Energy 112 (2016) 810–825

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Forecasting the natural gas demand in China using a self-adapting intelligent grey model

Bo Zeng [a,*], Chuan Li [b,*]

[a] College of Business Planning, Chongqing Technology and Business University, Chongqing 400067, China
[b] National Research Base of Intelligent Manufacturing Service, Chongqing Technology and Business University, Chongqing 400067, China

ARTICLE INFO

Article history:
Received 14 April 2015
Received in revised form
27 March 2016
Accepted 18 June 2016

Keywords:
Grey prediction model
Self-adapting intelligent model
SIGM model
China's natural gas demand prediction

ABSTRACT

Reasonably forecasting demands of natural gas in China is of significance as it could aid Chinese government in formulating energy policies and adjusting industrial structures. To this end, a self-adapting intelligent grey prediction model is proposed in this paper. Compared with conventional grey models which have the inherent drawbacks of fixed structure and poor adaptability, the proposed new model can automatically optimize model parameters according to the real data characteristics of modeling sequence. In this study, the proposed new model, discrete grey model, even difference grey model and classical grey model were employed, respectively, to simulate China's natural gas demands during 2002–2010 and forecast demands during 2011–2014. The results show the new model has the best simulative and predictive precision. Finally, the new model is used to forecast China's natural gas demand during 2015–2020. The forecast shows the demand will grow rapidly over the next six years. Therefore, in order to maintain the balance between the supplies and the demands for the natural gas in the future, Chinese government needs to take some measures, such as importing huge amounts of natural gas from abroad, increasing the domestic yield, using more alternative energy, and reducing the industrial reliance on natural gas.

1. Introduction

With the rapid development of global economy and fast increase of world population, energy consumption has continued to grow; hence our living environment faces a great challenge due to the discharge of greenhouse gases and other harmful substances. Under this situation, natural gas has become increasingly popular as it burns cleaner than other forms of fossil fuels and has high heating power. At present, natural gas has already played a significant role in global energy consumption. Even though the current technology in alternative energy sources, especially in renewable energy, is tremendously advanced, the majority of global energy consumption still relies heavily on non-renewable sources. The world energy consumption of the various primary sources of energy in 2012 was as follows: Oil (32.4%), coal (27.3%), natural gas (21.4%), biofuels and waste (10%), nuclear (5.7%), hydro (2.3%) and other (0.9%) [1]. It can be seen that natural gas is the third largest share among all the primary energy sources.

In recent years, China's economic growth and natural gas consumption both showed a clear upward trend. What's more, the growth rate of natural gas consumption was even faster than the Gross Domestic Product (GDP) growth rate during the same period. The rapid increase in natural gas consumption has become the one of the biggest constraint for sustainable economic growth and social development in China and can even be a threat to national economic security. A good forecast of natural gas demand is a prerequisite for the effective development of energy policies, as it can reduce the possibility of errors during energy system planning [2]. Therefore, accurate prediction of natural gas demand and production is very important.

So far there are a lot of predictive methods used to forecast energy problems [3], and these methods can be generally classified into three categories: statistical model (e.g., regression analysis model [3], Markov model [4]), nonlinear intelligent model (e.g., artificial neural network model [5], support vector machine [6]) and grey system prediction model (e.g., single variable grey model [7] and multivariate grey model [8]). Statistical model and nonlinear intelligent model are usually based on large sample sizes and cannot be employed to solve small-size problems. On the

* Corresponding author.
E-mail address: zbljh2@163.com (B. Zeng).

http://dx.doi.org/10.1016/j.energy.2016.06.090
0360-5442/

contrary, a grey prediction model is superior in terms of modeling systems with small samples and poor information [9], and has been widely used in many fields. As the sample size of the natural gas demand problem studied in this paper is relatively small (see Subsection 4.1 for details on sample data sources), models that work with large sample sizes may not be suitable. Grey predictive models, with the advantage of working well with small sample sizes, are chosen to forecast the natural gas demand in China.

In fact various grey prediction models and their improvement models have been widely employed to forecast the demand and output of energy. These grey models for energy prediction can be mainly categorized into three types. The first type, via grey models' self-optimization, improves the predictive performance of the original model. Examples include grey prediction model with rolling mechanism (GPRM) [10], grey generating and accumulated generating models [11], grey model with optimizing initial condition [12], background value [13,14], and GM(1,1) with fractional order accumulation [15]. The second type usually combines grey models with other modeling methods. The following are some examples: grey models combined with Markov model [16], neural network (NN) [17], fuzzy mathematics [18], support vector machines (SVM) [19], autoregressive integrated moving average (ARIMA) [20], Particle Swarm Optimization (PSO) [21], Genetic Algorithm (GA) [22], chaotic theory [23]. The third type of model upgrades grey model structures and explore some novel methods to improve the accuracy. These include discrete grey model, interval grey number prediction model [24], nonlinear grey Bernoulli model [25], and non-homogenous discrete grey model [26].

