

# Research on Factors Affecting Carbon Emission

Fan Yang

Shenyang University School of Information Engineering, Liaoning Shenyang, 110000, China

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## ABSTRACT

There are many factors affecting carbon emissions, involving energy consumption, industrial production, transportation and other aspects. In-depth study of these factors will not only help us understand the growth mechanism of carbon emissions, but also provide scientific basis for formulating effective emission reduction strategies. On the road of pursuing sustainable development, reducing carbon emissions and protecting the earth has become our common responsibility. In this paper, x indicators related to regional carbon emissions, economy, population and energy consumption and corresponding data are established to establish an indicator system. Secondly, the data is preprocessed before the establishment of the grey correlation model, which mainly includes the principal component analysis of the data and the selection of four indicators with large index scores. Finally, the grey correlation model is established to analyze the changes among related indicators and draw the conclusion of current situation analysis.

## KEYWORDS

Carbon emission; Economy; Population; Energy consumption; Grey correlation model.

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## 1. INTRODUCTION

Climate change has become an urgent global problem, which is not only the core issue of international environmental dialogue, but also the top priority to achieve carbon neutrality. With the acceleration of urbanization, greenhouse gas emissions are rising year by year, which brings more and more serious environmental problems, posing a huge threat to human survival and development. In this context, countries around the world are actively seeking ways to reduce emissions. China, as a responsible country, is committed to building a green and low-carbon social environment under the guidance of the "double carbon" goal. However, compared with developed countries such as Europe and the United States, China's current carbon dioxide emissions are still large and concentrated, and energy demand will continue to increase in the coming period of time, which makes us still have a long way to go to achieve the goal of "dual carbon". Therefore, an in-depth analysis of the influencing factors of carbon dioxide emissions under China's national conditions is of great importance for exploring a low-carbon emission reduction path suitable for China. Only through scientific analysis and precise policies can we more effectively promote green development and make positive contributions to addressing climate change.

## 2. RESEARCH ON CARBON EMISSIONS

For the study of carbon dioxide emissions, scholars mostly focus on the dynamic evolution, measurement methods and regional differences. Qu Shenning et al. calculated the total carbon emissions under the digital economy and predicted that by 2030, the proportion of carbon emissions from the digital economy will reach about one-tenth. Zhao Qiang et al. studied the carbon dioxide

emissions in the central region of China and found that the concentration of carbon emissions decreased year by year, with differences among provinces. Fan Jianshuang et al. proposed that carbon dioxide emissions from China's construction industry are increasing year by year and have spatial agglomeration. The closer the agglomeration point is to the central and southern regions, the more obvious the spatial agglomeration effect will be. Xu Guoquan et al. proposed that the impact of economic progress on per capita carbon emissions would gradually weaken, and the improvement of energy efficiency would significantly reduce carbon dioxide emissions.

### **3. ESTABLISHMENT OF INDEX SYSTEM**

#### **3.1. Principles for selecting indicators**

When selecting metrics, it is important to follow three core principles: ease of quantification, comprehensiveness of content, and relevance.

First of all, quantification is the basis of index selection. In this paper, 35 specific indicators are carefully selected at the level of secondary indicators, most of which can be transformed into specific data through investigation, thus effectively avoiding the measurement problems of non-quantitative indicators and ensuring the accuracy and operability of the data.

Second, the comprehensiveness of the indicators is equally important. Starting from the first level of basic indicators, this paper extends to 35 specific indicators, which not only covers the core indicators that directly affect regional carbon emissions, economy, population, and energy consumption, but also includes various considerations such as social environment to ensure the broad and multi-angle selection of indicators.

Finally, the selection of indicators needs to fit the reality. While comprehensively considering the high-frequency indicators in other literatures, this paper also selects some indicators that are easy to quantify based on the actual situation, avoiding the interference of irrelevant variables and unquantifiable variables, so as to ensure the practicability and effectiveness of indicator selection.

