Prediction and analysis of generation installed capacity in China

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Abstract. Electricity is one of the most important sources of energy. Generation installed capacity mainly include thermal power, hydroelectricity, nuclear power and wind power capacity. Renewable electricity helps relieve pressure of electricity supply and further sustainable development could be achieved. In this paper, a novel grey model with the fractional order accumulation is put forward, which is abbreviated as FOGM(1,1), based on the grey system theory, which is to accurately predict the generation installed capacity and further make full use of the electricity sources. The case studies of predicting the generation installed capacity of China form 2000 to 2015, and the FOPGM(1,1) was calibrated. Finally the FOPGM(1,1) model is used to forecast the generation installed capacity of China from 2016 to 2020 and analyze the trend of development for generation installed capacity.

1. Introduction
Electricity is one of the most important sources of energy. Generation installed capacity mainly include thermal power[1], hydroelectricity[2], nuclear power[3] and wind power capacity[4-5].

Grey model proposed by Deng[6] is used for small sample forecasting. GM (1,1), i.e. The grey prediction models play an important role in the grey system theory. These models are often named as grey models (GM) as they are developed based on the grey system theory, which has been successfully applied in many disciplines[7-10]. However, the existing GM (1,1) model cannot be used for accurate prediction for many actual systems. In recent researches the improved grey prediction models are popularly used for energy consumption. Ma and Liu[11] have proposed a novel time-delayed polynomial grey model to predict the natural gas consumption in China. Akay and Atak[12] have proposed a novel method based on the basic GM(1,1) model with rolling mechanism to forecast the electricity demand of Turkey. Wu and Shen[13] have proposed a grey-related least squares support vector machine optimization model and its application in predicting natural gas consumption demand. Ma et al.[14] have proposed a novel kernel regularized nonhomogeneous grey model and its applications in petroleum production forecasting. Kumar and Jain[15] have used the Grey–Markov and GM(1,1) model with rolling mechanism to predict the energy consumption in India. Ren et al.[16] have used the grey model for cumulative plastic deformation under cyclic loads. Lee and Tong[17] have proposed a novel grey prediction model combined with genetic programming to forecast the Chinese energy consumption. Ma and Liu[18] have proposed a novel kernel regularized nonlinear GMC(1,n) model and its application in the condensate gas production. Pao and Tsai[19] have used the GM(1, 1) model to predict the energy consumption in Brazil compared with the ARIMA model. Ayvaz and Kusakci[20] have used the nonhomogeneous discrete grey model to predict the electricity consumption forecasting for Turkey. These researches all indicate that the grey models are efficient to predict the consumption of many kinds of energy for many countries.
The rest of this paper is organized as follows: the details modeling procedures of the FOGM(1,1) model is given in Section 2; the application of FOGM(1,1) to generation installed capacity prediction in Section 3; and the conclusions are drawn in Section 4.

2. The proposed grey system model with the fractional order accumulation

In this section, we will present the grey system model with the fractional order accumulation, abbreviated as the FOGM(1,1) model including the principles and the computational steps.

2.1 Grey model with the fractional order accumulation

Let the \( X^{(r)}(k) \) be the order accumulated generating operator of the original nonnegative sequence \( X(0), X(1), X(2), \ldots, X(n) \), then

\[
X^{(r)}(k) = \sum_{i=0}^{k} \binom{k-i+r-1}{k-i} \cdot X^{(0)}(i), \quad k = 1, 2, \ldots, n,
\]

where \( \binom{k-i+r-1}{k-i} = \frac{(r+k-i-1)(r+k-i-2)\ldots(r+1)}{(k-i)!} \)

Fractional derivatives accumulate the whole history of the system in weighted form. \( x^{(i)}(k) \) in Grey system theory denotes the weight of \( x^{(i)}(i)(i = 1, 2, \ldots, k) \) as 1. The larger \( r \) of \( x^{(r)}(k) \) is, the larger the weight of old data is; the smaller \( r \) of \( x^{(r)}(k) \) is, the smaller the weight of old data is. Reducing \( r \) can reduce the weights of old data, which can put more emphasis on the newer data.

The original form of the GM\(^{(1,1)}\) model

\[
x^{\left[\frac{p}{q}\right]}(k) - x^{\left[\frac{p}{q}\right]}(k-1) + az^{\left[\frac{p}{q}\right]}(k) = b
\]

If \( r = \frac{p}{q} \), then \( 0 < \frac{p}{q} \leq 1 \) order inverse accumulated generating operator of \( X^{(0)} \), we write

\[
\alpha^{\left[\frac{1-p}{q}\right]} X^{(0)} = \alpha^{(1)} x^{\left[\frac{1-p}{q}\right]}(k) = \left\{ \alpha^{(1)} x^{\left[\frac{1-p}{q}\right]}(1), \alpha^{(1)} x^{\left[\frac{1-p}{q}\right]}(2), \ldots, \alpha^{(1)} x^{\left[\frac{1-p}{q}\right]}(n) \right\}
\]

2.2 The solution of the FOGM(1, 1) model

Within a given original sequence \( X^{(0)} = \{ x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n) \} \), the least squares criteria for the FOGM(1,1) model can be described as the following unconstrained optimization problem:

\[
\min_{\alpha, b, c, d} \sum_{k=2}^{n} \left[ x^{\left[\frac{p}{q}\right]}(k) - x^{\left[\frac{p}{q}\right]}(k-1) + \lambda_1 z^{\left[\frac{p}{q}\right]}(k) - \lambda_2 \sum_{\tau=1}^{k} \tau - \lambda_3 \right]^2
\]

