Available online at www.alphanumericjournal.com

alphanumeric journal
The Journal of Operations Research, Statistics, Econometrics and Management Information Systems

Volume 5, Issue 2, 2017

Received: October 25, 2017
Accepted: December 11, 2017
Published Online: December 11, 2017

AJ ID: 2017.05.02.OR.06
DOI: 10.17093/alphanumeric.359942

Application of Seasonal and Multivariable Grey Prediction Models for Short-Term Load Forecasting

Tuncay Özcan, Ph.D. *

Assist. Prof., Department of Industrial Engineering, Faculty of Engineering, Istanbul University, Istanbul, Turkey, tuncay.ozcan@istanbul.edu.tr

* İstanbul Üniversitesi Mühendislik Fakültesi, Endüstri Mühendisliği Bölümü, İ. Ü. Avcılar Kampüsü 34320 Avcılar İstanbul / Türkiye

ABSTRACT

Short-term electricity load forecasting is one of the most important operations in electricity markets. The success in the operations of electricity market participants partially depends on the accuracy of load forecasts. In this paper, three grey prediction models, which are seasonal grey model (SGM), multivariable grey model (GM (1,N)) and genetic algorithm based multivariable grey model (GAGM (1,N)), are proposed for short-term load forecasting problem in day-ahead market. The effectiveness of these models is illustrated with two real-world data sets. Numerical results show that the genetic algorithm based multivariable grey model (GAGM (1,N)) is the most efficient grey forecasting model through its better forecast accuracy.

Keywords: Grey Prediction, Short Term Load Forecasting, Genetic Algorithm, Parameter Optimization

Kısa Dönem Yük Tahmini için Mevsimsel ve Çok Değişkenli Gri Tahmin Modellerinin Uygulanması

ÖZ

Kısa dönem elektrik yükü tahmini, elektrik piyasasında en önemli operasyonlardan biridir. Elektrik piyasasındaki işletmelerin operasyonlarındaki başarı, yük tahminlerinin doğruluğuna bağlıdır. Bu çalışmada, gün öncesi piyasasında kısa döneli yük tahmini problemi için mevsimsel gri model (SGM), çok değişkenli gri model (GM (1,N)) ve genetik algoritma esaslı gri model olmak üzere üç gri tahmin modeli önerilmiştir. Bu modellerin etkinliği, iki gerçek hayat veri kümesi ile gösterilmiştir. Sayısal sonuçlar, genetik algoritma esaslı gri modeli daha iyi tahmin doğruluğu sağlayarak en etkin gri tahmin modeli olduğunu göstermektedir.

Anahtar Kelimeler: Gri Tahmin, Kısa Dönem Yük Tahmini, Genetik Algoritma, Parametre Optimizasyonu

1. Introduction

Electricity is a crucial resource, which must be planned and managed carefully. Electricity market involves generation, transmission, distribution, wholesaler, retailer companies and governmental authorities. Electricity load forecasts are one type of information that these market participants need in their decision-making processes. Short and long-term success in the operations of these electricity market participants partially depends on the accuracy of load forecasts.

Electricity load forecasting can be divided into three categories. The first category includes long term load forecasting. The time span in consideration can be six months, one year or longer. It is particularly important for growth strategies at the governmental level and it also has importance on the strategic decision making process of the electricity market operators. The second category deals with medium term load forecasting. The time span is weeks or months. It is vital for electricity generation companies because the stock levels and resource management decisions need this information (Hoffman & Wood, 1976). The last category is short term, hourly load forecasts. Hourly load forecasting of the next day is an essential operation in electricity markets.

This study aims to predict short-term loads of one-day ahead electricity market using grey prediction models. At this point, a seasonal grey model (SGM), a multivariable grey model (GM(1,N)) and a multivariable grey model optimized with genetic algorithm (GAGM(1,N)) are proposed to predict the electricity loads of one-day-ahead hours.

Grey Theory, extremely high mathematical analysis of the systems that are partly known and partly unknown and defined as ‘’weak knowledge’’ and ‘’insufficient data’’, was first introduced by (Ju-Long, 1982). Grey forecasting is one of the most important parts in the grey theory. Grey forecasting methods have been used in many prediction problems such as airline passengers (Hsu & Wen, 1998), stock prices (Wang Y. F., 2002), tourism demand (Huang, Zheng, & Wu, 2004), foreign exchange rates (Chen, Chen, & Chen, 2008), high-tech industrial output (Wang & Hsu, 2008; Hsu L. C., 2009), energy consumption (Pi, Liu, & Qin, 2010; Feng, Ma, Song, & Ying, 2012), agricultural output (Ou, 2012).