#### **3.2. Establishment of index system**

As shown in Table 1, the index system is divided into two levels in this paper. The first level is economy, population, energy consumption and carbon emissions, while the second level is further subdivided based on the first level.

#### **3.3. Data Preprocessing**

##### **3.3.1. Principal Component Analysis**

Principal component analysis, as a statistical technique, aims to condense a large number of indicators into a few comprehensive indicators, thus simplifying the processing and evaluation process of data information. In this paper, we use the principal component analysis to reduce the dimension and calculate the comprehensive score based on it. At the same time, we process the missing values and outliers in the data to effectively eliminate the invalid information. The core of principal component analysis is to transform variables that might otherwise be related to each other into a new set of linearly independent variables, called principal components, through orthogonal transformations. Before the principal component analysis, in order to eliminate the impact of different dimensions on the data, we first standardized the data.

**Table 1. Index system**

Primary index	Secondary index	Unit	Remark
Economy	GDP		All final results of production activities in a given period of time (Current GDP÷Previous period GDP) -1
	GDP growth rate		
	Per capita GDP		
	CPI	Hundred	
	PPI	Million Yuan	Gross GDP/Total population
	Residents' consumption level	Yuan	Indicators of price changes related to people's livelihood Ex-factory price index of industrial products
Population	Foreign exchange reserve	Yuan	Quantity and quality of material goods and services consumed
		Hundreds of millions of dollars	Foreign exchange assets readily convertible into foreign currencies
			The ratio caused by natural and migratory changes in population
			The average number of years of survival
			Births during the year/Total population for the year
			Annual number of deaths/Average annual population
			Number of population(People)/Area(Square kilometer)
			Number of elderly people aged 60 and above/Population
			The proportion of urban population in total population
			Employment as a percentage of the labor force
			Unemployment as a percentage of the labor force
			The difference between the number of immigrants and the number of emigrants
Energy Consumption	Per Capita Disposable Income	Thousands of people	The ratio of urban population to rural population
	Gini Coefficient	Ten thousand yuan	The ratio of the number of living infants to the average number of women of reproductive age
			Income available to each resident for discretionary use
			An indicator that measures the income gap between residents in a region
	Agriculture And Forestry Consumption Sector	Thousand tce	
	Industrial Consumption Sector	Thousand tce	
	Transportation Consumption Sector	Thousand tce	

Carbon Emission	Construction Consumption Sector Household Living Consumption Per Capita Carbon Emissions Transport Sector Carbon Emissions Industrial Sector Carbon Emissions Carbon emissions From Agriculture And Forestry Consumption Sectors Industrial Consumption Sector Carbon Emissions Transportation Consumption Sector Construction Consumption Sector Carbon Emissions Per Unit Of GDP	Thousand Tco2
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In terms of specific operations, this paper first uses SPSS software to carry out principal component analysis for each index, and imports relevant data into the software for processing. By analyzing the correlation coefficient matrix of each channel, we can judge the correlation between channels. If the correlation is strong, it means that the factor has practical significance and can be retained for dimensionality reduction. On the contrary, if the correlation is weak, then consider dropping. Then, we further extracted the common factor variance of each channel, calculated the variance contribution rate and cumulative contribution rate of the indicators, and explained the total variance, which provided strong support for the in-depth analysis of the data.

Step 1: In SPSS software, click analysis option, select correlation, and then click bilateral variables. The final result is shown in Figure 1.

