

PAPER • OPEN ACCESS

Demand forecasting of electricity in Indonesia with limited historical data

To cite this article: Mujiati Dwi Kartikasari and Arif Rohmad Prayogi 2018 *J. Phys.: Conf. Ser.* **974** 012040

View the [article online](#) for updates and enhancements.

Related content

- [Research on China's Electricity Demand in 2017 and 2018](#)
Xiandong Tan, Shanshan Wu, Baoguo Shan et al.
- [Indonesia's Electricity Demand Dynamic Modelling](#)
J Sulistio, A Wirabhuana and M G Wiratama
- [Conjoint Analysis for New Service Development on Electricity Distribution in Indonesia](#)
D L Widaningrum, Chynthia, L D Astuti et al.



IOP | ebooks™

Bringing you innovative digital publishing with leading voices to create your essential collection of books in STEM research.

Start exploring the collection - download the first chapter of every title for free.

Demand forecasting of electricity in Indonesia with limited historical data

Mujiati Dwi Kartikasari, Arif Rohmad Prayogi

Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Islam Indonesia, Jalan Kaliurang Km 14.5 Sleman, Yogyakarta, Indonesia 55584

E-mail: mujiatikartikasari@uii.ac.id, arifrohmada31@gmail.com

Abstract. Demand forecasting of electricity is an important activity for electrical agents to know the description of electricity demand in future. Prediction of demand electricity can be done using time series models. In this paper, double moving average model, Holt's exponential smoothing model, and grey model GM(1,1) are used to predict electricity demand in Indonesia under the condition of limited historical data. The result shows that grey model GM(1,1) has the smallest value of MAE (mean absolute error), MSE (mean squared error), and MAPE (mean absolute percentage error).

1. Introduction

Every year electricity demand in Indonesia will increase to follow economic growth. Because of this, predicting of electricity demand is very necessary to know the description of electricity demand in today and future. Thus, the Indonesian electrical agents can determine the plan to provide capacities required of power plant.

In order to predict electricity demand in Indonesia, data of electricity demand are collected at several points in time. The kind of this data can be predicted using time series analysis. Many researches have predicted electricity demand using time series analysis. Erdogdu (2007) used cointegration and ARIMA to predict electricity demand in Turkey [1]. Ismail et al. (2009) used ARIMA, SARIMA, and rule based models to predict peak load electricity demand in Malaysia [2]. Kandanand (2011) used artificial neural network (ANN) approach to predict electricity demand in Thailand [3]. Goel et al. (2014) used ARIMA, multiple regression, and trend seasonality model to predict electricity demand in New Delhi [4].

Most of previous researches used large data in construction of time series models to predict electricity demand so there is no problem in selecting the time series models to be used. While the data used in this paper are limited, then only a few time series models can be used. Some suitable time series models under the condition of small data points for model construction are summarized in Table 1 [5].



Table 1. Several time series models with limited historical data.

Time Series Models	Data requirement
Moving average	2 to 30
Exponential smoothing	5 to 10
Grey model	4

To overcome the predicting process of electricity demand with limited historical data, in this paper, we will use three time series models summarized in Table 1. The three models are compared using MAE, MSE, and MAPE.

Following this section, in the next section we present the theoretical basis of the three time series models. The measure of comparison for each model will be provided in Section 3. Then the data are analysed in Section 4. In Section 5, we will draw a conclusion based on analysis result.

2. Time series models

The time series models which will be used in this paper are moving average, exponential smoothing, and grey model. The theories of those models are presented as follows.

2.1. Moving average

Moving average is one of time series models which can be used for smoothing past history data [6]. There are several kinds of moving average models, namely simple moving average, double moving average, and higher-order moving average. This study uses double moving average model. The double moving average model is able to cope with significant trend [6].

The double moving average is a moving average of a moving average. We denote $MA(M \times N)$ as an M -period MA of N -period MA . The general procedure of double moving average is described as follows [6]:

$$s'_t = \frac{(x_t + x_{t-1} + x_{t-2} + \cdots + x_{t-N+1})}{N}, \quad (1)$$

$$s''_t = \frac{(s'_t + s'_{t-1} + s'_{t-2} + \cdots + s'_{t-M+1})}{M}, \quad (2)$$

$$a_t = s'_t + (s'_t - s''_t) = 2s'_t - s''_t, \quad (3)$$

$$b_t = \frac{2}{M-1}(s'_t - s''_t), \quad (4)$$

$$\hat{x}_{t+m} = a_t + b_t(m). \quad (5)$$

The notation of s'_t denotes the simple moving average in the period of t , s''_t denotes the double moving average in the period of t , a_t denotes the adjustment of the single moving average in the period of t , and b_t denotes the estimate of trend from one time period the next. The value of prediction for m periods ahead is denoted by $\hat{x}_{t+m}$.

