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Applying the Grey Forecasting Model to the Energy Supply Management Engineering

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Abstract

The demand for energy supply has been increasing dramatically in recent years in the global. In addition, owing to the uncertain economic structure of the county, energy has a chaotic and nonlinear trend. In this paper, An improved grey G(1,1) prediction model is proposed to the energy management engineering. It is one approach that can be used to construct a model with limited samples to provide better forecasting advantage for long-term problems. The forecasting performance of the improved GM(1,1) model has been confirmed using the China's energy database. And the results, compared with those from artificial neural network (ANN) and times series. According to the experimental results, our proposed new method obviously can improve the prediction accuracy of the original grey model.

Keywords: Grey forecasting model , Energy supply, Management engineering;

1. Introduction

Recently the global economic recession leads to the fluctuation of energy prices, which has made energy supply to be increasingly unstable. Therefore, in order to take the way of sustainable development, it has the vital practical significance to complete the analysis of energy supply and demand gap forecast, and provide the decision data for the establishment of energy management engineering.

Multivariate modeling along with co-integrated techniques or regression analysis has been used in a number of studies to analyze and forecast energy consumption [1-4]. Recently, grey forecasting approach has gained popularity in energy demand forecasting. Zhou et al. [5] presented a univariate trigonometric grey predictive model for forecasting electricity demand in China. This method constructs residual series into generalized trigonometric model to increase the accuracy of GM(1,1) model. Akay et al. [6] observed that there are chaotic phenomenon and non-linear trend in historical electricity consumption data. It applied a method combining the grey prediction model with rolling mechanism, which is applicable for prediction with high accuracy, but limited to case with limited data or little calculation effort. Wang et al. [7-9] proposed the reconstruction of background value using interpolation algorithm, it improve prediction accuracy of models to some extent.

The aim of this paper is to focus on forecasts for China's energy management engineering using the combinative interpolation Grey predictive modeling. The rest of this paper is organized as follows. In Section 2, the present

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energy situation of China is described. Section 3 presents the conventional GM(1,1) model, and proposes combination interpolation method to reconstruct GM(1,1) model. The application of improved GM(1,1) model and model comparisons are explained in Section 4.The last section summarizes and proposes related solving suggestions for energy supply system engineering.

2. Analysis of China's energy supply management engineering

As the increasing of oil demand and the imported energy, China has played an important role in global energy markets. With China's rapid economic growth, the strong demand for energy of China will rise. The strong growth of energy demand in China mainly depends on China's rapid economic growth, and depends on China's large population, as well as depends on China's ongoing urbanization. The status quo of China's energy supply are mainly reflected in the following points:

Firstly, the accelerating process of industrialization, especially the demands of heavy industry for energy present new challenges constantly, in which the energy consumption of power, steel, nonferrous metals, building materials, oil refining and chemical industries account for about 70% of total energy consumption in China.

Next, the per capita energy consumption in China are 1.8 tons standard coal, and there are still a considerable growth room for China's per capita energy consumption compared to the per capita consumption of Western developed countries which are 7 tons of standard coal.

Moreover, China is in the process of urbanization, the accompanying energy growth will be very fast. Data showed that the average annual resources consumption of urban population are 3.5 times more than the rural population. And there are about 18 million rural people who flow into cities every year. The proportion of urban population will reach to about 75% by 2050, which will produce a large number of new increasing energy demand.

Finally, another critical factor is that China is a world factory, in which 40% of the products are for export. The export products are of high energy density, low added value, while the energy consumption of these products is calculated within China's total energy demand.

3. The establishment of forecasting model

3.1. Modeling idea of conventional GM(1,1) forecasting model

Assume that $X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), \cdots, X^{(0)}(n)\}$ is the original series. Applying accumulated generating operation *(AGO)*, it can get that:

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

where $X^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$ $(k = 1, 2, \cdots, n)$. $X^{(1)}(k)$ is called accumulated generating operation of $X^{(0)}(k)$ denoted as *1-AGO*.

The first order linear ordinary differential equation expressed as

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

which is called whitened differential equation of *GM(1,1)*, of which the difference form is:

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{2}$$

where *a,b* are parameters to be identified. *a* is called developing coefficient, and *b* is called grey input. Solve it using least square method and obtain:

$$[a,b]^T = (B^T B)^{-1} B^T Y_n \tag{3}$$

where

$$Y_n = [x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)]^T, \ B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{4}$$

In Eq.(4), the background value is formulated as

$$z^{(1)}(k+1) = \frac{1}{2}[x^{(1)}(k) + x^{(1)}(k+1)] \quad k = 1, 2, \ldots, n-1 \tag{5}$$

The discrete solution of Eq.(1) is:

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a}) \cdot e^{-ak} + \frac{b}{a} \tag{6}$$

The reduction value is:

$$\hat{x}^{(0)}(k+1) = x^{(1)}(k+1) - x^{(1)}(k) = (1-e^a)(x^{(0)}(1) - \frac{b}{a}) \cdot e^{-ak} \tag{7}$$

where $k = 1, 2, \cdots, n$.

