

Regional sulfur dioxide emissions: shall we achieve the goal?

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Abstract. Although economic growth is slowing down in the new normal period, air pollution is still a very serious problem in China. The 15% binding goal of sulfur dioxide emission reduction from 2016 to 2020, as stipulated in the 13th Five-Year Plan, has been an ambitious target for the Chinese government. This paper studies the synthetic evaluation and forecasting analysis of sulfur dioxide in China by means of a “grey model” approach combined with the grey relational analysis methods, with the panel data of 31 provinces from 2005 to 2015. Grey analysis used to analyse a system with imperfect information, such that a variety of available solutions is reviewed, and the optimal solution is identified. Some encouraging results show that national emissions and a majority of provinces will achieve the target. Over time, the gap of regional differences is rapidly closing. According to the results of grey relational analysis, we find industrial structure and energy consumption have a more significant impact on sulfur dioxide emissions than GDP. Atmospheric treatment investment and environmental protection manpower play a more important role in emissions variation. Based on the findings, we should distinguish different factors and take different measures to protect the environment.

1. Introduction

China has maintained a rapid economic growth since its economic reform and opening-up in 1978. According to the data from National Bureau of Statistics of China, in the 12th Five-Year Plan period, an average of about 8% annual GDP growth, much higher than the world average, has made China one of the fastest growing economies in the world. The dark side of that achievement is a heavy environmental cost that China has paid. The overall environmental quality becomes worse and worse, and air pollution, such as smog, has become a hot topic in the society. Even though in recent years, sulfur dioxide emissions have declined slowly, that could not mitigate the problems brought by sustained and rapid growth of emissions in the past few decades. After 2011, the beginning of the 11th Five-Year Plan, a mandatory emissions control was implemented. The 15% reduction goal of sulfur dioxide emission has been an ambitious but constraining target to both central and local government. But, can that goal be achieved?

To examine whether China can meet that goal or not, this paper forecasts the sulfur dioxide emissions trends in China. Many factors influence the emissions and most information is inadequate or difficult to obtain. All of these factors can be reflected in the time trend of sulfur dioxide emission. So, emission of sulfur dioxide is both a grey system and a fuzzy dynamic system. As an interdisciplinary scientific area, grey system theory is the very method of analysis and prediction using small data sets and inadequate information to achieve an effective forecast of future trends optimally.

In China, early in 1980s, Professor Deng brought forward the grey system theory[1], an applicable method to analyze an unknown situation and predict trends of certain terms with poor information or



limited observed data[2]. Soon afterwards, many scholars developed the theory. It expanded from management information system to social system, economic system, natural system, etc[3,4]. So far, it is applied extensively in several fields to forecast trends in economy, industry, environment, etc. Many scholars have been using a grey model approach to find solutions, adjust data [5,6], or improve models[7,8]. Among the methods in grey theory system, the method referred to as GM (1, 1) is used frequently by scholars as a prediction tool. Many modeling practices indicate that the GM (1, 1) model has a much higher accuracy than the exponential curve regression model[9,10]. The grey relational analysis method provides a quantitative tool to analyze a two-factor system development trend, indicating the characterization of numerical referred to as the grey relation [11,12]. It has been applied to various fields to measure the relationship between different variables, such as economics, chemistry, biology, environment and so on [13].

Admittedly, the GM (1, 1) model can forecast the regional emissions of sulfur dioxide in 2020, but it cannot tell the reasons behind the regional difference. So grey relational analysis method is conjointly used in our analysis, to mine the reasons behind sulfur dioxide emissions' variation. This article starts with a discussion on the GM (1, 1) model applied in environmental prediction and management. We study and forecast the sulfur dioxide emissions in China using the provincial data from 2005 to 2015. Furthermore, we apply grey relational analysis twice to search the relationship between emissions and social economy. This article intends to not only advance the prediction of the sulfur dioxide emissions during the 13th Five-Year Plan for Economic and Social Development of the People's Republic of China (the 13th Five-Year Plan) period, but also explain the reasons of emissions' variation with factors of economic development, industrial structure, and environmental protection efforts.