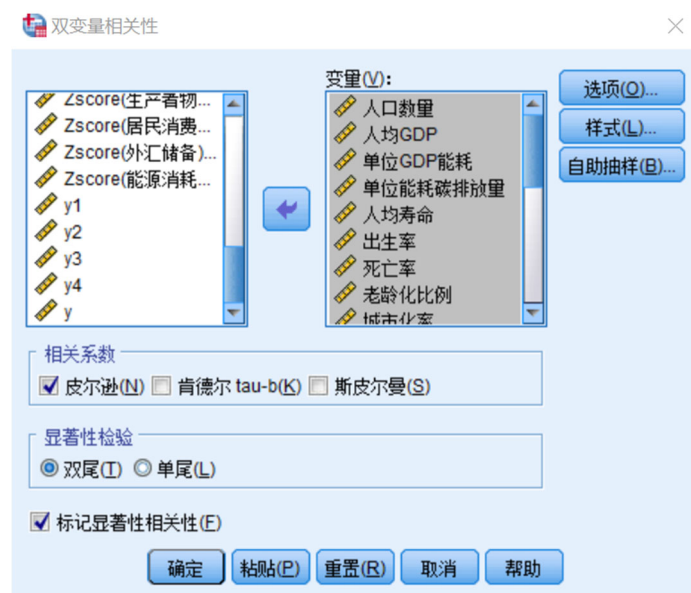
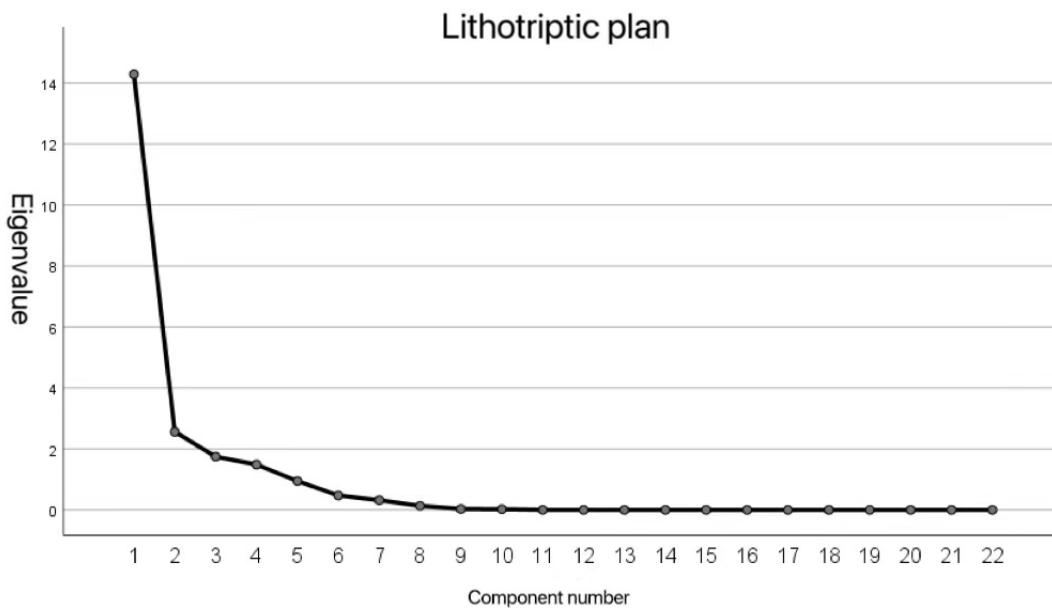


Figure 1. Correlation Of Indicators

Step 2: Common factor variance extraction for each channel. First of all, data description is carried out as shown in Figure 2. After clicking the Continue button, common factors are extracted and components with feature roots greater than 1 are selected, as shown in Figure 3.



**Figure 2.** SPSS Time Series Prediction Steps



**Figure 3.** Correlation Analysis Lithotripsy

In the lithotripsy chart, it can be clearly seen that the degree of correlation between the various indicators, starting from the first indicator, the trend drops sharply and then levels off. When the break line suddenly becomes smooth from step, the number of principal components corresponding to step to smooth is the number of principal components of reference extraction.

