, which indicated that the provinces had improved power consumption efficiency by adjusting the generation structure. Power-consumption efficiency refers to the unit power output. Higher unit power output indicated that the production of a unit of electricity could produce greater economic benefits. It could be understood that residents could achieve the same economic benefits with less electricity. Therefore, under the condition of the same life goal, electricity was saved and CO_2 emissions were reduced. But Fig. 1 showed that power-consumption efficiency was increasing, while CO_2 emissions also were increasing, which illustrated that power consumption efficiency had little effect on CO_2 emissions. Improving power consumption efficiency may not be effective in reducing CO_2 emissions.

There was no doubt that urbanization level was constantly improving. It could be seen from the Fig. 1 that the urbanization level was growing rapidly, which was closely related to improving living standards. The pursuit of a more convenient life, to some extent,

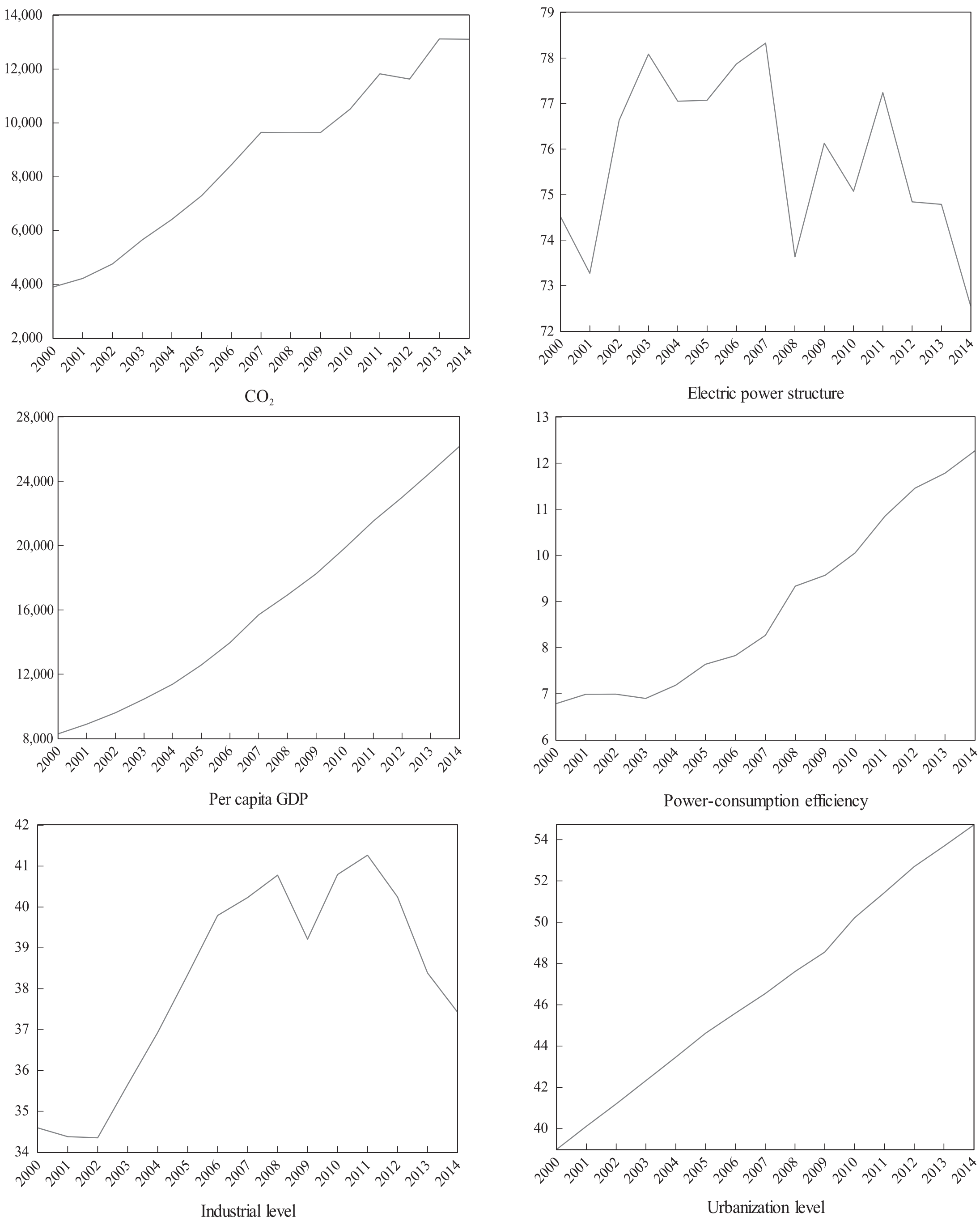

Fig. 1. CO_2 emissions from the power industry, per capita GDP, industrialization level, electric power structure, power-consuming efficiency, and urbanization level over 2000-2014.