2. Data and methods

2.1. Data selection

Based on the availability and validity of the data, in this article, data from 2005 to 2015 are selected from national and regional *Statistical Yearbook*, and 2015's data are mined from provincial *National Economy and Society Developed Statistical Bulletin*, including sulfur dioxide emissions, gross domestic product (GDP), per capita GDP, proportion of secondary industry, total energy consumption. Other data are selected from *Annual Statistic Report on Environment in China* from 2005 to 2015, including per capita environmental protection investment, every ten thousand people with staff in environmental protection systems, and the proportion of atmospheric treatment in environmental protection investment.

2.2. Methods description

Since some sectors' emissions data are not collected, the data of sulfur dioxide is a grey system. We construct the traditional grey GM (1, 1) model and briefly look at the relevant basics of analysis of both parameter a and b . Assume $X^{(0)}$ is the original sequence of data, $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$, which stands for the non-negative original historical time series data. Then indicate new generate series of data as $X^{(1)}$, and $X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)\}$. If there is a relationship between $x^{(0)}$ and $x^{(1)}$ as $x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i)^2$, it is called the first order accumulated generating operation, marked as 1-AGO, and $X^{(1)}$ is called the first order accumulating generation sequence of $X^{(0)}$. The sequence $Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)\}$ demonstrates the mean consecutive neighbor's generation operator for $X^{(1)}$, and $Z^{(1)}(k) = 0.5[x^{(1)}(k) + x^{(1)}(k-1)]$. The following differential equation represents the approximation of $x^{(0)}(k)$ data:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad (1)$$

Where a and b represent development coefficient and grey effect coefficient, both are estimated parameter in equation (1). Solving Eq. (1), we can obtain the discretization of the Eq. (2):

$$\Delta^{(1)}(x^{(1)}(k+1)) + az^{(1)}(x(k+1)) = b \quad (2)$$

It can be simplified:

$$x^{(0)}(k+1) = a[-\frac{1}{2}(x^{(1)}(k) + x^{(1)}(k+1))] + b \quad (3)$$

The matrix form of Eq. (1) will be described as follows:

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix} \quad (4)$$

The parameter matrixes are $\hat{a} = [\hat{a}, \hat{b}]^T = (B^T B)^{-1} B^T Y$,

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \text{ and } B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix} \quad (5)$$

If we plug the estimated result into Eq. (2), the time respond function of the grey differential equation is:

$$\hat{x}^{(1)}(k+1) = [x^{(1)}(1) - \frac{\hat{b}}{\hat{a}}]e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}} \quad (6)$$

We can obtain the formula with regard to original series data:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1 - e^{\hat{a}})[x^{(1)}(1) - \frac{\hat{b}}{\hat{a}}]e^{-\hat{a}k} \quad (7)$$

When the generation sequence approximately conforms to a linearity power function law and the sequence of data varies approximately according with the law of exponential function, GM (1, 1) method has a better prediction effect. The data of sulfur dioxide emissions of China from 2005 to 2015 and the accumulation generation sequence correspond to rules as above.

Based on the results of grey forecasting, combining the economic level and environmental management of different regions, we attempt to mine the reasons behind sulfur dioxide emissions growth or decline by grey relational analysis.

Assume X_0 is the consensus sequence of data, $X_0 = (x_0(1), x_0(2), \dots, x_0(n))$, which indicates the characteristics of the system behavior. The sequence of data $X_i = (x_i(1), x_i(2), \dots, x_i(n))$ is a comparative sequence, which represents the factors that affect the system. ρ is the identification coefficient, $0 < \rho < 1$. The relation coefficient of two sequences in moment k can be described as follows.

$$\xi_i(k) = \frac{\min |X_0(k) - X_i(k)| + \rho \max |X_0(k) - X_i(k)|}{|X_0(k) - X_i(k)| + \rho \max |X_0(k) - X_i(k)|} \quad (8)$$

It is customary to use the mean of results to describe the relation between consensus sequence and comparative sequence, since results in all moments are too myriad to compare, as follows.

$$\gamma(X_0, X_k) = \frac{1}{n} \xi_i(k) \quad (9)$$

Since $0 < \zeta_i(k) < 1$, $0 < \gamma < 1$. When grey relation γ tends to 1, it shows that the development trend of the two sequences is consistent. According to the degree of the relation between different elements, we can quantify and judge the factors' influence.