2.2. Exponential smoothing

Exponential smoothing is a model which use an exponentially weighted smoother for smoothing past history data. There are three kinds of common exponential smoothing models, namely simple exponential smoothing, Holt's exponential smoothing, and Holt-Winters exponential smoothing model. The Holt's exponential smoothing model which is a model frequently used to handle data with linear trend is applied in this study. The Holt's exponential smoothing

model requires two smoothing constants that are α as smoothing constant for the data and β as smoothing constant for trend estimate. The formula for Holt's exponential smoothing model is described as follows [6]:

$$s_t = \alpha x_t + (1 - \alpha)(s_{t-1} + b_{t-1}), \quad 0 < \alpha < 1, \quad (6)$$

$$b_t = \beta(s_t - s_{t-1}) + (1 - \beta)b_{t-1}, \quad 0 < \beta < 1. \quad (7)$$

The prediction value for m periods ahead can be calculated by

$$\hat{x}_{t+m} = s_t + b_t(m). \quad (8)$$

The recursive computation process in Holt's exponential smoothing model uses initial value $s_1 = x_1$ and $b_1 = x_2 - x_1$.

2.3. Grey Model

Grey model which will be described in this part is grey model GM(1,1). The GM(1,1) is one of the most common of grey prediction. This model is a part of grey system theory [7] and is known as a first order model with one variable. The GM(1,1) model is widely applied in predicting of time series data. The procedure of GM(1,1) is divided into three steps which is cited from Dang et al. [5] and is described as follows.

The first step is to arrange an original sequence $x^{(0)}(i)$ as follows:

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(i), \dots, x^{(0)}(n)\}. \quad (9)$$

The notation of $x^{(0)}$ denotes the value for the time period $i(i = 1, 2, \dots, n)$.

The second step is to generate sequence $x^{(1)}$ by a one time accumulated generating operation (1-AGO) based on the original sequence $x^{(0)}$. The expression of sequence $x^{(1)}$ is

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \dots, x^{(1)}(i), \dots, x^{(1)}(n)\} \quad (10)$$

where, $x^{(1)}(i) = \sum_{j=1}^i x^{(0)}(j)$.

The third step of GM(1,1) procedure is to form an equation of first-order differential with one variable. The equation is defined by

$$\frac{dx^{(1)}}{dt} + ux^{(1)} = v \quad (11)$$

where u and v are the developing coefficient and the grey input coefficient, respectively. By using the least square method, the coefficient of u and v can be determined. The formula for determining the coefficient of u and v is expressed as follows:

$$[u, v]^T = (P^T P)^{-1} P^T Q \quad (12)$$

where,

$$P = \begin{bmatrix} -(x^{(1)}(1) + x^{(1)}(2))/2 & 1 \\ -(x^{(1)}(2) + x^{(1)}(3))/2 & 1 \\ \vdots & \vdots \\ -(x^{(1)}(n-1) + x^{(1)}(n))/2 & 1 \end{bmatrix}$$

and

$$Q = [x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)]^T.$$

After the values of u and v coefficient are known, the time response function of the GM(1,1) can be determined by

$$\hat{x}^{(1)}(i) = \left[x^{(0)}(1) - \frac{v}{u} \right] e^{-u(i-1)} + \frac{v}{u} \quad (i = 2, 3, \dots, n). \quad (13)$$

The prediction value which is calculated by GM(1,1) procedure is denoted by $\hat{x}^{(0)}$. It can be calculated by the operation of a one time inverse accumulated generating operation (1-IAGO) based on the time response function of the GM(1,1) $\hat{x}^{(1)}(i)$. The expression of predicted value $\hat{x}^{(0)}$ is

$$\hat{x}^{(0)}(i) = \hat{x}^{(1)}(i) - \hat{x}^{(1)}(i-1) \quad (i = 2, 3, \dots, n) \quad (14)$$

with $\hat{x}^{(0)}(1) = \hat{x}^{(1)}(1)$.

3. Evaluation of Models

There are many kinds of measure which can be used to evaluate the performance of time series models. In this paper, we will use mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE) to compare the three time series models. The formula of MAE, MSE, and MAPE are defined as follows [6]:

$$MAE = \frac{1}{n} \sum_{t=1}^n |x_t - \hat{x}_t|, \quad (15)$$

$$MSE = \frac{1}{n} \sum_{t=1}^n (x_t - \hat{x}_t)^2, \quad (16)$$

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{x_t - \hat{x}_t}{x_t} \right| \times 100\%. \quad (17)$$

4. Results

Data used in this paper are data of electricity consumption in Indonesia obtained from report of Directorate General of Electricity Indonesia from 2007 to 2015 [8, 9, 10, 11]. Statistical data of electricity consumption are presented in Table 2.

