# Analysis and Prediction of the Influencing Factors of China's Secondary Industry Carbon Emission under the New Normal

**Yonggui He[a] and Shengjie Hu[*]**

Department of Economic and Management, North China Electric Power University, Baoding, Hebei 071003, China

*Corresponding author e-mail: hushengjiepaper@163.com, [a]hyg_1961@126.com

**Abstract**. Since 2012, China's economy has entered a new normal. Despite the accelerated optimization of industrial structure and the slowdown of energy consumption growth, with the pace of industrialization and urbanization, the energy demand still has a rigid growth. The problems of resources and environment still restrict the development of China's economy. The effective measurement and prediction of carbon emissions is the basis for the development of reasonable energy saving and emission reduction programs. This paper analyses the carbon emissions of China's secondary industries from 2000 to 2015, and uses carbon emissions as the standard for environmental pressure assessment. Research shows that carbon emissions of secondary industry accounted for a larger proportion of total carbon emissions, but growth has slowed. Based on the STIRPAT model, the time series analysis is used to estimate the elasticity coefficient of carbon emission. Indicating that the effect of technological advances to reduce energy intensity, that is, to reduce the energy consumption per unit of added value, which plays a positive role in reducing carbon emissions. The GM (1, 1) model was used to analyse and forecast the carbon emissions of secondary industry from 2016 to 2020. This paper analyzes the growth trends of carbon emissions, providing scientific basis for economic decision-making.

## 1. Introduction

Since 2012, China's economy has entered a new normal, its economic growth rate has changed from high-speed growth to moderate-high-speed growth, and economic growth has become more stable. The economic structure has been continuously optimized and upgraded, the proportion of the tertiary industry has increased, and the proportion of the secondary industry has decreased. The internal energy structure of the industry has been continuously optimized; economic growth has been driven more diversified, and it has changed from an element-driven, investment-driven to innovation-driven, and the development prospects have become more stable. In January 2017, the "Circular of the State Council on Printing and Distributing the Comprehensive Work Plan for Energy Saving and Emission Reduction during the Thirteenth Five-Year Plan" emphasized the importance and urgency of doing a good job of the "13th Five-Year Plan" energy-saving and emission reduction work. Despite the acceleration of industrial structure optimization and slower growth of energy consumption, along with the pace of industrialization and urbanization, there is still a rigid increase in energy demand, and resource and environmental issues continue to restrict the development of China's economy. The accurate measurement of carbon emissions from the second industry, in-depth study of its influencing factors, and the status analysis and trend forecasting, can provide scientific criteria for economic decision-making under China's "Thirteenth Five-Year Plan".

The carbon emissions of the secondary industry are the objects of analysis, covering more than 85% of the total carbon emissions in the mining, manufacturing, power and gas production and supply, and construction industries, aiming to study the impact of carbon emissions. The factors and their degree of influence, and the prediction of future carbon emissions from the secondary industry. Accurately grasping the carbon emission trends of the secondary industry and quantifying the carbon emission influencing factors are the key to identifying the future emission reduction targets for industries and formulating scientific plans for reducing emissions.

## 2. Research Methods and Models

### 2.1. STIRPAT Model

The use of the STIRPAT model to analyze the factors that affect carbon emissions has become more widespread. Ehrlich and Holden proposed for the first time the establishment of the IPAT equation to reflect the impact of population on the environment pressure, among which is the environmental pressure (Impact), P is the population (Population), A is the degree of affluence (Affluence), and T is the technical level (Technology). The STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model was put forward by Dietz and Rosa on the basis of the IPAT model, forming an analytical framework for the impact of various types of human drivers on environmental stress. The STIRPAT model is a widely used and very mature environmental stress assessment model.

The standard form of this model is:

$$\mathrm{I} = aP^{b}A^{c}T^{d}e \tag{1}$$

Take the logarithm of the two sides of the model, the model is as follows:

$$\ln I = \ln a + b\ln P + c\ln A + d\ln T + \ln e \tag{2}$$

Formula (2) is linear in its expression, and can be estimated by time series analysis methods in econometrics, so as to obtain an estimate of the elasticity coefficient of the carbon emission impact factors on carbon emission changes. In the formula, a is the model coefficient; b, c, d are the elasticity coefficients of population, wealth, and technical level; e is Errors. This paper uses this model to analyze the influencing factors of carbon emissions from the secondary industry.