This paper measures the influence of different factors on the emissions and emissions reductions of sulfur dioxide via two approaches. Firstly, we estimate economy, industrial structure and energy consumption's impact on sulfur dioxide emissions, trying to find reasons for the emissions variations. Secondly, we calculate the grey relation between environmental protection investment, atmospheric governance investment, and labor and emission variation.

3. Result Analysis and Discussion

3.1. Grey model forecasting for the nation

We obtain the value of estimated parameter \hat{a} and \hat{b} . $\hat{a} = 0.0323$, $\hat{b} = 2655.858$. Backward error-detection is necessary to test the model accuracy. Two indicators used in this paper are C (variance ratio) and P (small error probability), obtained by calculation of the formulas as below, where S_x^2 means variances of original sequence and S_ε^2 means residual error sequence.

$$S_x^2 = \frac{1}{n-1} \sum_{k=1}^n (x^{(0)}(k) - \bar{x}^{(0)})^2 \quad (10)$$

$$S_\varepsilon^2 = \frac{1}{n-1} \sum_{k=2}^n (\varepsilon^{(0)}(k) - \bar{\varepsilon}^{(0)})^2 \quad (11)$$

$$C = S_\varepsilon^2 / S_x^2, \quad P = P\{0.6745 S_x > |\varepsilon^{(0)}(k) - \bar{\varepsilon}^{(0)}|\} \quad (12)$$

Table 1. Accuracy grade of grey model.

Grade	R	C	P
excellent	$r \leq 0.01$	$C \leq 0.35$	$0.95 \leq P$
well	$0.01 < r \leq 0.05$	$0.35 < C \leq 0.50$	$0.80 \leq P < 0.95$
qualified	$0.05 < r \leq 0.1$	$0.50 < C \leq 0.65$	$0.70 \leq P < 0.80$
unqualified	$0.1 < r$	$0.65 < C$	$P < 0.70$

We obtain the values of C and P , and test results by calculating as following:

$$C = 0.0400, \quad P = 1.6990$$

From the grade in Table 1, it is obvious that this model can be applied to forecast with an excellent precision. The results of GM(1,1) are shown in Table 2. The maximum relative error of prediction value is -3.78%; the minimum one is 0.67%, and its mean relative error is -1.90%.

Table 2. GM (1, 1) analysis results of national data¹.

Year	sulfur dioxide emission	value of simulation	Residue (r)	relative error (%)	Year	sulfur dioxide emission	value of simulation	Residue (r)	relative error (%)
2005	2549.40	2549.40	-	-	2011	2217.91	2154.17	63.74	2.87%
2006	2588.80	2532.24	56.56	2.18%	2012	2117.60	2085.61	31.99	1.51%
2007	2468.10	2451.66	16.44	0.67%	2013	2043.00	2019.24	23.76	1.16%
2008	2321.20	2373.64	-52.44	-2.26%	2014	1974.40	1954.98	19.42	0.98%
2009	2214.40	2298.10	-83.70	-3.78%	2015	1859.10	1892.77	-33.67	-1.81%
2010	2185.15	2224.97	-39.82	-1.82%					

¹ Units of sulfur dioxide emission is 10000 tons, similarly hereinafter.

According to the results, sulfur dioxide emissions in 2020 will be 1610.17 ten thousand tons, which is 14.93% less than that in 2015. This number is close to the emission reduction targets of the 13th Five-Year Plan (-15%), which looks encouraging on a national basis.

3.2. Regional sulfur dioxide emissions prediction

Figure 1 shows provincial sulfur dioxide emissions in 2015 and 2020 based on the results of GM (1, 1). In light of the accuracy grade and Table 4, most provincial models have good precision, such that the maximum relative error of provincial prediction value is 8.49% (Guangxi) and the minimum one is 0.64% (Anhui).