In general, it can be concluded from the output results that the eigenvalues of the first four indicators are greater than 1 and need to be retained. The first four indicators are population size, per capita GDP, energy consumption per unit GDP and carbon emission per unit energy consumption respectively. The first principal component feature root utilization was standardized on this basis, and the results were shown in Figure 4 below:

Z人均GDP	Z单位GDP能耗	Z单位能耗碳排放量	Z人均寿命	Z出生率	Z死亡率	Z老龄化比例
-1.47419	1.32597	38449	-1.43150	-19102	46444	-1.24306
-1.21109	1.51922	-77427	-1.16964	58910	1.36600	-1.06548
-92403	1.12772	-1.97086	-91651	1.32936	1.06548	-88790
-61801	.57106	56501	-66338	45244	1.06548	-65113
-33484	.07020	45848	-40152	90798	76496	-41435
-00109	-22258	58479	.11347	-13977	-73764	-23677
.30632	-45766	65327	36660	75993	-1.63920	.11839
.62163	-69047	43566	62846	23036	-1.03816	.41435
.94535	-89617	63501	.77685	-78322	-43712	82871
1.24419	-1.03720	.74001	.92524	-1.03947	-1.36660	1.36145
1.44576	-1.31008	-1.71159	1.77192	-2.11569	-73764	1.77580

Figure 4. Standardization Results

The formula for calculating score values is shown in the following table:

Table 2. Formula of Score Value

Name	Formula
$y_1$	$0.263 * Z \text{ Number of people} + 0.263 * Z \text{ GDP per capita} + 0.262 * Z \text{ Energy consumption per unit of GDP} + 0.262 * Z \text{ Carbon emissions per unit of energy consumption} + 0.259 * Z \text{ Life expectancy} - 0.258 * Z \text{ Birth rate} + 0.258 * Z \text{ Mortality rate} + 0.257 * Z \text{ Proportion of aging} - 0.254 * Z \text{ Urbanization rate} + 0.251 * Z \text{ Employment rate} + 0.247 * Z \text{ Unemployment rate} + 0.245 * Z \text{ Net migration} - 0.236 * Z \text{ Proportion of urban and rural population} - 0.193 * Z \text{-Fertility rate} + 0.184 * Z \text{ Per capita disposable income} - 0.178 * Z \text{ Gini coefficient} - 0.046 * Z \text{GDP growth rate} - 0.049 * Z \text{ Consumer Price index} - 0.129 * Z \text{ Producer Price index} - 0.138 * Z \text{ Residents' consumption level} - 0.001 * Z \text{ Foreign exchange reserves} + 0.037 * Z \text{ Energy consumption}$
$y_2$	$- 0.025 * Z \text{ Number of people} - 0.038 * Z \text{ GDP per capita} - 0.004 * Z \text{ Energy consumption per unit of GDP} - 0.007 * Z \text{ Carbon emissions per unit of energy consumption} - 0.048 * Z \text{ Life expectancy} + 0.063 * Z \text{ birth rate} - 0.091 * Z \text{ Mortality rate} + 0.003 * Z \text{ Proportion of aging} + 0.044 * Z \text{ Urbanization rate} - 0.126 * Z \text{ Employment rate} - 0.083 * Z \text{ Unemployment rate} + 0.201 * Z \text{ Net migration} - 0.231 * Z \text{ Proportion of urban and rural population} - 0.056 * Z \text{-Fertility rate} + 0.23 * Z \text{ Per capita disposable income} - 0.073 * Z \text{ Gini coefficient} + 0.571 * Z \text{GDP growth rate} - 0.473 * Z \text{ Consumer Price index} + 0.433 * Z \text{ Producer Price index} - 0.166 * Z \text{ Residents' consumption level} + 0.183 * Z \text{ Foreign exchange reserves} + 0.046 * Z \text{ Energy consumption.}$
$y_3$	$-0.024 * Z \text{ Population} - 0.018 * Z \text{ GDP per capita} - 0.013 * Z \text{ Energy consumption per unit GDP} - 0.068 * Z \text{ carbon emissions per unit energy consumption} - 0.108 * Z \text{ life expectancy} - 0.024 * Z \text{ birth rate} + 0.044 * Z \text{ death rate} - 0.137 * Z \text{ aging ratio} + 0.129 * Z \text{ urbanization rate} + 0.117 * Z \text{ employment rate} + 0.103 * Z \text{ unemployment rate} - 0.066 * Z \text{ net migration population} + 0.006 * Z \text{ urban and rural population ratio} - 0.355 * Z \text{ fertility rate} + 0.346 * Z \text{ per capita disposable income} + 0.406 * Z \text{ Gini Coefficient} + 0.017 * Z \text{GDP growth rate} + 0.190 * Z \text{ Consumer Price Index} - 0.249 * Z \text{ Producer Price Index} - 0.432 * Z \text{ consumer consumption level} + 0.359 * Z \text{ foreign exchange reserves} + 0.461 * Z \text{ Energy consumption.}$
$y_4$	$-0.002 * Z \text{ Population} + 0.013 * Z \text{ per capita GDP} - 0.001 * Z \text{ Energy consumption per unit GDP} + 0.013 * Z \text{ carbon emissions per unit energy consumption} + 0.031 * Z \text{ life expectancy} + 0.064 * Z \text{ birth rate} + 0.045 * Z \text{ Mortality rate} + 0.009 * Z \text{ aging ratio} - 0.123 * Z \text{ urbanization rate} + 0.043 * Z \text{ employment rate} + 0.111 * Z \text{ unemployment rate} + 0.017 * Z \text{ net migration population} - 0.010 * Z \text{ urban and rural population ratio} + 0.135 * Z \text{ fertility rate} + 0.187 * Z \text{ per capita disposable income} + 0.199 * Z \text{ Gini coefficient} + 0.026 * Z \text{GDP growth rate} + 0.113 * Z \text{ Consumer Price Index} - 0.032 * Z \text{ Producer Price index} + 0.253 * Z \text{ consumer consumption level} + 0.643 * Z \text{ foreign exchange reserves} - 0.612 * Z \text{ Energy consumption}$