The solution of this optimization problem can be written as the following linear system

\[
[\lambda_1, \lambda_2, \lambda_3]^\top = (B^\top B)^{-1} B^\top Y
\]

where
The linear differential equation

\[
\frac{dx^{[p_q]}(t)}{dt} + \lambda_1x^{[p_q]}(t) = \lambda_2 \sum_{\tau=1}^{t} \tau + \lambda_3
\]  

(6)

The solution of the whitenization Eq. 6 for FOGM(1,1) is given by

\[
x^{[p_q]}(k) = x^{[p_q]}(1)e^{-\lambda(k-1)} + \sum_{\tau=2}^{k} \left[ e^{-\lambda(\tau-1)} f(\tau) + e^{-\lambda(\tau+1)} f(\tau-1) \right]
\]  

(7)

Within the initial condition \( x^{(1)}(1) = x^{(0)}(1) \), by applying the trapezoid formula, we can obtain the discrete response function as

\[
x^{[p_q]}(k) = x^{(0)}(1)e^{-\lambda(k-1)} + \frac{1}{2} \sum_{\tau=2}^{k} \left[ e^{-\lambda(\tau-1)} f(\tau) + e^{-\lambda(\tau+1)} f(\tau-1) \right].
\]  

(8)

The response function (8) is used to compute the values of the series \( x^{[p_q]}(k) \), and the predicted values of the original series \( x^{(0)}(k) \) can be obtained using the first order inverse accumulative generation operation as follows:

\[
\alpha^{[p_q]}X^{(a)} = \alpha^{(1)}X^{[1-p_q]}(1), \alpha^{(1)}x^{[1-p_q]}(2), ..., \alpha^{(1)}x^{[1-p_q]}(n)
\]  

(9)

3. Forecasting application study of generation installed capacity in China

3.1 Raw data collection

The raw data of the generation installed capacity (10^4 kW) of China are collected from the official website National Bureau of Statistics of China (http://www.stats.gov.cn/tjsj/ndsj/) as shown in Table 1. The data from 2005 to 2011 are used to build the prediction models, and the data from 2012 to 2015 are used to validate the modeling accuracy.
Table 1 Generation installed capacity ($10^4$ kW) of China from 2000 to 2015.

| Year | Total power capacity | thermal power | hydroelectricity | nuclear power | Wind power |
|------|----------------------|---------------|------------------|---------------|------------|
| 2000 | 31932                | 23754         | 7935             | 210           | 34         |
| 2001 | 33849                | 25301         | 8301             | 210           | 38         |
| 2002 | 35657                | 26555         | 8607             | 447           | 47         |
| 2003 | 39141                | 28977         | 9490             | 619           | 55         |
| 2004 | 44239                | 32948         | 10524            | 696           | 82         |
| 2005 | 51718                | 39138         | 11739            | 696           | 106        |
| 2006 | 62370                | 48382         | 13029            | 696           | 207        |
| 2007 | 71822                | 55607         | 1482             | 908           | 420        |
| 2008 | 79273                | 60286         | 17260            | 908           | 839        |
| 2009 | 87410                | 65108         | 19629            | 908           | 1760       |
| 2010 | 96641                | 70967         | 21606            | 1082          | 2958       |
| 2011 | 106253               | 76834         | 23298            | 1257          | 4623       |
| 2012 | 114676               | 81968         | 24947            | 1257          | 6142       |
| 2013 | 125768               | 87009         | 28044            | 1466          | 7652       |
| 2014 | 137018               | 92363         | 30486            | 2008          | 9657       |
| 2015 | 152527               | 100554        | 31954            | 2717          | 13075      |

3.2 Numerical result

The numerical results of the FOGM(1,1) model for generation installed capacity including thermal power, hydroelectricity, nuclear power and wind power capacity, and the raw data are also plotted in Fig. 1. The Fig.1 shows that the fitting effect of original data and prediction data is good for thermal power, hydroelectricity, nuclear power and wind power respectively.

![Figure 1. Numerical results of generation installed capacity of China from 2000 to 2015](image)

As the FOGM(1,1) model shows the well performance in the Fig.1, we use it to predict the generation installed capacity in China from 2016 to 2020. Fig.2 shows that predication results of generation installed capacity of China from 2016 to 2020. Wind power capacity growth rate is the
fastest than thermal power, hydroelectricity and nuclear power. The growth rate of nuclear power is the slowest.

Unit percentage of thermal power, hydroelectricity, nuclear power and wind power capacity in China from 2016 to 2020 is given in the Fig. 3. It is clear that unit percentage of wind power increasing rapidly year by year. However, the unit percentage of thermal power decreasing rapidly year by year, and the change of unit percentage of hydroelectricity and nuclear power is not obvious.

Figure 2. Predication results of generation installed capacity of China from 2016 to 2020

Figure. 3. Change of unit percentage for thermal power, hydroelectricity, nuclear power and wind power capacity of China from 2016 to 2020
4. Conclusions
Accurately predicting the generation installed capacity is propitious to make full use of the power resources. So, the FOGM(1,1) model is established, which is to forecast China's generation installed capacity. Based on a series of validated and calibrated for the novel grey prediction system, the following conclusions could be drawn: 1) The FOGM(1,1) model is established, and it is appropriate and propitious to forecast generation installed capacity of China. 2) The generation installed capacity of wind power in China will apace increase in the next decades, and the wind power of China play an increasingly important role.

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