Many studies can be found in the literature concerning the application of grey forecasting methods for short-term load forecasting problem. These studies are summarized below:

Yao et al. (2003) presented an improved GM(1,1) based prediction algorithm to forecast a very short electric power demand. In that study, the forecast error is reduced using adaptive model parameters. Li et al. (2006) proposed an improved GM(2,1) model to perform short term load forecasting. Zhou et al. (2006) suggested GM(1, 1) model with the trigonometric residual modification technique for forecasting electricity demand. Niu et al. (2008) developed genetic algorithm based GM(1,1) model to solve the problem of short-term load forecasting. In the proposed model, the value of parameter in the GM(1,1) is optimized using genetic algorithm. Bianco et al. (2010) used a trigonometric grey model with rolling mechanism for nonresidential electricity consumption in Romania. Li et al. (2012) proposed the adaptive grey model for forecasting short term load. In this study, the performance of the proposed grey model is compared with other methods based on back propagation neural networks and support vector regression. Jin et al. (2012) developed a hybrid optimization grey model using grey correlation contest for short-term power load forecasting. The efficiency of developed model is illustrated by comparing with the results of basic grey models. Bahrami et al. (2014) presented a new model which is based on combination of the wavelet transform and GM(1,N) model. In this paper, to improve the forecast accuracy, the parameters of GM(1,N) model are determined using particle swarm optimization.

In this paper, performance analysis is conducted of grey prediction models for short-term load forecasting problem. Also, in order to improve the forecast performance of the original GM (1,N) model, genetic algorithms is used to estimate the parameters of this model.

The organization of the paper is as follows. Section 2 describes the time series representation of load forecasting and defines basic performance criteria used in load forecasting. Section 3 gives brief introduction about seasonal grey model (SGM), multivariable grey model (GM(1,N)) and GM(1,N) model optimized with genetic algorithm. In section 4, an application of the proposed models with the experimentations on real data for the short-term load forecasting is given. The results are discussed in Section 5.

2. Short Term Load Forecasting Problem

Short-term load forecasting of hourly electricity load, usually handled by time series approach. If t is the index of the hour to be forecasted and D_t is the load of the hour t; training dataset S^T with an autoregressive time series structure at each row is generated by Equation (1).

$$D_t = \alpha_0 + \alpha_1 D_{t-1} + \alpha_2 D_{t-2} + ... + \alpha_p D_{t-p} + \varepsilon_t \tag{1}$$

Apart from load values itself, temperature and other environmental or economic parameters can also be added to the data.

Mean Absolute Percentage Error (MAPE) is a commonly used performance criteria in load forecasting. Its formula can be seen in Equation (2). Here, Ai is the actual load value and Fi is the forecasted value for the same hour.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \frac{|A_i - F_i|}{A_i} \tag{2}$$

Seasonality is an important aspect in load forecasting. Several types of seasonality should be handled accordingly. The main types are day of the week seasonality and monthly seasonality. Generally, weekdays and weekends should be modeled separately. But even in this case, day of the week seasonality occurs, i.e. the behavior of the load pattern may be different on Mondays and Fridays.

3. Forecasting Algorithms

Seasonal grey model (SGM), multivariable grey model (GM (1,N)) and genetic algorithm based multivariable grey model (GAGM (1,N)) are introduced in this section.

3.1. Seasonal Grey Model

As mentioned earlier, grey prediction is one of the most important parts in the grey theory. The GM (1,1) model, which provides good prediction using limited data, is the basic grey forecasting model. GM (1,1) indicates one variable and one order grey forecasting model (Wang & Hsu, 2008). Short-term electricity consumption data has multiple seasonal patterns such as monthly, weekly, daily and hourly periodicity. Therefore, the use of the GM (1,1) model without considering of seasonal factors leads to inaccuracy load demand prediction. At this point, Xia and Wong (2014) proposed a seasonal discrete grey forecasting model. The steps of this model can be summarized as follows (Xia & Wong, 2014):

Step 1. Assume $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(i), \ldots, x^{(0)}(n)\}$ be an original time series data. A new sequence $X^{(1)}$ is obtained by cycle truncation accumulated generating operation (CTAGO).

$$x^{(1)}(k) = CTAGO(\mathrm{x}^{(0)}(k)) = \sum_{j=1}^{q} x^{(0)}(k+j-1) \quad \forall k = 1, 2, \ldots, n-q+1 \tag{3}$$

where q is the periodicity of the time series.