During the above *GM(1,1)* modeling process, it can be found that developing coefficient *a* and grey input *b* have great influences on simulation and prediction accuracy of the model. However, it shows that the values of *a* and *b* depend on the construction of the background value. Therefore, to construct a new background value form is the key to optimize and modify conventional *GM(1,1)* model.

3.2. Improvement and optimization of GM(1,1) model

In the conventional model, using consecutive neighbors means ($z^{(1)}(k+1) = \frac{1}{2}[x^{(1)}(k) + x^{(1)}(k+1)]$), trapezoidal area with exponential curve side of $x^{(1)}(t)$ is replaced by straight-edge trapezoidal area. The shortcoming is that, as the exponential increases, data sequence varies greatly and the prediction result will have big error (ΔS). That will influence the applicability of the model to some extent.

In order to overcome this shortcoming, we first present a new construction method of the background value - combinative interpolation optimization method, which uses numerical approximation idea combining interpolation algorithm to resolve this problem and reduce error.

Next, make some numerical treatment on the background value $z^{(1)}(k+1)$. The algorithm steps are as follow:

***Step* 1:** Divide the interval $[k, k+1]$ into three equal intervals. They are $(k+\frac{1}{3}, x^{(1)}(k+\frac{1}{3}))$, $(k+\frac{2}{3}, x^{(1)}(k+\frac{2}{3}))$ and $(k+1, x^{(1)}(k+1))$;

***Step* 2:** Solve $x^{(1)}(k+\frac{i}{3}), (i=1,2)$;

Establish quadric *Lagrange* interpolation polynomial $P_2(t)$ which is submit to

$$P_2(t) \approx x^{(1)}(t), \qquad (t \in [k, k+1])$$

then

$$x^{(1)}(k+\frac{i}{3}) \approx P_2(k+\frac{i}{3}), (i=1,2$$

where

$$P_2(t) = x^{(1)}(k)\frac{(t-k-1)(t-k-2)}{(-1)\cdot(-2\ \ )} + x^{(1)}(k+1)\frac{(t-k)(t-k-2)}{1\cdot(-1)} + x^{(1)}(k+2)\frac{(t-k)(t-k-1)}{1\cdot 2} \tag{8}$$

From Eq.(10), we get:

$$x^{(1)}(k+\frac{1}{3}) \approx P_2(k+\frac{1}{3}) = \frac{5}{9}x^{(1)}(k) + \frac{5}{9}x^{(1)}(k+1) - \frac{1}{9}x^{(1)}(k+2 \tag{9}$$

$$x^{(1)}(k+\frac{2}{3}) \approx P_2(k+\frac{2}{3}) = \frac{2}{9}x^{(1)}(k)+\frac{8}{9}x^{(1)}(k+1)-\frac{1}{9}x^{(1)}(k+2 \tag{10}$$

***Step* 3:** Obtain the piecewise interpolation function in the interval $[k, k+1]$.

$$S_k(t)=\begin{cases} 3[x^{(1)}(k+\frac{1}{3})-x^{(1)}(k)]t+x^{(1)}(k)-3k[x^{(1)}(k+\frac{1}{3})-x^{(1)}(k)], & k \le t \le k+\frac{1}{3} \\ 3[x^{(1)}(k+\frac{2}{3})-x^{(1)}(k+\frac{1}{3})]t+x^{(1)}(k+\frac{1}{3})-3(k+\frac{1}{3})[x^{(1)}(k+\frac{2}{3})-x^{(1)}(k+\frac{1}{3})], & k+\frac{1}{3} \le t \le k+\frac{2}{3} \\ 3[x^{(1)}(k+1)-x^{(1)}(k+\frac{2}{3})]t+x^{(1)}(k+\frac{2}{3})-3(k+\frac{2}{3})[x^{(1)}(k+1)-x^{(1)}(k+\frac{2}{3})], & k+\frac{2}{3} \le t \le k+1 \end{cases}$$

***Step* 4:** Calculate the numerical integration of the background value $z^{(1)}(k+1)=\int_k^{k+1} x^{(1)}(t)dt$.

$$\begin{aligned} \int_k^{k+1} x^{(1)}(t)dt &\approx \int_k^{k+1} S_k(t)dt \\ &= \int_k^{k+\frac{1}{3}} S_k(t)dt + \int_{k+\frac{1}{3}}^{k+\frac{2}{3}} S_k(t)dt + \int_{k+\frac{2}{3}}^{k+1} S_k(t)dt \\ &= \frac{1}{6}x^{(1)}(k+1)+\frac{1}{3}x^{(1)}(k+\frac{2}{3})+\frac{1}{3}x^{(1)}(k+\frac{1}{3})+\frac{1}{6}x^{(1)}(k) \end{aligned} \tag{11}$$

Substitute the conclusion of Step2 into Eq.(13) and get the optimized background value.

$$\begin{aligned} z^{(1)}(k+1) &= \int_k^{k+1} x^{(1)}(t)dt \approx \int_k^{k+1} S_k(t)dt \\ &= \frac{23}{54}x^{(1)}(k)+\frac{35}{54}x^{(1)}(k+1)-\frac{2}{27}x^{(1)}(k+2) \end{aligned} \tag{12}$$

Eq.(14) is the novel background value of *GM(1,1)* obtained from the combinative interpolation optimization idea.