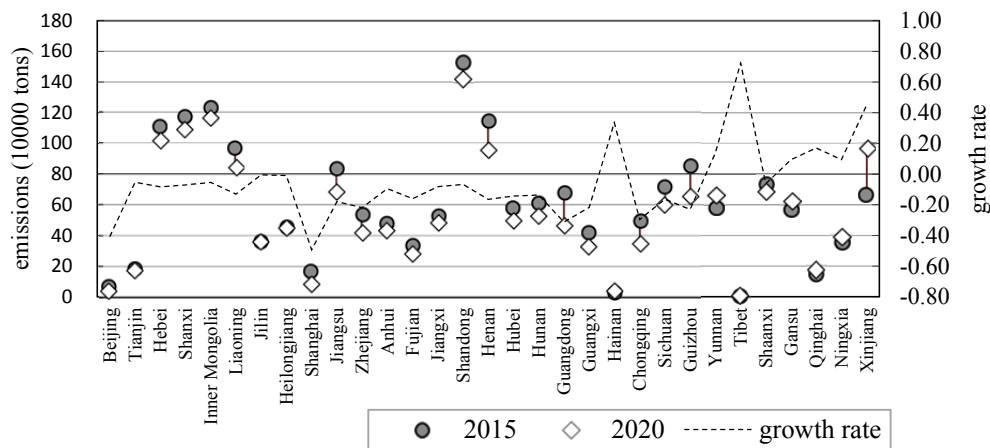


Figure 1. Provincial sulfur dioxide emissions in 2015 and 2020.

Compared with 2015, shown in Figure 1, in the light of its own system trends and present environmental management, 7 provinces' sulfur dioxide emissions will increase in 2020, most of which are located in western inland areas, such as Tibet, Xinjiang, Qinghai, and Gansu. In all, 11 provinces have better emission reduction rates than the national average and they achieve the reduction target of -15%, most of which are eastern developed regions, such as Shanghai, Beijing, and Guangdong.

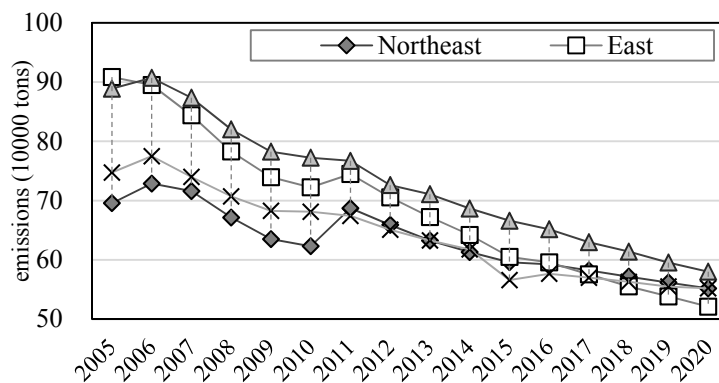


Figure 2. Sulfur dioxide emissions trend of the Four Areas).

According to the forecasting results of 31 provinces, over time, middle areas' average sulfur dioxide emissions still are higher than northeast and west areas, but Figure 2 shows that the gap nationwide is rapidly closing. Among the four areas, the eastern area has the biggest emission reduction, and this area has a more developed economy generally. We find that economic development brings large amounts of emissions but also substantial funding for emissions reductions. That is to say, the advanced economy is the main driver of emissions reduction in these provinces as large injections

of funds are available to improve the technology of environmental production and coal-fired power plants.

3.3. Influencing factor analysis

In the factor analysis, we first estimate economy, industrial structure and energy consumption's impact on sulfur dioxide emissions, with indicators of "per capita GDP (p_GDP)", "total energy consumption (Energy_consump)", "proportion of secondary industry (Prop_S-industry)", mentioned above. The results shown in Figure 3 help explain the factors which influence the regional emissions, with wide difference among regions.

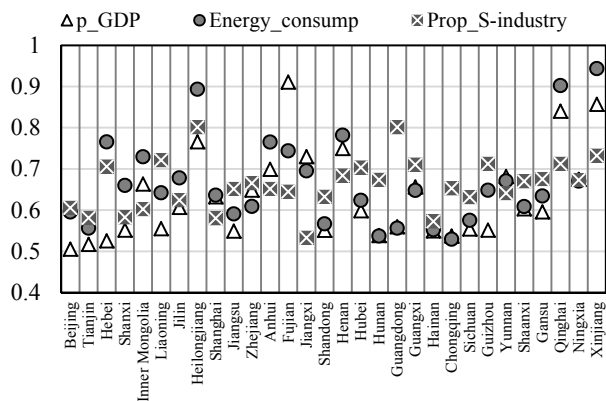


Figure 3. Influencing factors on sulfur dioxide emissions.