Step 2. The seasonal grey forecasting model is established as follows.

$$\hat{x}^{(1)}(k+1) = d_1(x^{(1)}(k) + \lambda) + d_2, \qquad \forall k = 1, 2, \ldots, n\text{-}q \tag{4}$$

Step 3. In the Equation (4), the values of parameter d_1, d_2 and λ can be calculated as follows using the least square method.

$$d = \left[d_1, d_2\right]^T = (A^T A)^{-1} A^T Q \tag{5}$$

where

$$A = \begin{bmatrix} x^{(1)}(1) & x^{(1)}(2) & x^{(1)}(3) & \ldots & x^{(1)}(n-q) \\ 1 & 1 & 1 & \ldots & 1 \end{bmatrix}^T \tag{6}$$

$$Q = \left[x^{(1)}(2) \quad x^{(1)}(3) \quad \ldots \quad x^{(1)}(\mathrm{n-q+1}) \right]^T \tag{7}$$

$$\lambda = \frac{\sum_{i=1}^{k-1} (x^{(1)}(i+1) - d_1 x^{(1)}(i) - d_2)}{d_1(k-1)} \tag{8}$$

Step 4. Finally, the predicted values of the original sequence are calculated by using Equation (9).

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k-q+2) - x^{(1)}(k-q+1) + x^{(0)}(k-q+1) \quad \forall k = q, q+1, \ldots, n \tag{9}$$

3.2. Multivariable Grey Model - GM(1,N)

Short-term electric load is affected by many factors such as temperature, humidity and time. These factors should be taken into account for a better-forecast accuracy. At this point, GM (1,1) and SGM (1,1) models are inadequate.

The calculation steps of GM(1,N) model which is multi variables first-order grey model, are described as follows (Tseng, Yu, & Tzeng, 2001; Hsu L. C., 2009):

Step 1. Assume $X_i^{(0)} = \{x_i^{(0)}(1), x_i^{(0)}(2), \ldots, x_i^{(0)}(n)\}$ be an original sequence of variable *i*. For *i*=1, this sequence includes output values of the data set, the others contain input data sets.

Step 2. For each input data set and output data set, new sequences are generated using accumulated generating operation (AGO).

$$X_i^{(1)} = \{x_i^{(1)}(1), x_i^{(1)}(2), \ldots, x_i^{(1)}(n)\} \tag{10}$$

$$x_i^{(1)}(k) = \sum_{j=1}^{k} x_i^{(0)}(j) \tag{11}$$

Step 3. A sequence $Z^{(1)} = \{z^{(1)}(2), \ldots, z^{(1)}(i), \ldots, z^{(1)}(n)\}$ is obtained by consecutive values of sequence $X_1^{(1)}$.

$$z^{(1)}(k) = \alpha x_1^{(1)}(k) + (1-\alpha)x_1^{(1)}(k-1), \qquad \forall k = 2,3,\ldots,n, \ \ 0 \le \alpha \le 1 \tag{12}$$

Step 4. The first order –multi variables grey differential equation of GM(1,N) is established as follows (Pai, Chiou, & Wen, 2008):

$$x_1^{(0)}(k) + \mathrm{a}z_1^{(1)}(k) = \sum_{j=2}^{N} b_j x_j^{(1)}(k) = b_2 x_2^{(1)}(k) + b_3 x_3^{(1)}(k) + \ldots + b_N x_N^{(1)}(k) \tag{13}$$

In this equation, parameters $a, b_2, b_3, \ldots, b_N$ can be calculated as follows using the least square method.

$$\left[a, b_2, b_3, \ldots, b_N\right]^T = (B^T B)^{-1} B^T Y \tag{14}$$

where

$$Y = \left[x_1^{(0)}(2) \quad x_1^{(0)}(3) \quad \ldots \quad x_1^{(0)}(n)\right]^T \tag{15}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & -x_2^{(1)}(2) & \cdots & -x_N^{(1)}(2) \\ -z^{(1)}(3) & -x_2^{(1)}(3) & \cdots & -x_N^{(1)}(3) \\ \vdots & \vdots & \vdots & \vdots \\ -z^{(1)}(n) & -x_2^{(1)}(n) & \cdots & -x_N^{(1)}(n) \end{bmatrix} \tag{16}$$

Step 5. The predicted values of the accumulated sequence are obtained using following equation.