### 2.2. Grey Prediction GM (1, 1) Model

In the grey model, the most general meaning is the GM (n, h) model described by the n-order differential equations of h variables. The GM (1, 1) model is the most common kind of special case and it is composed of only one a model consisting of unilabiate first-order differential equations. This paper uses the grey GM (1, 1) model to analyze and predict the carbon emissions of China's secondary industry from 2016 to 2020.

The grey GM (1, 1) prediction model requires only one sequence$x_i^{(0)}$. The original data sequence with the variable$x_i^{(0)}$.

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = \left(1 - e^{\hat{a}}\right)\left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right)e^{-\hat{a}k} \tag{3}$$

Where $\hat{x}^{(0)}(k)(\mathrm{k}=1, 2, \cdots, \mathrm{n})$the original data is sequence $x^{(0)}(k)(\mathrm{k}=1, 2, \cdots, \mathrm{n})$ the fitting value; $\hat{x}^{(0)}(k)(k>n)$ is the predicted value of the original data sequence. Where a is the development grey number and b is the endogenous control grey number.

### 2.3. *Grey Prediction Model Accuracy Test*

The accuracy of the gray model's modeling can be analyzed using the post-test difference test method. Post-inspection test is a method of testing according to the statistical situation between the model predicted value and the actual value, which is transplanted from the probability prediction method. Based on the residual, based on the magnitude of the absolute value of residuals in each period, the probability of occurrence of the point with smaller residual error and the size of the index related to the variance of the prediction error are examined.

Post-test difference test requires two data, that is, the posterior test difference ratio C, the small error probability P. The smaller the indicator C, the better. The larger the indicator P, the better. Table 1 shows the accuracy rating table available for the inspection model.

**Table 1.** Comprehensive assessment forecast model accuracy rating table

| Prediction accuracy level | P | C | Prediction accuracy level | P | C |
|---|---|---|---|---|---|
| Excellent(Level1) | >95% | <35% | Passed(Level3) | >70% | <65% |
| Good(Level2) | >80% | <50% | Failed(Level4) | ≤70% | ≥65% |

## 3. Data acquisition and carbon emission estimation

### 3.1. *Data Sources*

For the environmental pressure variable I, it is mainly measured by carbon emissions. For the calculation of the carbon emissions of the second industry, see the description in section 3.2. The variable P is the number of the population. This article uses the number of employees in the second industry in the "Number of Employment by Three Industries" on the website of the National Bureau of Statistics to indicate the impact of population on the industrial environment. The variable A indicates the degree of affluence. This paper uses the per capita secondary industry's added value to indicate that the second industry is divided by the second industry's employment. The higher the per capita value created in the industry, the more prosperous the industry is. The variable T is the technological level, expressed in terms of energy intensity, that is, the ratio of energy consumption to the added value of the secondary industry (10,000 tons of standard coal/100 million yuan). The higher the technical level, the less energy is consumed per unit of added value and the smaller the T is. The above data comes from the website of the National Bureau of Statistics

### 3.2. *Carbon Emission Calculation Method.*

The fossil fuel consumption data of China's sub-industries comes from the website of the National Bureau of Statistics, and the available year is from 2000 to 2015. The conversion of various fossil fuels into standard coal coefficients originates from the "Reference Table of Reference Coefficients for Various Energy Conversion Standard Coals" in the appendix of "China Energy Statistical Yearbook". The carbon emission coefficient data was converted from the "IPCC Guidelines for National Greenhouse Gas Inventories" issued by the United Nations Intergovernmental Panel on Climate Change (IPCC) in 2006.

**Table 2.** Conversion coefficient and carbon emission factors

| Energy Type | Coal | Coke | Crude oil | Gasoline | Kerosene | Diesel | Fuel oil | Natural gas |
|---|---|---|---|---|---|---|---|---|
| Standard Coal Conversion Coefficient | 0.7143 tce/t | 0.9714 tce/t | 1.4286 tce/t | 1.4714 tce/t | 1.4714 tce/t | 1.4571 tce/t | 1.4286 tce/t | 13.30 tce/$10^4$m$^3$ |
| Carbon Emission Coefficient (t carbon/t standard coal) | 0.7559 | 0.8550 | 0.5857 | 0.5538 | 0.5714 | 0.5921 | 0.6185 | 0.4483 |

According to the Kaya identity, the carbon emission calculation model can be obtained:

$$C_t = \sum_{i=1}^{8} E_i\, T_i F_i \tag{4}$$

For each specific industry, $C_t$ represents the carbon emissions in year t, expressed in 10,000 tons; $E_i$represents the actual consumption of category i energy in year t, expressed in tons; $T_i$ represents the conversion of energy from class i into standard coal; $F_i$ represents the carbon emission coefficient corresponding to the category i energy source.