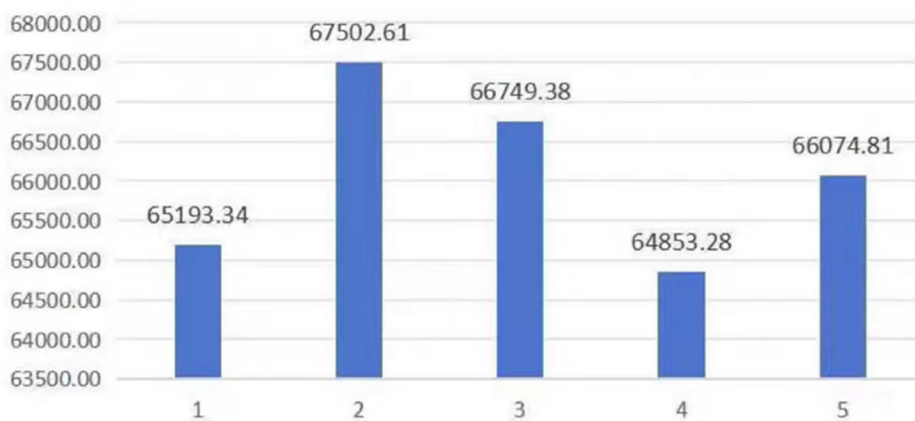
Results:  $y = 0.6494y_1 + 0.1164y_2 + 0.0793y_3 + 0.0675y_4$  , Then the score values of these four indicators are calculated respectively, and the final output result is shown in Figure 5 below.

$y_1$	$y_2$	$y_3$	$y_4$	$y$
-0.31	1.97	-0.46	0.24	0.01
-0.25	1.57	0.78	0.21	0.10
0.19	0.95	0.30	0.17	0.27
0.34	0.46	0.82	1.11	0.41
0.26	0.00	0.67	1.36	0.31
0.72	-0.57	-0.11	-0.54	0.36
-0.49	-0.31	-0.04	-0.66	-0.40
-0.33	0.54	-1.24	-0.28	-0.27
-0.37	-0.57	-0.78	-0.65	-0.41
-0.22	-1.42	-0.46	-0.77	-0.40
0.47	-2.61	0.52	-0.19	0.03