$$\hat{x}_1^{(1)}(k+1) = (x_1^{(0)}(1) - \sum_{i=2}^{N} \frac{b_i}{a} x_i^{(1)}(k+1))\,\mathrm{e}^{-ak} + \sum_{i=2}^{N} \frac{b_i}{a} x_i^{(1)}(k+1) \tag{17}$$

Step 6. The predicted values of the original sequence are calculated by using the inverse accumulated generating operation (IAGO).

$$\hat{x}_1^{(0)}(k+1) = \hat{x}_1^{(1)}(k+1) - \hat{x}_1^{(1)}(k) \quad k \ge 2 \tag{18}$$

3.3. Genetic algorithm based multivariable grey model – GAGM(1,N)

In the literature, metaheuristic algorithms such as genetic algorithms (Wang & Hsu, 2008; Lee & Tong, 2011; Ou, 2012) and particle swarm optimization (Zhou, Fang, Li, Zhang, & Peng, 2009; Bahrami, Hooshmand, & Parastegari, 2014) have been successfully applied to estimate the parameters of grey forecasting models.

Traditional GM(1,N) forecasting model often sets the parameter α to 0.5. This value is not optimal for all data sets. Therefore, in this study, in order to improve the forecast performance of the original GM (1,N) model, genetic algorithms can be used to estimate the parameters of this model. To this end, the following model is established.

$$\min \quad Z=\frac{1}{n}\sum_{k=1}^{n}\left|\frac{\hat{x}_0(k)-x_0(k)}{x_0(k)}\right|\cdot 100\% \tag{19}$$

$$0\le \alpha \le 1 \tag{20}$$

where $x_0(k)$ is actual value, $\hat{x}_0(k)$ is predicted value and n is the number of sequence data.

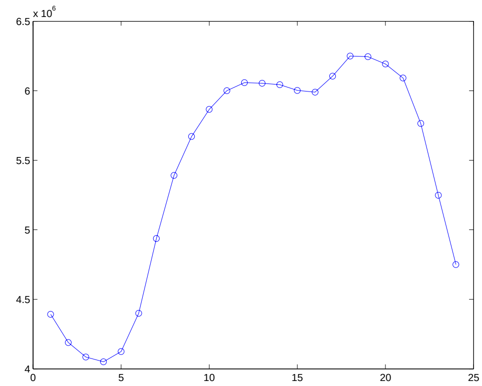
4. Short-Term Load Forecasting with Proposed Algorithms

In this section, application and adaptation of the previously explained algorithms to hourly load forecasting is introduced. In day-ahead market, the problem of load forecasting concerns making forecasts for each hour of the next day. The historical data and temperature data are used to make load prediction for each hour of the next day. In other words, short-term load forecasting for day-ahead market makes 24 different predictions for the next day.

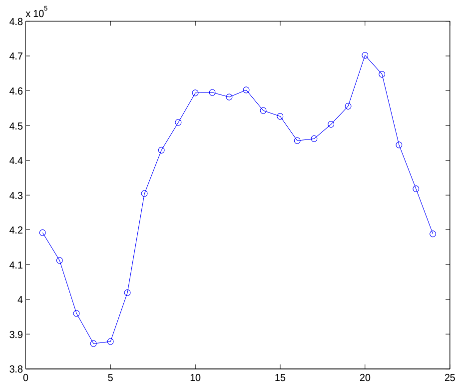
4.1. Data Sets

In this study, two different load datasets used for benchmarking. BSE dataset (Hong, Wang, & Willis, 2011)contains hourly loads of an electricity distribution company between 01/01/2003 and 12/31/2008 and accompanying hourly temperature values are included in. In this study, each weekday of 2008 is forecasted by using this trained model.

EUNITE dataset (Chen & Chang, 2004) originally contains half hourly loads. But they are combined into hourly values in this study. The data range is between 01/01/1997 and 12/31/1998 and accompanying daily temperature values are also presented. The first month of 1999 is predicted with the proposed methods. Hourly average load values of these datasets can be seen in Figure 1 and 2.



(a)



(b)

Figure 1. (a) Average hourly load of BSE dataset; (b) Average hourly load of EUNITE dataset

4.2. Methodology

In this study, two different approaches are proposed for each dataset. First, all data is used to build single training datasets, which include all hourly loads for all hours. In the second approach, each hour is modeled separately; consequently 24 different models is developed in this approach. Predictions for each hour are done with its own trained model.

