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# City Air Quality Forecasting and Impact Factors Analysis Based on Grey Model

Lin Pan[a], Baosheng Sun[a]*, Wei Wang[a]

[a] *School of Environmental Science and Technology, Tianjin University, Tianjin 300072, China*

**Abstract**

As an important environmental problem, air quality influences urban population's health and economic development. To investigate air quality changing trend and main factors affecting the quality of Tianjin in China, we employed grey dynamic model group and grey relational analysis. For forecasting, we first use model group to fit the annual average air pollution concentration of Tianjin from 2001-2009, the fitting results shows that model group has high accuracy, so then we use it to forecast the air quality until 2015. In the future, the air quality in Tianjin will continuously improve, the concentration of $PM_{10}$, $SO_2$, and $NO_2$ will decrease obviously. From the grey relational analysis to social economics factors, result shows that industrial pollution and energy consumption have great influence to pollutions' concentration, and urban green project can improve the integrate city air quality in a large level, also, some other factors such as automobile exhaust and central heating have some influences on the air quality.



*Keywords:* Air quality; Grey dynamic model group; Forecasting; Grey Correlation; Impact factors

## 1. Introduction

Ambient air quality has been given continuous attention in the whole world for many years and air pollution not only affects human health, but also restricts the city's economic development. Recent years, lots of researchers have made more and more perfect and comprehensive analysis, and also the methods for ambient air quality management have been continuously developed. Many studies have showed that city air quality was decided by both natural processes and human emissions. Not only has the local

* Corresponding author. Tel.: +86-22-8740-2126; fax: +86-22-8740-2126.
*E-mail address*: Baosheng_sun@sina.com .

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weather strong influences on the air pollutions' concentration [1], but also the interaction of pressure of increasing air pollution sources and environmental protection measures have big function on it [2],[3]. Moreover, scientists are forecasting the trend of air quality more accurately. Patricio Perez *et al* used integrated neural network model forecast short time $PM_{10}$ concentration [4], then they forecasted $PM_{2.5}$ concentration in the same city using multilayer neural network, linear algorithm and clustering three types of methods, and made comparison [5]. More and more studiers have been doing supplement and improvement to neural network model, and verifying their accuracy with real data [6]. Because air quality data is obtained in limited time and space, it's incomplete and inaccurate. We can regard air environment system as a grey system, and grey system theory is an analysis method that can weaken unknown information through available information, truly reflect the nature of system. So this paper will adopt grey forecasting model and grey relational analysis to investigate the air quality changing trend in Tianjin, China and main impact factors, hope to provide the basis for controlling the total air pollution.

## 2. City Air Quality Changing Trend Forecasting

### *2.1. Forecasting model*

First build up single GM (1, 1) model, make $PM_{10}$, $SO_2$, $NO_2$ concentration as original series $\{x^{(0)}(n)\}$, then cumulatively add $\{x^{(0)}(n)\}$, get new series $\{x^{(1)}(k)\}$, build up constant differential equation:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \tag{1}$$

The solutions for the equation are given as:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1-e^{a})(x^{(0)}(1) - \frac{u}{a})e^{-ak} \qquad (k=0,1,...n-1) \tag{2}$$

Where parameters are defined as:

$$\hat{a} = \begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T Y_N \tag{3}$$

$$B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ \cdots\cdots & \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix} \tag{4}$$

$$Y_N = \left[ x^{(0)}(2), x^{(0)}(3) \cdots x^{(0)}(n) \right]^T \tag{5}$$

In order to verify the fitting degree of single model, we do the test as follow:

$$C=S_1/S_2 \tag{6}$$

$$P = \left\{ \left| q^{(0)}(t) - \bar{q}^{(0)} \right| < 0.6745 S_2 \right\} \tag{7}$$

Where $C$ is mean square error ratio, $S_1$ is residual covariance, $S_2$ is original data's covariance, $P$ is little error probability, $q^{(0)}$ is residual; $\bar{q}^{(0)}$ is mean residual. According to accuracy degree testing table, when $P>0.8$, $C<0.5$, the model's accuracy is above the 2nd level, meantime, we make relative error test.