Prediction of air quality indicators for the Beijing-Tianjin-Hebei region

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Abstract:

The Beijing-Tianjin-Hebei region is facing a very serious air pollution problem. To obtain the future trend of air quality, the GM(1,1) model with the fractional order accumulation (FGM(1,1)) is used to predict the average annual concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, 8-hour O_3, and 24-hour O_3 in the Beijing-Tianjin-Hebei region from 2017 to 2020. The concentrations of $PM_{2.5}$ and SO_2 will decrease and the 8-hour O_3 and 24-hour O_3 will increase in this region. The concentrations of PM_{10} and NO_2 will decrease in the Taihang-Mountain-adjacent region (Baoding, Shijiazhuang, Xingtai, Handan and Hengshui) and increase in the Northern region (Zhangjiakou, Chengde and Qinhuangdao). The concentration of PM_{10} will decrease and NO_2 will increase in the Bohai Sea region (Tangshan, Tianjin, Cangzhou, Beijing and Langfang). Our results can be directly exploited in the decision-making processes for air quality management.

Keywords: Air quality indicators; Beijing-Tianjin-Hebei; GM(1,1) with fractional order accumulation

1. Introduction

Air quality is an increasing concern of the public. Therefore, the air pollution control is inevitable, and the accurate forecasting of air quality is the most important part of air quality management. At present, researchers have carried out in-depth studies on forecasting methods of air quality indicators, and predicted the air quality in different regions. For example, binary glowworm swarm optimization combined with a rough set approach has been applied to forecast the key factors that influence haze badly for the datasets of Beijing, Guangzhou and Shanghai in China (Cheng et al., 2017). The operational prediction of air quality model was evaluated for the monitoring data of 2015 in Tianjin (Gao et al., 2016). A feed forward neural network model was used to forecast the hourly $PM_{2.5}$ concentration in Santiago, Chile (Patricio and Ernesto,

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2016). William (2016) focused on the forecasting of air quality for recent changes and future challenges. The $PM_{2.5}$, PM_{10}, and SO_2 data collected from Tianjin and Shanghai in China were used to evaluate the effectiveness and efficiency of a hybrid model (Xu et al., 2017). Probabilistic forecasting technique was developed to forecast extreme NO_2 pollution episodes in Madrid (Jose, 2017). Exponential smoothing technique and autoregressive models were developed to forecast PM_{10} concentration for Allahabad city (Vibha and Satyendra, 2017). A framework based on random forests, genetic algorithm and back propagation neural networks techniques has been proposed to forecast the daily PM_{10} concentration in Brunei Darussalam (Sam et al., 2017). The trend of $PM_{2.5}$ concentration was analyzed by using a combination of different forecasting models (Liu and Li, 2015). A novel hybrid decomposition-ensemble learning paradigm with error correction was proposed to forecast the PM_{10} concentration from Beijing and Harbin in China (Luo et al., 2018). The principal component analysis and least squares support vector machine were optimized by cuckoo search to establish a $PM_{2.5}$ concentration forecasting model for Baoding city in China (Wei and Sun, 2017). To reveal the performance of the hybrid model, an early-warning system was tested with the hourly data during August 21st 2015 and September 29th 2016 in Beijing, Tianjin and Shijiazhuang (Li and Jin, 2018). Daily air quality index from Xingtai in China were predicted by using hybrid models (Zhu et al., 2017). A first-order and one-variable grey differential equation model (GM(1,1)) was constructed to forecast hourly roadside particulate matter (including PM_{10} and $PM_{2.5}$) concentrations in Taipei County of Taiwan (Pai et al., 2013). The seasonal autoregressive integrated moving average approach was used to forecast the level of SO_2 air quality parameter in Aksaray of Turkey (Gamze and Cem, 2017). The daily air quality index was predicted by using principal component regression technique (Anikender and Pramila, 2011). The two daily air quality index series from Beijing and Shanghai located in China were predicted by using the hybrid model (Wang et al., 2017).

Literature on air pollutant forecasting has mainly focused on hourly (or daily) data. The annual data forecasting of air pollutants were not available, which is the research gap of the air pollutant forecasting field. To bridge this gap, long term air quality forecasting is necessary. What's more, areas affected by air pollution in China are much larger than those cities in Britain and the

United States. Addressing air pollution in China is much more complicated than that in European and American countries. And it's also hard to solve the problem in a short term (Chinadaily, 2017a). Long-term management mechanisms should be put into place. Therefore, long term air quality forecasting is also necessary. In this paper, the annual data forecasting of the air pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_2, 8-hour O_3, and 24-hour O_3) is carried out.