### *3.3. Sample Data Calculation Results*

The calculation results of China's second industry carbon emission data from 2000 to 2015 are shown in Table 3, which represents the variable I, that is, the environmental impact. The input values of population (P), affluence (A), and technical level (T) variables are shown in Table 3, respectively.

**Table 3.** Carbon emissions from secondary industries and their influencing factors from 2000 to 2015.

| year | Second industry carbon emissions (10,000 tons) | Employment in secondary industry (ten thousand people) | Per capita secondary industry added value (CNY) | Energy intensity of the second industry (10,000 tons of standard coal/100 million CNY) |
|---|---|---|---|---|
| 2000 | 101897.13 | 16219.10 | 28234.43 | 3.21 |
| 2001 | 105045.54 | 16233.70 | 30677.60 | 3.12 |
| 2002 | 110673.54 | 15681.90 | 34599.38 | 3.13 |
| 2003 | 130256.07 | 15927.00 | 39476.74 | 3.13 |
| 2004 | 150184.29 | 16709.40 | 44584.07 | 3.09 |
| 2005 | 169576.73 | 17766.00 | 49736.01 | 2.96 |
| 2006 | 186435.51 | 18894.50 | 55406.86 | 2.74 |
| 2007 | 198693.73 | 20186.00 | 62935.65 | 2.45 |
| 2008 | 206195.93 | 20553.40 | 73241.02 | 2.13 |
| 2009 | 217595.17 | 21080.20 | 76269.2 | 2.09 |
| 2010 | 233178.36 | 21842.10 | 88080.22 | 1.87 |
| 2011 | 254696.19 | 22543.90 | 101166.7 | 1.70 |
| 2012 | 263597.43 | 23241.00 | 105762.1 | 1.64 |
| 2013 | 308247.12 | 23170.00 | 113610 | 1.58 |
| 2014 | 305649.82 | 23099.00 | 120670.5 | 1.53 |
| 2015 | 297742.16 | 22693.00 | 124766.7 | 1.52 |

## 4. Empirical analysis

### *4.1. Secondary Industry Carbon Emission Analysis*

From 2000 to 2015, the carbon emissions of the secondary industry showed an overall upward trend and reached a peak by 2013. In 2014 and 2015, it fell for two consecutive years, but the growth rate slowed down and the annual growth rate showed a downward trend. In 2015, China’s carbon emissions from the secondary industry were 297,742,160 tons, which was a decrease of 79,076,600 tons from the same period in 2014, indicating that the energy-saving and emission-reduction policies have achieved initial results in recent years

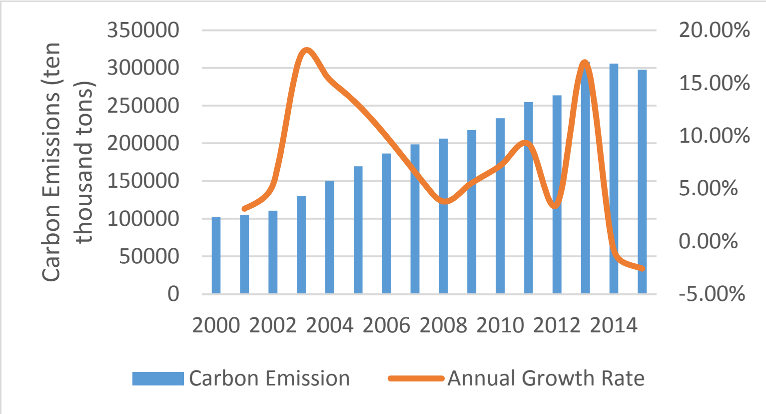


**Figure 1.** Carbon emissions and growth rates of secondary industry from 2000 to 2015

From the perspective of the distribution of carbon emissions from industries, the overall carbon emissions in 2015 accounted for 3% of household consumption, the primary industry accounted for 1%, the secondary industry accounted for 88%, and the tertiary industry accounted for 8%. The carbon emissions of the two industries accounted for an absolute majority. In the secondary industry, carbon emissions from manufacturing account for 57%, electricity, gas and water production and supply account for 32%, mining accounts for 10%, and construction accounts for only 1%.

*4.2. Measurement Regression Analysis of Carbon Emission Influencing Factors*

From the STIRPAT model, the main factors affecting carbon emissions include P (population number), A (richness), and T (technical level). Estimation of parameters by means of econometric regression analysis gives an estimate of the coefficient of elasticity of carbon emissions impacts on carbon emissions. In order to find the greatest impact on the carbon emissions of the second industry.