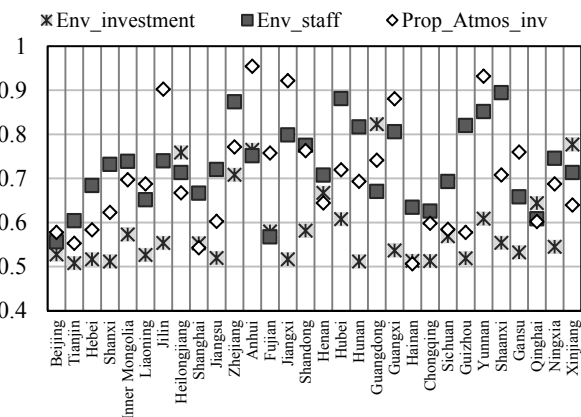


Figure 4. Influencing factors on sulfur dioxide emissions variation.

Secondly, we estimate the grey relation among environmental protection investment, atmospheric governance investment, and labor and emission variation, with indicators of "per capita environmental protection investment (Env_investment)", "every ten thousand people with staff in environmental protection system (Env_staff)", "proportion of atmospheric treatment investment in environmental protection investment (Prop_Atmos_inv)".

Figure 4 shows the results of the grey relational analysis, with features of wide regional differences. Generally, environmental protection investment has little effect on sulfur dioxide emission variation. On the contrary, proportion of atmospheric treatment investment in environmental protection investment has significant impact on it, which is reasonable. In some regions, to name only a few, Jinlin, Anhui, Jiangxi, Guangxi, manpower input plays the most important role in emissions variation, which can partly explain that the magnitude of the environmental regulation is very important.

4. Discussion

It's gratifying that China will be likely to achieve the emission reduction targets of the 13th Five-Year Plan. Most regions will achieve sulfur dioxide emissions reduction, while some western inland regions will go to the contrary, such as Xinjiang, Qinghai, and Gansu, which need to strengthen prevention and treatment.

In this paper, the grey relational analysis method is applied to mine the reasons for sulfur dioxide emissions and emissions variation. We find industrial structure and energy consumption have more significant impact on sulfur dioxide emissions than GDP. In view of emissions variation, atmospheric treatment investment level and environmental protection manpower play a more important role in most regions. Overall, a critical element is the different levels of resources applied to this problem, including political will, economic investment, and technological resources and so on. The advanced regions, to only name a few, Beijing, Shanghai, have more resources to determine their own development path and structure, and to choose better methods of pollution control, as opposed to less advanced regions that assume more passive roles. It is difficult to consider the political factor into the grey relational analysis model in this paper, and that is a topic for a future discussion.

Based on the findings, different regions should adjust measures to local conditions. For advanced regions, such as Beijing, Tianjin, Shanghai, since their forecasted emissions and grey relations are generally smaller, it's feasible to maintain the existing economic growth pace and environmental protection efforts. The regions with increasing forecasted emissions should make more efforts on the points where their relational values are high. Especially for the western inland regions, just name only a few, Xinjiang, Qinghai, Gansu, not only influence factors of reduction but also of emissions should be considered. Those regions should explore solution from the essential development patterns, energy conservation and emissions reduction, for instance, more clean energy instead of fossil energy consumption to optimize the energy consumption structure.

5. Conclusions

We have forecasted regional sulfur dioxide emission growth of 2015 to 2020, and proposed a potential relationship among emission reduction, economic development and environmental protection efforts with an approach of grey relational analysis. Economic development brings large amounts of emissions but also substantial of funding for emissions reductions. The strength of the current environmental protection is generally inadequate in the western inland regions. For different regions, we should distinguish different influence factors and take different measures to promote emissions reduction and environmental protection.

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