FGM(1,1) appeals considerable interest in recent researches due to its effectiveness in short time series forecasting (Wu et al., 2015). Many cases demonstrated that FGM(1,1) outperform the traditional GM(1,1) (Jiang et al., 2018). The simulation results illustrated that the fractional-order calculus could be used to depict the GM(1,1) precisely with more degrees of freedom (Yang and Xue, 2017). The performance of the self-adaptive intelligence FGM(1,1) is better than GM(1,1) (Zeng and Liu, 2017). It is noted that the growth rate of forecasting results for the FGM(1,1) is changeable (Wu, 2016). It is more consistent with the change trend of real time series. Compared with the existing research, the main novelties and contributions of this paper are presented as follows. Firstly, FGM(1,1) performs better than the traditional GM(1,1) for the air pollutants forecasting. This indicates that the FGM(1,1) is able to predict the tendency of air pollutants concentration. Secondly, according to its geolocation and the atmospheric pollution conditions, the Beijing-Tianjin-Hebei region is divided into three regions. Thirdly, due to its ability to analyze forecasting problem when there are only a few data points, FGM(1,1) is used to predict the average annual concentrations (including $PM_{2.5}$, PM_{10}, SO_2, NO_2, 8-hour O_3, and 24-hour O_3) in the three regions. Fourthly, the forecasting results can provide important information for the air quality management in the Beijing-Tianjin-Hebei region.

This paper is organized as follows. An overview on air pollutant in the Beijing-Tianjin-Hebei is given in Section 2. The forecasting method is introduced in Section 3. The data source and the empirical analysis are presented in Section 4. The conclusions are discussed and the suggestions are offered in Section 5.

2. Overview of air pollutant in the Beijing-Tianjin-Hebei region

The concentrations of the main air pollutants reflect the overall air quality for a given time and place. In recent years, China has adopted multiple air control measures. Air quality has significantly improved. However, for the Beijing-Tianjin-Hebei region, which is most affected by air pollution, the situation remains grim. In 2013, seven cities (Xingtai, Shijiazhuang, Baoding, Handan, Hengshui, Tangshan, and Langfang) in Hebei made the top-ten worst polluted city chart (Chinadaily, 2014). In 2016, all of the top ten cities with the worst air quality are in northern China, with six of them located in Hebei. They are Xingtai, Shijiazhuang, Baoding, Handan, Hengshui, and Tangshan (Chinadaily, 2017b). In mid-January 2013, the concentration of $PM_{2.5}$ exceeded 1000 $\mu g/m^3$ in Beijing (BBC, 2013). These events illustrate the urgency of air pollution control and the importance of air quality forecasting for this region.

The Beijing-Tianjin-Hebei region is the capital district of China. It is located in the North China Plain and bordered by the Taihang Mountains. According to its geolocation and atmospheric pollution conditions, the Beijing-Tianjin-Hebei region is divided into three regions. They are the Northern region (including Zhangjiakou, Chengde, and Qinhuangdao), the Bohai Sea region (including Tangshan, Tianjin, Cangzhou, Beijing, and Langfang), and the Taihang-Mountain-adjacent region (including Baoding, Shijiazhuang, Xingtai, Handan, and Hengshui). The cities within a region are similar in geographical environment, thus their atmospheric environments are also very similar. The simple map of the study area is shown in Fig.1.

[Insert Fig.1 about here]

In the National Human Rights Action Plan of China, the ratio of days with good air quality in cities above the prefecture level shall exceed 80% by 2020 (SCIO, 2016). Managing atmospheric haze is an important part of promoting the development of an ecologically sound civilization. However, air quality management does not yield results overnight. It requires long-term planning and collaborative governance. Predicting average annual air quality indicator concentrations from 2017 to 2020 can provide the technical support to local governments for the future air quality management.

3. Data and Methods

The average annual concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, 8-hour O_3, and 24-hour O_3

are selected as the forecasting indicators. The indicators data are from the Air Quality Assessment Report IV (CSSPKU, 2017). The current air quality data depends on a new standard (GB 3095-2012) published in 2012. The $PM_{2.5}$ values were mandatorily included in this new standard for the first time. Only a few sets of annual data are available.

Due to the limited data, other prediction methods are not applicable. Hence, the grey prediction theory, which can deal with the forecasting problem with limited sample (Wu et al., 2013a), is considered. In this paper, the high precision FGM(1,1) model was used to predict the average annual concentrations of the major air quality indicators in the Beijing-Tianjin-Hebei region from 2017 to 2020.

Given a non-negative time series $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\}$, the FGM(1,1) modelling process is as follows (Wu et al., 2013b).