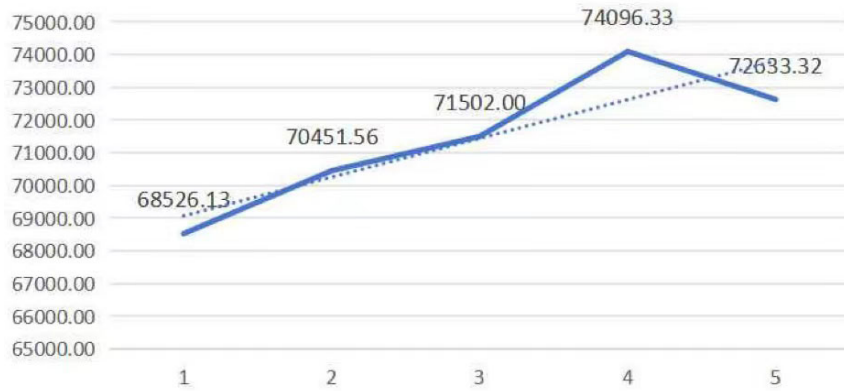
In the table, the larger the Y value obtained, the higher the corresponding contribution degree; Therefore, we can conclude that: Population contributed the most to regional carbon emissions in 2010, 2011, 2012, 2017, 2018 and 2019, total carbon emissions contributed the most to regional carbon emissions in 2013 and 2014, and economy contributed the most to regional carbon emissions in 2015. The contribution of energy consumption to regional carbon emissions in 2016 and 2020 is the largest.

### 3.3.2. Changes in carbon emissions

During the 12th Five-Year Plan and 13th Five-Year Plan period, the change trend chart of carbon emissions is shown in Figure 6-9.



**Figure 6.** Columnar Change Of Carbon Emissions During The 12th Five-Year Plan Period (2011-2015)



**Figure 7.** Broken Line Change Of Carbon Emissions In 13th Five-Year Plan (2011-2015)



**Figure 8.** Columnar Change Chart Of Carbon Emissions In 13th Five-Year Plan (2011-2015)

As shown in Figure 6, during the 12th Five-Year Plan period, carbon emissions showed an overall trend of first rising sharply, then decreasing and finally rising. Among them, carbon emissions reached their highest point in 2012, but also an inflection point, and the overall five years have fluctuated up and down.

As shown in FIG. 7-8, during the 13th Five-Year Plan period, the trend of carbon emissions was as follows: first, it continued to rise and then began to decline; Among them, the highest point of carbon emissions is reached in 2019, and it is also the turning point that begins to decline. Compared with the 12th Five-Year Plan, the carbon emission value of each year is closer to that of the 13th Five-Year Plan period.

First, under the Green Revolution, the structure of the economy will undergo revolutionary changes, and the relationship between economic growth and emission reduction will need to be balanced in the process of such changes. Secondly, while reducing "carbon emissions", it is necessary to deal with social problems and ensure the stable development of economic society. It is not advisable to focus only on the dual carbon goal and ignore the economic development.

In addition, policy guidance is an important means to achieve carbon peak and carbon neutrality, because in the above analysis, carbon emissions continue to rise in the first few years of each five-year plan; Therefore, the region should continue to improve the green and low-carbon policy and monitoring and supervision system. Secondly, this region can adopt the construction of a clean, low-carbon, safe and efficient energy system. In the annex table, the energy consumption structure of this region shows that the proportion of many clean energy and new energy in the structure has remained relatively low, so it can be used as a breakthrough in the dual-carbon path.

## 4. GREY CORRELATION

Grey correlation model is mainly suitable for multi-factor correlation analysis and prediction and evaluation problems, and can deal with a small amount of data or poor data quality. It can solve the uncertainty of influencing factors among multiple indicators and supplement the defects of traditional statistical models. Therefore, this paper chooses grey correlation to measure the relative strength of carbon emissions in a certain region affected by other factors.