However, for all the above grey models, their latest restored forms are all shown as either homogeneous or non-homogenous exponential form, and this leads to fixed structure and poor adaptability of these models. In order to solve this problem, a self-adapting intelligent grey prediction model (SIGM) is proposed in this paper. The SIGM model may be a homogeneous exponential model, a non-homogeneous exponential model, or a linear function model. It can automatically optimize model parameters and choose a reasonable model structure to adapt to the real data characteristics of the modeling sequence. Furthermore, the parameters of the proposed SIGM model are estimated by a differential equation, and the time response function of grey model is also deduced by this equation. Hence the modeling process of SIGM avoids the inconsistency problem between the parameter estimation method that is based on difference equations and the time response functions of grey models that are based on differential equations, leading to more accurate simulation and prediction.

The rest of this paper is organized as follows. In Section 2, we create the intelligent grey prediction model (SIGM), deduce its final restored formula and analyze its properties. In Section 3, the simulation and prediction results of the SIGM, GM (1,1) [9] and DGM(1,1) [27] for five representative sequences are compared. In Section 4, we use the SIGM model to simulate and to forecast China's natural gas demand and then compare its errors with other grey models. Here the demand of China's natural gas during 2015–2020 is predicted. According to the forecast results, some suggestions are provided for the policy making of Chinese government. Conclusions are presented in Section 5.

2. SIGM model

This paper will study the predictive problem of the demand of China's natural gas by using the grey prediction model. Firstly, the drawbacks of the existing grey prediction models will be analyzed in this section, and then a novel grey prediction model will be proposed. The improved modeling method and model's properties will be studied in depth, and these will provide a methodological basis for forecasting the demand of natural gas in China in Section. 3 of this paper.

2.1. GM (1, 1) model and its expanded form

Definition 1 [9] Assume that a sequence is $X^{(0)}=(x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n))$, where $x^{(0)}(k)\geq 0$, $k=1,2,\ldots n$. $X^{(1)}$ is the 1-AGO (Accumulating Generation Operator) sequence of $X^{(0)}$, i.e.,

$$X^{(1)}=\left(x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\right)$$

Where

$$x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i),\ \ k=1,2,\cdots n.$$

From sequence $X^{(1)}$, one can derive a new sequence$Z^{(1)}$, i.e.,

$$Z^{(1)}=\left(z^{(1)}(2),z^{(1)}(3),\cdots,z^{(1)}(n)\right)$$

where

$$z^{(1)}(k)=0.5\times\left[x^{(1)}(k)+x^{(1)}(k-1)\right],k=2,3\cdots,n$$

$Z^{(1)}$ is called the Mean sequence generated by consecutive neighbors of $X^{(1)}$.

Accumulating generation operation (AGO) is a method employed to whitenize a grey process. It plays an extremely important role in grey system theory. Through AGO, one can potentially uncover a development tendency existing in the process of accumulating grey quantities so that the characteristics and laws of integration hidden in the chaotic original data can be sufficiently revealed. For instance, when looking at the financial outflows of a family, if we do our computations on a daily basis, we might not see any obvious pattern. However, if our calculations are done on a monthly basis, some pattern of spending, which is somehow related to the monthly income of the family, will possibly emerge [29].

Definition 2 [9] Assuming that $X^{(0)}$,$X^{(1)}$ and $Z^{(1)}$ are given by **Definition 1**, the following equation

$$x^{(0)}(k)+az^{(1)}(k)=b \tag{1}$$

is called the grey differential equation of GM (1, 1) model, and the equation

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=b \tag{2}$$

is named the whitenization equation of grey model with one order and one variable, GM(1, 1) for short. In Equation (1), we can estimate the parameter a and b using the least square method, which is

$$\hat{a}=(a,b)^T=\left(B^TB\right)^{-1}B^TY$$

where

$$B=\begin{bmatrix}-z^{(1)}(2) & 1\\ -z^{(1)}(3) & 1\\ \vdots & \vdots\\ -z^{(1)}(n) & 1\end{bmatrix},\quad Y=\begin{bmatrix}x^{(0)}(2)\\ x^{(0)}(3)\\ \vdots\\ x^{(0)}(n)\end{bmatrix}.$$

Theorem 1 [9] Assuming that$B$, Y and $\hat{a}$ are the same as those in