Step 1: By using $x^{(r)} = \Sigma_{i=1}^{k} C_{k-i+r-1}^{k-i} x^{(0)}(i)$, the r-order accumulation sequence is

$$X^{(r)} = \{x^{(r)}(1), x^{(r)}(2), \cdots, x^{(r)}(n)\}, \tag{1}$$

where

$$C_{r-1}^{0} = 1, C_{k}^{k+1} = 0, C_{k-i+r-1}^{k-i} = \frac{(k-i+r-1)(k-i+r-2)\cdots(r+1)r}{(k-i)!}, \tag{2}$$

The original time series has been represented by superscription (0). The r-order accumulation time series has been represented by superscription (r).

Step 2: For the r-order accumulation sequence $X^{(r)}$, the first-order differential equation with one variable (i.e., the FGM(1,1) model) can be expressed as below:

$$\frac{dx^{(r)}(t)}{dt} + ax^{(r)}(t) = b, \tag{3}$$

Where a is a coefficient for the development and b is the grey action quantity. The solution of Eq.(3) is

$$x^{(r)}(t+1) = [x^{(0)}(1) - \frac{b}{a}]e^{-at} + \frac{b}{a}, \tag{4}$$

Because the least squares estimate minimizes the sum of the squared residuals, the parameters are obtained by using the least squares. The unknown parameters $\hat{a}, \hat{b}$ can be solved by using the following formulas:

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y, \tag{5}$$

where

$$Y = \begin{bmatrix} x^{(r)}(2) - x^{(r)}(1) \\ x^{(r)}(3) - x^{(r)}(2) \\ \vdots \\ x^{(r)}(n) - x^{(r)}(n-1) \end{bmatrix}, B = \begin{bmatrix} -0.5(x^{(r)}(1) + x^{(r)}(2)) & 1 \\ -0.5(x^{(r)}(2) + x^{(r)}(3)) & 1 \\ \vdots & \vdots \\ -0.5(x^{(r)}(n-1) + x^{(r)}(n)) & 1 \end{bmatrix}, \tag{6}$$

Step 3: Inputting $\hat{a}$ and $\hat{b}$ into the time response function

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

$\hat{x}^{(r)}(k+1)$ is the fitting value at time $k+1$.

Step 4: For $\hat{X}^{(r)} = \{\hat{x}^{(r)}(1), \hat{x}^{(r)}(2), \cdots, \hat{x}^{(r)}(n), \cdots\}$, the predictive sequence is

$$\alpha^{(r)}\hat{X}^{(r)} = \{\alpha^{(1)}\hat{x}^{(r)(1-r)}(1), \alpha^{(1)}\hat{x}^{(r)(1-r)}(2), \cdots, \alpha^{(1)}\hat{x}^{(r)(1-r)}(n)\}, \tag{8}$$

where $\alpha^{(1)}\hat{x}^{(r)(1-r)}(k) = \hat{x}^{(r)(1-r)}(k) - \hat{x}^{(r)(1-r)}(k-1)$. Then the forecasting values are $\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(n), \cdots$.

Step 5: The mean absolute percentage error (MAPE) is used for evaluating the models, which is calculated as:

$$\text{MAPE} = 100\% \frac{1}{n} \sum_{k=1}^{n} |\frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}|, \tag{9}$$

When $r = 1$, FGM(1,1) is the traditional GM(1,1).

4. Empirical analysis and result discussions

Take the Taihang-Mountain-adjacent region as an example. The data from 2013 to 2016 are taken as the sample set. The traditional GM(1,1) model and the FGM(1,1) model are established respectively. The FGM(1,1) modelling process is as follows.

(1) The average annual concentration of SO_2 is $X^{(0)} = \{88.4, 62.2, 48.5, 45.3\}$. The 0.1-order accumulation sequence is $X^{(0.1)} = \{x^{(0.1)}(1), x^{(0.1)}(2), x^{(0.1)}(3), x^{(0.1)}(4)\} = \{88.4, 71.0, 59.6, 56.9\}$. The unknown parameters $\hat{a}, \hat{b}$ can be solved by the following formulas:

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y = \begin{bmatrix} 0.64674 \\ 33.3542 \end{bmatrix}, \tag{10}$$

where

$$Y = \begin{bmatrix} 17.36 \\ 11.46 \\ 2.61 \end{bmatrix}, B = \begin{bmatrix} -79.72 & 1 \\ -65.31 & 1 \\ -58.28 & 1 \end{bmatrix}, \tag{11}$$

(2) Then, the time response function is

$$\hat{x}^{(0.1)}(k+1) = [88.4 - \frac{33.3542}{0.64674}]e^{-0.64674t} + \frac{33.3542}{0.64674}, \tag{12}$$