Step 1: Select a reference sequence  $X_0 = (X_{01}, X_{02}, X_{03}, X_{04}, X_{05}, X_{06}, X_{07})$ ; Comparison sequence  $X_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}, x_{i6}, x_{i7})$ , among  $i = 1, 2, 3, \dots, n$

Step 2: Dimensionless processing of variables. Common methods include initial value method and mean value method. The initial value method is used here to obtain  $X'_i = X_i / x_{i1} = (x'_{i1}, x'_{i2}, \dots, x'_{in})$   $i = 0, 1, 2, \dots, m$

Step 3: Find the travel sequence, maximum difference and minimum difference. Differential column:  $\Delta 0_i(k) = |x'_{i0}(k) - x'_i(k)|$   $k = 1, 2, \dots, n$  the maximum difference is  $M = \max_i \max_k \Delta_i(k)$  The minimum difference is  $m = \min_i \min_k \Delta_i(k)$

Step 4: Calculate the correlation coefficient  $r(x_0(k), x_i(k)) = (m + \xi M) / (\Delta 0_i(k) + \xi M)$   $\xi \in (0, 1)$   $k = 1, 2, \dots, n$ ;  $i = 0, 1, 2, \dots, m$ , Where  $\xi$  is the resolution factor, frequently-fetch  $\xi = 0.5$

Step 5: Find the correlation degree:  $r(x_0, x_i) = \sum r(x_0(k), x_i(k)); i = 0, 1, 2, \dots, m$

Step 6: Analyze the results. If  $r(x_0, x_i) > r(x_0, x_j) > r(x_0, x_k) > \dots > r(x_0, x_z)$ , Then means  $X_i$  superior to  $X_j$ ,  $X_j$  superior to  $X_k$ , and so on. Remember  $X_i > X_j > X_k > \dots > X_z$  Among them,  $X_i > X_j$  representation factor  $X_i$  pair reference sequence  $X_0$  the grey correlation degree is greater than  $X_j$ . The greater the degree of correlation, the stronger the degree of closeness between the group of factors and the parent factors.

Grey correlation coefficient is used to represent the rigidities of feature sequences and comparison sequences, and its range is (0,1). The calculation formula is as follows:

$$L[X_0(K), X_i(k)] = \frac{\Delta \min + \rho \Delta \max}{\Delta i + \rho \Delta \max} \quad (4-1)$$

Is the correlation coefficient of and where; Respectively are the maximum and minimum values of the absolute value of the difference between and at; Is the absolute value of the difference between the sum and the place; Is the resolution coefficient, generally 0.5.

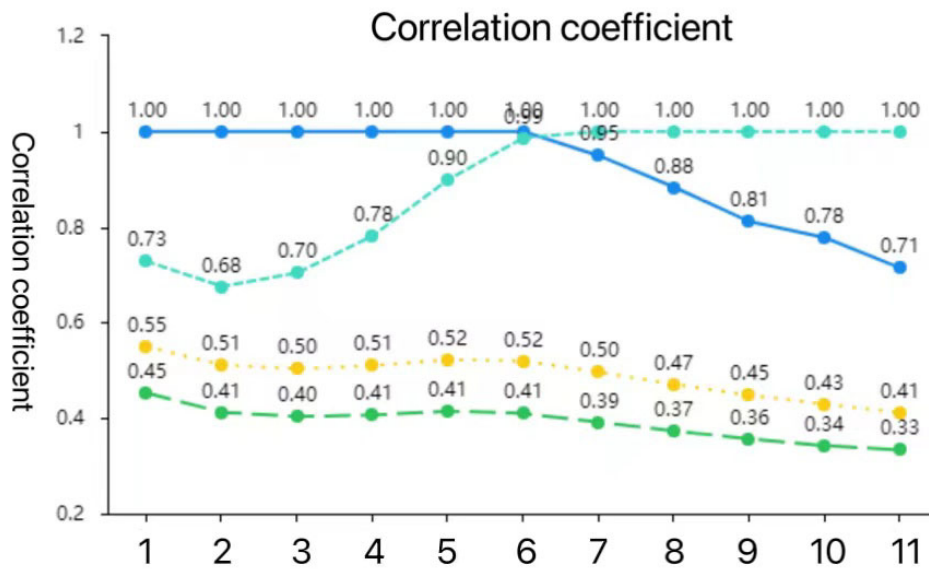
The model solving results are shown in Table 3:

**Table 3.** Results Of Correlation Coefficients

Item	Total carbon emissions	Economy	Population	Energy consumption
Item 1	1.000	0.728	0.453	0.550
Item 2	1.000	0.676	0.412	0.511
Item 3	1.000	0.704	0.403	0.504
Item 4	1.000	0.782	0.406	0.510
Item 5	1.000	0.899	0.415	0.522
Item 6	1.000	0.987	0.410	0.520
Item 7	0.949	1.000	0.392	0.496
Item 8	0.883	1.000	0.373	0.471
Item 9	0.811	1.000	0.357	0.448
Item 10	0.778	1.000	0.342	0.429
Item 11	0.714	1.000	0.333	0.412

## 5. CONCLUSION

As can be seen from the above table, gray correlation analysis is carried out for 4 evaluation items (total carbon emission, economy, population, energy consumption) and 11 data items. Since no "reference value" is entered, the maximum value of each evaluation item is taken as the "reference value" for analysis by default. When grey correlation analysis is used, the resolution coefficient is 0.50. The correlation value is calculated by combining the correlation coefficient calculation formula, and according to the correlation value, the correlation degree value is calculated for evaluation and judgment. The result is shown in Figure 9.



**Figure 9.** Variation Diagram of Correlation Coefficient

**Table 4.** Results Of Correlation Degree

Evaluation item	Correlation degree	Ranking
Total carbon emissions	0.921	1
Economy	0.889	2
Population	0.391	4
Energy consumption	0.488	3

According to the above correlation coefficient results, the weighted processing is carried out to obtain the correlation degree value, and the evaluation ranking is conducted for 11 evaluation objects by using the correlation degree value. The correlation degree value is between 0 and 1, and the larger the value, the stronger the correlation between it and the "reference value" (parent sequence), that is, the higher the evaluation. As can be seen from the above table, for this evaluation item, excluding the correlation value of the total carbon emission index to regional carbon emission, the economic index (correlation degree: 0.889) has the highest correlation degree with regional carbon emission, and is more affected by it, in which energy consumption has the weakest impact on regional carbon emission.

## REFERENCES

- [1] Hu B, Zuo Y. The impact of energy structure and green technology innovation on carbon dioxide emissions in China [J]. *Journal of Tianjin University of Technology*,1-9.
- [2] Zhao Qiang, ZHOU Yue-Ling, FANG Qian-Sheng, YI Ming-Jian. Spatial and temporal evolution of carbon emission and its influencing factors in Central China [J]. *Chinese Journal of Environmental Sciences*, 2019,43(02):354-364.
- [3] Qu Shenning, Shi Dan, Yang Danhui. Carbon emissions from China's digital economy: Total estimation and trend outlook [J]. *China Population, Resources and Environment*,202,32(09):11-21. (in Chinese)
- [4] Xu Guoquan, CAI Zhu, Feng Shiwei. Spatial and temporal differences and influencing factors of carbon emissions based on two-stage LMDI model: A case study of Jiangsu Province [J]. *Soft Science*, 2019,35(10):107-113.
- [5] Liu Jinpei, SONG Xiaoxia, Chen Huayou, WANG Guanzhen, WANG Zhen. Long-term equilibrium and causal dynamic relationship of influencing factors of per capita carbon emissions in China: An empirical analysis based on structural mutation ARDL-VECM model [J]. *Operations Research and Management*,2019,28(09):57-65.
- [6] [Fan J S, Zhou L. Spatiotemporal characteristics and provincial contribution of carbon emissions from construction industry in China. *Resources Science*,2019,41(05):897-907.