*4.2.1. Stability test of the data:* In this paper, the time series of four variables including lnI, lnP, lnA and lnT are respectively tested by three unit root test methods: Augmented Dickey-Fuller (ADF), Dickey-Fuller GLS, and Phillips-Perron (PP). The sequence of lnI, lnP, lnA, and InT are the same as those of the second order and can be tested by cointegration.

*4.2.2. Engel-Granger method for cointegration test*: The result shows that the residual resid is lower than the Engel-Granger threshold at a 1% significance level. The difference sequence is stationary. Therefore, the four variables lnI, lnP, lnA, and InT are cointegrated, and the variables can be subjected to regression analysis.

*4.2.3. Ordinary least squares regression*: The least squares method is used to perform regression fitting on the STIRPAT model, and the fitting effect is good. The relationship equation between variables can be written as:

$$\ln \boldsymbol{I} = -4.4479 + 0.6026 \ln \boldsymbol{P} + 0.9169 \ln \boldsymbol{A} + 0.6086 \ln \boldsymbol{T} \tag{5}$$

$$\boldsymbol{R^2} = 0.9929 \quad \boldsymbol{D.W.} = 1.3998 \quad \boldsymbol{F} = 560.7 \tag{6}$$

The actual meaning of the independent variable parameter in the equation is the elasticity coefficient of the carbon emission impact factors of the second industry. The results show that:

I. The population factor has a significant impact on the environment, and the direction of influence from the coefficient is positive. For every 1% increase in the number of employed persons in the secondary industry, the carbon emissions of the secondary industry will increase by 0.6026%.

II. The degree of affluence has the greatest impact on the environment. The symbol of the regression coefficient is available. The degree of affluence of the second industry has a positive impact on the carbon emissions of the second industry. For each additional 1% increase in the secondary industry's added value, carbon emissions from the secondary industry increased by 0.9169%.

III. The level of technology has a significant impact on the environment. As the level of technology in the model is expressed in terms of energy intensity, that is, the amount of energy consumed per unit of added value, the improvement in the level of technology is reflected in the decline in the value of energy intensity. Therefore, for every 1% reduction in energy intensity in the secondary industry, carbon emissions from the secondary industry will decrease by 0.6086%.

### *4.3. Carbon Emission Forecast and Accuracy Inspection*

Because there is no difference in the factors and driving methods of carbon emissions in the industry, the growth rate and trend of carbon emissions do not have complete consistency. Therefore, it is necessary to predict and analyze the secondary industry based on the grey GM (1, 1). The data processing process is implemented using Matlab software.

Taking the carbon emissions of China's secondary industry from 2000 to 2015 as the raw data, we forecast carbon emissions from 2016 to 2020. The fitted curves of the actual and predicted values are shown in Figure 2.

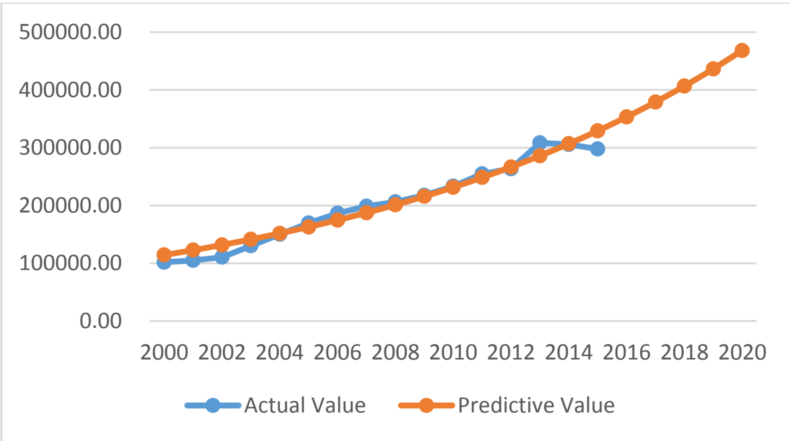


**Figure 2.** China's 2000-2020 carbon emissions forecast for secondary industry

As shown in the results of the analysis, China’s carbon emissions from the secondary industry increase by an average of 7.30% per year. By 2020, emissions will reach 468.157 million tons, which is 4.59 times that of 2000. The curve of the real value and the predicted value shown in the figure basically overlap, the precision of the predicted value is high, and the accuracy level needs to be given in the following text to give a specific calculation. The predicted carbon emissions of the secondary industry in 2016-2020 in China are shown in Table 4.