4. Application of forecasting model on China's energy management engineering

The mail goal of this study is to based on combinative interpolation improve the conventional grey forecasting model. And it has been applied to the energy supply management engineering. The energy supply (ES) data and energy demand (ED) data for China from 1995 to 2008 were obtained from the China's energy database. The forecasting value of energy supply gap is forecasting value of energy supply subtract forecasting value of energy consumption. The forecasting result is shown in table 1:

Table 1. Comparison of different predictive model for energy supply management engineering from 1995 to 2008

Unit: million tons of standard coal

Year	Actual Value	Conventional Grey Method	ANN	Time Series	Improved Grey Method
1995	-16.41	-17.90	-18.15	-14.79	-17.15
1996	-45.15	-40.67	-41.98	-40.23	-43.56
1997	-44.49	-48.09	-46.87	-36.37	-41.74
1998	-38.46	-33.97	-43.94	-30.88	-37.29
1999	-42.90	-40.38	-37.05	-46.24	-44.37
2000	-20.18	-19.14	-18.91	-23.54	-21.38
2001	-16.05	-17.23	-14.88	-14.56	-14.83
2002	-39.03	-42.04	-43.12	-35.62	-40.45
2003	-28.61	-26.82	-23.84	-27.15	-27.39
2004	-28.83	-26.89	-27.32	-32.23	-31.36

2005	-14.69	-16.62	-15.98	-13.26	-13.98
2006	-21.69	-24.35	-25.05	-19.93	-20.55
2007	-44.72	-39.70	-41.97	-48.78	-46.90
2008	-44.37	-49.98	-40.78	-50.73	-41.97
Average relative error(%)		9.0797	9.6674	11.3817	5.0914

Forecasting China's energy management engineering in the following seven years according to the combinative interpolation Grey forecasting model, the result is shown in table 2:

Table 2. The predictive results of improved grey forecasting model for energy supply management engineering from 2009 to 2015

Unit: million tons of standard coal

Year	Forecasting value of ES	Forecasting value of ED	Forecasting value
2009	3026.71	3066.47	-39.76
2010	3200.08	3249.65	-49.57
2011	3369.74	3424.06	-54.32
2012	3532.45	3589.32	-56.87
2013	3694.84	3748.58	-53.74
2014	3977.59	4035.98	-58.39
2015	4177.39	4236.84	-59.45

Along with the growth of the population and economy, the energy demand is increasing unceasingly. By 2015, China's energy consumption demand will be 4.23 billion tons of standard coal. China's supply gap will be 59.45 million tons of standard coal.

The forecasting result of grey forecasting model cannot be completely precise because any kind of models is established based on historical data directly or indirectly. As time goes on, the change of internal and external environmental conditions associated with historical data will occur in a complex system.

5. Conclusions

Forecasting trends in the energy management engineering using empirical methods is very difficult, because the energy supply is strongly affected by economic cycles environmental changes. Consequently, the issue of how to obtain an accurate forecast is very important. The GM(1,1) model not only requires minimal data but also is the best among all existing models at long-term foresting. This work only examines forecasting models to determine which has better- accuracy prediction results, and numerous related influences each other in the energy management engineering. Grey relational analysis can be applied to determine relationships among these influences, an area that should be researched further in the future.

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References

1. Canyurt OE, Ceylan H, Ozturk HK, Hepbasli A. Energy demand estimation based on two-different genetic algorithm approaches. Energy Sources 2004;26(14):1313 – 20.

2. Gorucu FB, Geris PU, Gumrah F. Artificial neural network modeling for forecasting gas consumption. Energy Sources 2004;26:299 – 307.

3. H.Y. Xiong, X.Y. Chen, W.B. Wang. Predict ion of China's energy consumpt ion based on combinat ion model. Science Technology and Engineering 2010;42:67–70.

4. H.Q. Wang, D. Hu. The construct ion and applicat ion of combinat ion forecast ing model in Chinese energy consumpt ion system. Statistics and Decision 2008;25:64–66.

5. P.Zhou, B.W.Ang, K.L.Poh. A trigonometric grey prediction approach to forecasting electricity demand[J]. Energy, 2006(31): 2839-2847.

6. Diyar Akay, Mehmet Atak. Grey prediction with rolling mechanism for electricity demand forecasting of Turkey[J]. Energy, 2007(32): 1670-1675.

7. Wang Xiaojia, Yang Shanlin , Haijiang Wang, etc. Dynamic GM(1,1) Model Based on Cubic Spline for Electricity Consumption Prediction in Smart Grid, China Communications,2010,7(4):83-88.

8. Wang Xiaojia, Yang Shanlin, Hou Liqiang, etc. Simulation of Orthogonalization Prediction Based on Grey Markov Chain for Electricity Consumption, Journal of System Simulation, 2010,22(10):2253-2256.

9. Wang Xiaojia, Yang Shanlin, Xu Dayu. Application Research on Improved PSO Algorithm for Data Prediction Mining, Journal of the China Society for Scientific and Technical Information, 2011,30(8):840-845.