Moving cross-validation procedure is used in this study. In this procedure, a part of the data is employed as training data, and the model generated by this training data is used in forecasting (test) phase. Then, for each new day, training data is shifted, thus, the actual values of the previously forecasted day become the last line of the training dataset.

In the first approach, t-1 (previous day), t-2 (the day before), t-5 (the same day in the previous week) are. In the second approach, when whole data is used to make predictions, then the structure is t-24, t-25, t-120. Here, the load of the same hour is used in the previous day and so on. For the selected datasets, temperature data is also available. Same lag structure is used as temperature input in the time series models. In the seasonal grey model, the value of the periodicity of the data sets (q) is taken as 24.

In the GAGM(1,N) model, the parameters of GA are as follows: the population size is 20, the crossover rate and mutation rate is set to be 0.8 and 0.1 respectively. The default values of the MATLAB optimization toolbox are used for the other parameters such as stopping criteria, elite count and selection function.

Forecast range for each dataset is reported in Table 1. Proposed algorithms are programmed on MATLAB 2016b.

Data Set	Data Range	Training Data	Testing Data
BSE	01/01/2003-12/31/2008	01/01/2003-31/12/2007	Hourly loads of each weekday of 2008
EUNITE	01/01/1997-01/31/1999	01/01/1997-12/31/1998	Hourly loads of each workday of Jan. 1999

Table 1. Datasets used in experimental analysis

5. Conclusions

Result on BSE dataset can be seen in Table 2. Also results from EUNITE dataset is given in Table 3. In the approach lines of the tables, single model represents training a single forecasting model with the whole data, including all hours. Besides separate models represent building 24 different models for each hour.

Algorithm	**SGM**		**GM(1,N)**		**GAGM(1,N)**	
Approach	Single model	Separate models	Single model	Separate models	Single model	Separate models
MAPE	6.81%	4.19%	4.72%	4.51%	3.89%	3.86%

Table 2. Performances of the proposed grey prediction algorithms on BSE dataset

Algorithm	**SGM**		**GM(1,N)**		**GAGM(1,N)**	
Approach	Single model	Separate models	Single model	Separate models	Single model	Separate models
MAPE	8.08%	4.98%	5.55%	5.43%	3.55%	3.56%

Table 3. Performances of the proposed grey prediction algorithms on EUNITE dataset

Forecasting results are also represented in Figure 2 for EUNITE dataset. Forecasting results show that GAGM (1,N) model is promising techniques in hourly load forecasting. For the BSE dataset, Hong et al. (2011) has reached a minimum MAPE of 4.98% with updating their forecast model every day. In this study, GAGM (1,N) model has reached a minimum MAPE of 3.86% by using separate models for each hour. Similarly, in EUNITE dataset, GAGM (1,N) model has reached a MAPE value of 3.13%.

Further studies may include modeling impacts of holidays and other special days in load data by applying outlier analysis. Also for the distribution companies, unread meters are a source of problem. Some meters are read rarely, therefore there are big gaps in the load data for some customers. Future models may handle this randomness and imperfectness.

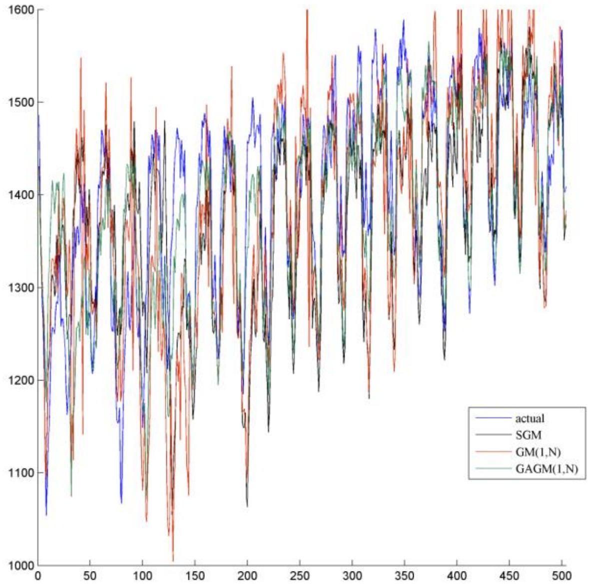


Figure 2. Forecasting results of EUNITE dataset in case of a single trained model

References

Bahrami, S., Hooshmand, R. A., & Parastegari, M. (2014). Short term electric load forecasting by wavelet transform and grey model improved by PSO (particle swarm optimization) algorithm. Energy(72), 434-442.