Table 4. Four regions divided by projection pursuit.

Regions	Provinces
The first category	Shanghai, Beijing, Tianjin, Jiangsu, Shandong, Guangdong, Liaoning, Heilongjiang, Zhejiang
The second category	Hebei, Jilin, Inner Mongolia, Henan, Shanxi, Anhui, Fujian
The third category	Shaanxi, Chongqing, Xinjiang, Jiangxi, Hainan, Ningxia, Hubei, Hunan
The forth category	Gansu, Guizhou, Sichuan, Yunnan, Guangxi, Qinghai

would also promote the consumption of electricity, which caused the increase of CO_2 emissions in the power industry.

Clustering Analysis

Based on the projection pursuit clustering analysis and six indicators (per capita GDP, industrialization level, power-consumption efficiency, power generation structure, urbanization level, and CO_2 emissions), the 30 provinces were divided into 4 categories (Table 4). According to the cluster analysis results, we can know that there was a huge difference in the CO_2 emissions of the 30 provinces in China. The differences were determined by the economic development level, resource allocation, geographical location, and many other factors.

The first category consists of Beijing, Shanghai and other eastern coastal developed areas and Heilongjiang, Liaoning province. In Shanghai, Beijing, Tianjin, Shandong, Zhejiang, and Jiangsu provinces, the economy is developing faster, the urbanization level is high, and the people are living well. Therefore, the electricity consumption of residents was higher than other areas. But coal resources were scarce in these areas, and almost no power plant was established, CO_2 emissions from thermal power generation were very small. Therefore, the increase in CO_2 emissions from the power industry of these areas was driven by the growth of power consumption from urban residents and urban development. As for Liaoning and Heilongjiang, the regions are vast and there are many power plants. Therefore, a significant increase in coal consumption in Liaoning and Heilongjiang has led to an increase in the power industry's CO_2 emissions.

The second category consists of Inner Mongolia, Shanxi, and other areas of the Yellow River basin. In these areas, economic development is slower than that of the other three types, and there are the minimum per capita GDP and the low level of urbanization. Therefore, the power consumption of residents is not high, which will not lead to too much CO_2 emissions. However, these areas are rich in coal resources and host the majority of power plants, and the proportion of thermal power generation was large. The proportion of coal in the energy structure was very large, and industry was excessively heavy. Therefore, the increase in CO_2 emission from the power industry in these areas was mainly due to power generation in thermal power plants.

The third category consists of Shaanxi, Chongqing, and other central regions. These provinces see relatively slower economic development, higher per capita GDP, higher levels of urbanization, higher living standards, and more electricity consumption than the second category, which results in more CO_2 emissions. Because coal resources are not very rich and few power plants are built, CO_2 emissions from coal-fired power generation is rare. Therefore, CO_2 emissions from the power industry in these areas are generally less.

The fourth category consists of Gansu, Guizhou, Sichuan, and other southwest regions. In these areas, economic development is slow and living standards are not high. People's livelihood is mainly supplied by energy resources such as biomass energy, so the residents use very little electricity. Besides, because of the scarcity of coal resources in thes areas, almost no power plants have been built, and urban and domestic electricity is purchased from other provinces. Therefore, CO_2 emissions from the power industry are the least among four groups.

Conclusion and Policy Implication

In this paper we analyzed the power industry's CO_2 emissions from 2000 to 2014 in China by employing the STIRPAT model and the Projection Pursuit model. Based on STIRPAT, we determined five influencing factors: per capita GDP, urbanization level, electric power structure, industrialization level, and power-consumption efficiency. There were positive correlations between the five influencing factors and CO_2 emissions, especially per capita GDP, power-consumption efficiency, and urbanization level. The influence of industrialization level and electric power structure fluctuates greatly. And through the projection pursuit model, 30 provinces were divided into four groups. The regional features of each type were analyzed.

Based on the five influence factors and the clustering results, the following policy implications were proposed.