We can obtain

$$\hat{X}^{(0.1)} = \{\hat{x}^{(0.1)}(1), \hat{x}^{(0.1)}(2), \cdots, \hat{x}^{(0.1)}(8)\} = \{88.4, 70.9, 61.7, 56.9, 54.3, 53.0, 52.3, 52.0\} \tag{13}$$

Therefore,

$$\begin{aligned} \hat{X}^{(1)} &= \{\hat{x}^{(0.1)(0.9)}(1), \hat{x}^{(0.1)(0.9)}(2), \cdots, \hat{x}^{(0.1)(0.9)}(7), \hat{x}^{(0.1)(0.9)}(8)\} \\ &= \{88.4, 150.4, 201.0, 246.0, 288.1, 328.4, 367.8, 406.5\} \end{aligned} \tag{14}$$

The predictive sequence is

$$\hat{X}^{(1)} = \{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(7), \hat{x}^{(0)}(8)\} = \{88.4, 62.0, 50.6, 45.0, 42.0, 40.4, 39.4, 38.7\} \tag{15}$$

The fitting results for the average annual concentrations of SO_2 in the Taihang-Mountain-adjacent region are shown in Table 1. The MAPE of the FGM(1,1) model is significantly lower than that of the traditional GM(1,1) model. The result of FGM(1,1) model with the best fractional order is obtained by particle swarm optimization on Matlab2016a. In this order, the MAPE is minimal, and the fitting accuracy is higher. Therefore, the FGM(1,1) model is more suitable for predicting the average annual concentration of SO_2 in the Taihang-Mountain-adjacent region. Then FGM(1,1) is used to predict the average annual concentrations of SO_2 from 2017 to 2020. The predictive results of SO_2 in the Taihang-Mountain-adjacent region are listed in Table 2.

Table 1 Fitting results of SO_2 in the Taihang-Mountain-adjacent region

Year	Actual value ($\mu g/m^3$)	GM(1,1)	FGM(1,1)
2013	88.4	88.4	88.4
2014	62.2	60.8	62.0
2015	48.5	51.4	50.6
2016	45.3	43.5	45.0
MAPE		3.1	1.3

Table 2 SO_2 prediction results

Year	predicted value ($\mu g/m^3$)
2017	42.0
2018	40.4
2019	39.4
2020	38.7

Similarly, these indicators data (the average annual concentrations of $PM_{2.5}$, PM_{10}, NO_2, 8-hour O_3, and 24-hour O_3) are also limited. The grey prediction theory is also suitable. To obtain the high precision, the FGM(1,1) model is also more suitable for predicting these indicators. Hence, the average annual concentrations of $PM_{2.5}$, PM_{10}, NO_2, 8-hour O_3, and 24-hour O_3 are respectively predicted by the FGM(1,1) model in the Taihang-Mountain-adjacent region from 2017 to 2020.

The change trend of air quality indicators in the Taihang-Mountain-adjacent region is shown in Fig.2. It is evident that the average annual concentrations of each indicator in the Taihang-Mountain-adjacent region fluctuate only slightly. Among these indicators, the average annual concentration of $PM_{2.5}$ from 2017 to 2020 exceeds 75 $\mu g/m^3$. This indicates that Taihang-Mountain-adjacent region will have slight pollution over the next few years. The average annual concentration of PM_{10} remains high and significantly exceeds the level II concentration limit in China's environmental air quality standard (The air quality levels and corresponding concentration limits of different pollutants are be depicted in Table 3). The average annual concentration of SO_2 is lower than the Level II concentration limit, and has a downward trend. The average annual concentrations of NO_2 do not vary greatly and exceed the concentration limit only slightly, which indicates that quality control is not significantly effective. In contrast to the slight declines in other pollutants, the average annual concentrations of 8-hour O_3 and 24-hour O_3 are increased. As indicated in Fig.2, most of the indicators concentration decline, but their levels are still within the range of slight pollution. Moreover, the ozone concentrations continue to rise. The situation is not very promising. It indicates that an overall improvement of air quality is still necessary. The five cities in the Taihang-Mountain-adjacent region need to intensify their air quality control measures, control the $PM_{2.5}$ concentration, and curb the increase in ozone emission.

[Insert Fig.2 about here]

Table 3 The air quality levels and corresponding concentration limits of different pollutants

pollutants	average time	Level I ($\mu g/m^3$)	Level II ($\mu g/m^3$)
SO_2	annual	20	60
NO_2	annual	40	40
O_3	8-hour	100	160
PM_{10}	annual	40	70
$PM_{2.5}$	annual	15	35

By using a similar method, the average annual concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, 8-hour O_3, and 24-hour O_3 are predicted respectively in the Bohai Sea region and the Northern region.