Bianco, V., Manca, O., Nardini, S., & Minea, A. A. (2010). Analysis and forecasting of nonresidential electricity consumption in Romania. Applied Energy, 87(11), 3584-3590.

Chen, B. J., & Chang, M. W. (2004). Load forecasting using support vector machines: A study on EUNITE competition 2001. IEEE transactions on power systems, 19(4), 1821-1830.

Chen, C. I., Chen, H. L., & Chen, S. P. (2008). Forecasting of foreign exchange rates of Taiwan's major trading partners by novel nonlinear Grey Bernoulli model NGBM (1, 1). Communications in Nonlinear Science and Numerical Simulation, 13(6), 1194-1204.

Feng, S. J., Ma, Y. D., Song, Z. L., & Ying, J. (2012). Forecasting the energy consumption of China by the grey prediction model. Energy Sources, Part B: Economics, Planning, and Policy, 7(4), 376-389.

Hoffman, K. C., & Wood, D. O. (1976). Energy system modeling and forecasting. Annual review of energy, 1(1), 423-453.

Hong, T., Wang, P., & Willis, H. L. (2011). A naïve multiple linear regression benchmark for short term load forecasting. In Power and Energy Society General Meeting (s. 1-6). IEEE.

Hsu, C. I., & Wen, Y. H. (1998). Improved grey prediction models for the trans-pacific air passenger market. Transportation planning and Technology, 22(2), 87-107.

Hsu, L. C. (2009). Forecasting the output of integrated circuit industry using genetic algorithm based multivariable grey optimization models. Expert systems with applications, 36(4), 7898-7903.

Huang, Y. F., Zheng, M. C., & Wu, C. H. (2004). Comparison of various different approaches to tourist demand forecasting. Journal of grey system, 7(1), 21-27.

Jin, M., Zhou, X., Zhang, Z. M., & Tentzeris, M. M. (2012). Short-term power load forecasting using grey correlation contest modeling. Expert Systems with Applications, 39(1), 773-779.

Ju-Long, D. (1982). Control problems of grey systems. Systems & Control Letters, 1(5), 288-294.

Lee, Y. S., & Tong, L. I. (2011). Forecasting energy consumption using a grey model improved by incorporating genetic programming. Energy Conversion and Management, 52(1), 147-152.

Li, D. C., Chang, C. J., Chen, C. C., & Chen, W. C. (2012). Forecasting short-term electricity consumption using the adaptive grey-based approach—An Asian case. Omega, 40(6), 767-773.

Li, G. D., Yamaguchi, D., & Nagai, M. (2006). Application of improved grey prediction model to short term load forecasting. In Proceedings of International Conference on Electrical Engineering , (s. 1-6).

Niu, D. X., Li, W., Han, Z. H., & Yuan, X. E. (2008). Power Load Forecasting based on Improved Genetic Algorithm–GM (1, 1) Model. In Natural Computation, 2008. ICNC'08 (s. 630-634). IEEE.

Ou, S. L. (2012). Forecasting agricultural output with an improved grey forecasting model based on the genetic algorithm. Computers and electronics in agriculture, 85, 33-39.

Pai, T. Y., Chiou, R. J., & Wen, H. H. (2008). Evaluating impact level of different factors in environmental impact assessment for incinerator plants using GM (1, N) model. Waste Management, 28(10), 1915-1922.

Pi, D., Liu, J., & Qin, X. (2010). A grey prediction approach to forecasting energy demand in China. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 32(16), 1517-1528.

Tseng, F. M., Yu, H. C., & Tzeng, G. H. (2001). Applied hybrid grey model to forecast seasonal time series. Technological Forecasting and Social Change, 67(2), 291-302.

Wang, C. H., & Hsu, L. C. (2008). Using genetic algorithms grey theory to forecast high technology industrial output. Applied Mathematics and Computation, 195(1), 256-263.

Wang, Y. F. (2002). Predicting stock price using fuzzy grey prediction system. Expert systems with applications, 22(1), 33-38.

Xia, M., & Wong, W. K. (2014). A seasonal discrete grey forecasting model for fashion retailing. Knowledge-Based Systems, 57, 119-126.

Yao, A. W., Chi, S. C., & Chen, J. H. (2003). An improved grey-based approach for electricity demand forecasting. Electric Power Systems Research, 67(3), 217-224.

Zhou, J., Fang, R., Li, Y., Zhang, Y., & Peng, B. (2009). Parameter optimization of nonlinear grey Bernoulli model using particle swarm optimization. Applied Mathematics and Computation, 207(2), 292-299.