**Table 4.** China's secondary industry carbon emission forecast from 2016 to 2020.

| Year | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| Carbon emission forecast (ten thousand tons) | 353237.26 | 379007.58 | 406657.97 | 436325.58 | 468157.59 |

According to the posterior test difference test method, the posterior difference ratio C and the small error probability P of the carbon emission sequences of the three industries are calculated, where C is 12.52%, P is 100%. According to Table 1, the prediction accuracy level can be concluded as Excellent (Level 1). The difference between the predicted and actual values is small, and the forecasting result is reasonable.

## 5. Conclusion

Firstly, from the perspective of total carbon emissions, carbon emissions from the secondary industry showed an upward trend from 2000 to 2013, but the growth rate slowed year by year, peaked in 2013, and declined for two consecutive years in 2014 and 2015, indicating that energy conservation and emission reduction policies have achieved initial results. From the perspective of the distribution of carbon emissions, carbon emissions from the secondary industry accounts account about 88% of China's total carbon emissions. In order to achieve the goal of energy conservation and emission reduction in China, more emphasis should be placed on reducing emissions from the secondary industry.

Secondly, in this paper, the STIRPAT model is applied to the regression analysis of the factors affecting the carbon emissions of the second industry. According to the analysis, the increase in the number of employees in the secondary industry and the increase in the value-added of the secondary industry per capita all lead to an increase in carbon emissions, and the reduction in energy intensity due to technological progress will lead to a reduction in carbon emissions. China should actively promote the technological progress of the secondary industry, especially for high-energy-consuming industries, in order to reduce energy consumption and pollution.

Lastly, according to the forecast of the GM (1, 1) model, carbon emissions from the secondary industry in 2020 will reach 468.157 million tons. Annual average annual growth of 7.30%. The accuracy evaluation of GM (1, 1) carbon emission forecasting model shows that the forecasting accuracy is excellent, which means the forecasting result is reasonable. It shows that the GM (1, 1) model is feasible in the prediction of carbon emissions, and it can provide a scientific basis for the formulation of energy conservation and emission reduction targets in the future. We should rationally look at the future trend of China's secondary industry's carbon emissions, formulate sound policies, and promote low-carbon economic development through technological advances.

## Acknowledgments

This work was financially supported by 2017 National Social Science Fund Project "Evaluation and Policy Study on the Conductive Effect of Carbon Trading on China's Export Competitiveness under the Multi-Scenario Simulation (17BGL252)".

## References

[1] Chen Cheng, Hong Yaling, Fang Lingna, et al. Carbon emission estimation and analysis of road transport industry in Fujian Province. Journal of Chongqing Jiaotong University (Science and Technology), 2017, (9): 98-103.
[2] Song Jinzhao, Yuan Xiangyang, Wang Xiaoping. Analysis of Factors Affecting Carbon Emission in China Construction Industry. Environmental Engineering, 2018, (1): 178 - 182.
[3] Du Qiang, Lu Xinran, Feng Xinyu, et al. Research on carbon emission characteristics and influencing factors of construction industry in China's provinces. Resource Development & Market, 2017, (10): 1201-1208. DOI: 10.3969/j. Issn.1005 - 8141. 2017. 10.010.
[4] Wang Changjian, Zhang Hongou, Ye Yuyao, et al. Multivariate driving factors for carbon emissions from energy consumption in Guangdong Province: Based on an extended STIRPAT model. Science and Technology Management Research, 2017, 37 (3): 210 - 214.
[5] Huo Litian, Zhan Yisen, Liu Bingxiang. A carbon emission forecasting model based on GM (1, 1). Information and Computer (Theory), 2017, (03): 53 - 54.
[6] Wang Yongzhe, Ma Liping. Analysis and Prediction of the Related Influencing Factors of Energy Consumption Carbon Emission in Jilin Province: Based on Grey Relational Analysis and GM

(1, 1) Model. Ecological Economy, 2016, (11): 65 - 70.
[7] Xi Ruijin, Hu Yunhong, Kang Lina. The application of metabolic gray model in the prediction of carbon emissions in China. Mathematics in Practice and Theory, 2016, (11): 18 - 26.
[8] Wang Dong, Wu Changlan. Current status and prediction of carbon emissions in Guangdong. Open Herald, 2015, (06): 91 - 94.
[9] "Notice of the State Council on Printing and Distributing the Comprehensive Work Plan for Energy Saving and Emission Reduction during the 13th Five Year Plan" Guofa [2016] No. 74.