The change trend of air quality indicators in the Bohai Sea region is shown in Fig.3. It shows a slightly decreasing trend in the $PM_{2.5}$, PM_{10}, and SO_2 concentrations in the Bohai Sea region, while the concentrations of NO_2, 8-hour O_3, and 24-hour O_3 increase slightly. Compared with the Taihang-Mountain-adjacent region, the average annual concentrations of $PM_{2.5}$, PM_{10}, and SO_2 in the Bohai Sea region are significantly lower. However, the $PM_{2.5}$ and PM_{10} all exceed the level II concentration limits. SO_2 control is very effective, as shown by the lower concentration. The concentrations of NO_2, 8-hour O_3, and 24-hour O_3 are similar to those of the Taihang-Mountain-adjacent region. These results indicate that the five cities of the Bohai Sea region need to implement highly effective control measures, especially for $PM_{2.5}$ and PM_{10}. Furthermore, persistent air quality control measures for NO_2, 8-hour O_3, and 24-hour O_3 is also requested in order to improve the air quality.

[Insert Fig.3 about here]

[Insert Fig.4 about here]

The change trend of air quality indicators in the Northern region is shown in Fig.4. With the exception of the 8-hour O_3 and 24-hour O_3, the concentrations of the other indicators in the Northern region were lower than those in the Taihang-Mountain-adjacent region and Bohai Sea region. The three cities in the Northern region are all at high altitude, and the 2013-2016 data indicate that they had better air quality. The predicted average annual concentrations of $PM_{2.5}$ and PM_{10} for 2017-2020 slightly exceed the level II concentration limits. The average annual concentration of SO_2 is far below the standard limit, and it has a downward trend. The concentration of NO_2 increases slowly, thus more intensive control measures are required. However, the concentrations of the 8-hour O_3 and 24-hour O_3 show a consistently increasing trend. This means that the three cities in the Northern region should adopt more direct and effective measures to control their ozone emissions and to maintain the current level of the other air quality indicators.

The Taihang-Mountain-adjacent region, the Bohai Sea region and the Northern region all belong to the same meteorological zone. So they share the same air pollution control measures, such as those for $PM_{2.5}$. However, they also have some differences, such as their O_3 concentration levels. This implies that the three regions have different pollution sources. Hence their control measures should have different emphasis. In the Taihang-Mountain-adjacent region, the concentrations of $PM_{2.5}$ and PM_{10} are the highest. Therefore this problem is the most significant one to be dealt with. The challenge lies in controlling the increase of the particulate matter and implementing strong control measures for coal combustion and industrial production. In the Bohai Sea region, the NO_2 concentration increases continually. The challenge lies in controlling the motor vehicle exhaust emissions, which increase NO_2. In the Northern region, the challenge lies in controlling the increasing ozone concentrations.

The air quality is influenced by many factors, such as human factors and natural factors. The ways of production and styles of life belong to human factors. The weather and season belong to natural factors. In order to improve the air quality, the governments need to make the long-term policy according to the forecasting result. The policy should aim at the human factors.

5. Conclusion

The fitting accuracy of the FGM(1,1) model is significantly higher than that of the traditional GM(1,1) model. The average annual concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, 8-hour O_3, and 24-hour O_3 in the Beijing-Tianjin-Hebei region were predicted in this paper by using the high performance FGM(1,1) model. The prediction results from 2017 to 2020 indicate that the concentrations of $PM_{2.5}$, PM_{10}, SO_2, and NO_2 will decrease, whereas the 8-hour O_3 and 24-hour O_3 concentrations will increase. The prediction results indicated that air quality has been improved under the existing regulation. However, in order to fully improve the air quality, it is essential to adjust the direction of control measures and strengthen governance.

With regard to the suggestions, in view of the predicted air quality indicator values from 2017 to 2020, in each region, all levels of government should adopt the corresponding measures based on their actual air quality. They should focus the control measures on the highly concentrated air pollutants, while also ensuring that the concentrations of the other pollutants do not increase. Only when all of the air pollutants are controlled, can the best air quality be achieved.

In respect of the future work, one suggestion is that the modelling results will be put in monthly. It is due to the fact that the air pollution indicators changed significantly in different time during the whole year. This kind of change is caused by the weather and season. Monthly forecasting of air pollution is an issue that deserves further attention. In addition, it is also suggested that the FGM(1,1) can be tested for the air quality forecasting in other regions.

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