Table 2. Electricity Consumption in Indonesia (MWh).

Year	2007	2008	2009	2010	2011	2012	2013	2104	2015
Consumption	129,019	129,019	151,334	165,969	178,279	194,289	208,935	221,296	232,520

Based on the data shown in Table 2, we analyse this data using three time series models that are double moving average, Holt's exponential smoothing, and GM(1,1) model. The predicted results are reported in Figure 1.

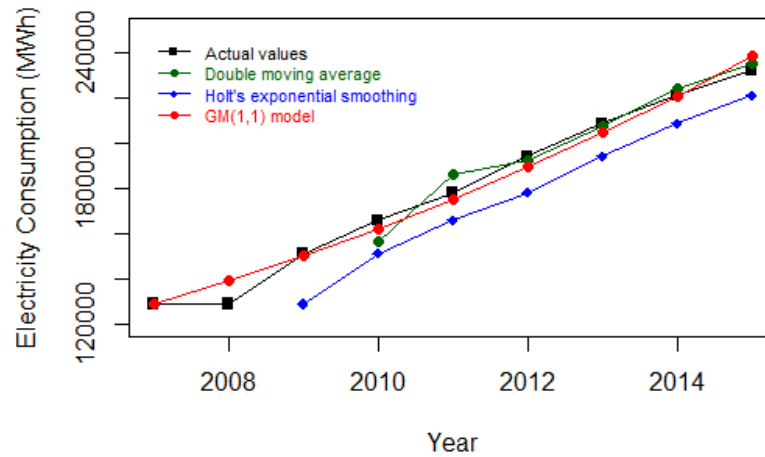


Figure 1. Predicted results of electricity demand in Indonesia.

Figure 1 shows the comparison between the prediction data using double moving average model, Holt's exponential smoothing model, and GM(1,1) model and the actual value. From figure 1 we can see that the prediction data from the double moving average and the GM(1,1) model have closer distance to the actual value compared to Holt's exponential smoothing model. To compare the performance of three models accurately, Table 3 provides the value of the MAE, MSE, and MAPE of each model.

Table 3. Performance of each model for predicting electricity demand in Indonesia.

Model	Evaluation		
	MAE	MSE	MAPE
Double moving average model	4,444.542	28,711,727	2.399113%
Holt's exponential smoothing model	4,664.472	74,449,210	2.840955%
Grey model GM(1,1)	3,642.755	22,894,478	2.156962%

According to the results of the models performance shown in Table 3, GM(1,1) model gives a fewer value of MAE, MSE, and MAPE than double moving average and Holt's exponential smoothing model. Thus, we can say that the GM(1,1) model is more appropriately used than the other models to predict electricity demand in Indonesia

5. Conclusion

We have compared the prediction model of the electricity demand in indonesia using double moving average, Holt's exponential smoothing, and grey model GM(1,1) under the condition of limited historical data. Based on the result, grey model GM(1,1) has the smallest value of MAE, MSE, and MAPE compared to the other models. We conclude that grey model GM(1,1) is the best model in the case studies of electricity demand prediction in Indonesia.

References

- [1] Erdogdu E 2007 Electricity demand analysis using cointegration and ARIMA modelling: a case study of Turkey *Munich Personal RePEc Archive*. MPRA Paper No. 19099
- [2] Ismail Z, Yahya A and Mahpol KA 2009 Forecasting peak load electricity demand using statistics and rule based approach *American J. Appl. Sciences*. **6**(8) 1618-25
- [3] Kandananond K 2011 Forecasting electricity demand in Thailand with an artificial neural network approach *Energies*. **4** 1246-57
- [4] Goel A and Goel A 2014 Regression based forecast of electricity demand of New Delhi *Int. J. Scientific and Research Publications*. **4**
- [5] Dang HS, Huang YF, Wang CN and Nguyen TMT 2016 An application of the short term forecasting with limited data in the healthcare traveling industry *Sustainability*. **8** 1037
- [6] Makridakis S, Wheelwright SC and McGee VE 1983 *Forecasting: methods and applications Second Edition* (Canada: John Wiley & Sons, Inc)
- [7] Julong D 1989 Introduction to Grey System Theory *The Journal of Grey System*. **1** 1-24
- [8] Directorate General of Electricity 2013 *The Book of Electricity Statistics Number 26 - 2013* (Jakarta: Directorate General of Electricity)
- [9] Directorate General of Electricity 2014 *The Book of Electricity Statistics Number 27 - 2014* (Jakarta: Directorate General of Electricity)
- [10] Directorate General of Electricity 2015 *The Book of Electricity Statistics Number 28 - 2015* (Jakarta: Directorate General of Electricity)
- [11] Directorate General of Electricity 2016 *The Book of Electricity Statistics Number 29 - 2016* (Jakarta: Directorate General of Electricity)