First, the primary task is to optimize the electric power structure and actively reduce the proportion of thermal power generation. Reducing CO_2 emissions from power generation is one of the approaches for sustainable development of power enterprises. In the process of electricity production, CO_2 emissions mainly come from coal consumption of the thermal power plant, and in the process of power consumption, mainly caused by the heat generated. Therefore, according to the clustering results and the regional characteristics and development requirements of the provinces, it is necessary to reduce coal-based thermal power and develop new and clean energy to generate power. China has become the world's largest solar photovoltaic in 2015, and has made great progress in the field of renewable energy, such as hydro-power, wind energy, and solar energy [22]. For the eastern coastal developed areas, due to dense population and low environmental carrying capacity, solar power should be used to generate electricity. For Xinjiang and other western regions, because of the vast territory, wind power generation would be employed. In Sichuan and Yunnan provinces, rich in water resources, hydroelectric power could be adopted. For Shanxi, Inner Mongolia, and other central regions that are rich in coal resources and have more thermal power generation, the government should formulate CO_2 emissions standards and improve the utilization of coal. In addition, rural areas could be encouraged to employ bio-gas power generation.

Secondly, it is required to effectively improve the power-consumption efficiency by advanced technology and equipment. The improvement of power-consumption efficiency is related to the equipment and technology of the power industry. On the one hand, advanced technology and equipment should be introduced and popularized. With the rapid development of the eastern region, electrical equipment has been relatively perfect, and some power technology is also very mature. While the development of the western region is backward, the investment in power equipment is not large and the technology is not mature. Therefore, the state should encourage the central and western regions to learn advanced technology from the eastern region, and update the generation and utilization of electricity – thereby improving the efficiency of the terminal use of electricity. On the other hand, the government should encourage electric power enterprises to save electricity and strengthen the construction of the national power grid, especially the eastern areas with higher power consumption.

Thirdly, while accelerating the process of urbanization and industrialization, the government should promote the development and utilization of new energy resources. The process of urbanization should take the path to low-carbon city, which is indispensable to control the growth of CO_2 emissions. For one thing, the government should advocate an energy conservation and environmental protection lifestyle, which is necessary to improve the energy-saving function and the efficiency of household appliances. Vehicles powered by gasoline or other energy sources are supposed to be substituted by electric vehicles. The government should increase investment and support in new vehicles, making new-energy vehicles more popular, thereby reducing CO_2 emissions from the high-carbon car exhaust emissions. For another, energy-saving construction should be encouraged. Some high-carbon materials could be replaced by low-carbon economic materials. And the government should absorb the intensive investment in infrastructure construction to promote urbanization and industrialization and strengthen the construction of small and medium-sized cities and new countryside to disperse the environmental and resource pressure of big cities. Besides, it is essential to raise residents' awareness of energy conservation and environmental protection, and appeal to residents to take public transport and buy new-energy vehicles.

Four, the government should adhere to sustainable development and change the mode of economic growth, from the extensive growth mode of high energy consumption and low efficiency into the intensive growth mode of low energy consumption and high efficiency. The government should promote economic and environmental coordination and sustainable development, reducing CO_2 emissions while ensuring the development of urbanization and industrialization.

Finally, establishing an effective regional cooperative mechanism among the provinces in China is indispensable. For those where total CO_2 emissions from the power industry are low but the deterioration is faster (such as Qinghai and Yunnan provinces), the government should pay great attention to CO_2 emission reduction based on the conditions of 30 provinces. The cities that reduce carbon emissions can sell the right to emit CO_2 to those regions that produce more [22]. In some provinces of China, such as Anhui and Fujian, there are large economic scales, but the economic development models are crude. So the transformation from extensive economy to intensive economy is necessary, which not only could reduce CO_2 emissions and energy consumption but ensure economic benefits. Therefore, the establishment of CO_2 emissions accounting and comparison system is urgently required, and certain relevant professionals are required for guidance and analysis.

The purpose of the study is completed, and the expected results are obtained. Due to the limitations of research experience and various conditions, the following aspects need to be improved: first of all, carbon emission factors in power industry need to be further refined. There are vast factors effecting carbon emissions, and more accurate data need to be collected for further analysis and discussion. Secondly, the 30 provinces could be divided into smaller and more detailed segments in order to better analyze regional characteristics.

Conflict of Interest

The authors declare no conflict of interest.

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