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FORECASTS OF ELECTRICITY DEMAND IN BANGLADESH BY USING GREY PREDICTION MODEL GM(1,1) , EWMA AND ARIMA MODEL

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Abstract

Electricity demand forecasting is an important matter for governments. Although there are different forecasting models, choosing the suitable model is of great significance. This paper focuses on utilizing the performance of grey prediction model GM(1,1),exponential weighted moving average model and ARIMA(1,1,1) model to the yearly electricity demand for Bangladesh from year 2010 to 2018.The results show that the ARIMA(1,1,1) model exhibits good forecasting ability according to the MAPE criteria. Moreover, the forecasting results are compared with the results of EWMA and GM (1,1) models. The three techniques do similarly well in forecasting process. However, ARIMA (1,1,1) outperforms the GM(1,1) and EWMA techniques according to forecasting error accuracy measure MAPE.

Keywords: GM (1,1), EWMA,ARIMA(1,1,1), MAPE.

1.1 Introduction

Electricity demand forecasting place a key role in making important decisions on power the power supply. The importance of accurate forecasting is that the power development board will produce the right amount of electricity for the upcoming year. Obviously any errors in forecasting can lead to bed planning which will be costly. Too high a forecast leads an extra production of electricity which is a great loss of money. Too low forecast cannot fulfill the required demand of the customer. Electricity demand forecasting is a process used to forecast future electric load, given historical load data as well as current and forecasted information. Therefore, forecasting electric demand is of great importance for various sector in Bangladesh.

The Grey model (GM) is a forecasting dynamic model and has been used in various application. The results obtained from the various models show that the forecasting accuracy of the GM (1,1) is better than other model. The greatest characteristics of Grey forecasting model GM (1,1) shall be the simple algorithm and it can build a model with little data which is quite convenient for the modeling and operation. As Bangladesh's power development board doesn't release data relating to electricity demand monthly, so the sample size is limited and so statistical modeling methods on large sets of data are not applicable. Grey system theory is an effective method of studying and modeling system consisting of small sample sizes that contain a limited amount of information and is widely used in various fields [1]. However, the actual electricity demand cannot strictly change in an exponential manner due to seasonal fluctuations. Therefore, we use exponential weighted moving average method and autoregressive integrated moving average method to forecast the electricity demand and compare with the GM (1,1).

1.2. Problem Statement

Nowadays, life is impossible without electricity. Electricity provides homes and public places with lights and heat. Without it, health, education, finance, technology and other critical services collapse. Therefore, electricity consumption and demand are without any doubt an important issue that has been of interest over the past few years. It is always more challenging to examine densely populated places. For instance, Bangladesh is a South

Asian country which has a population over 167.4 million. As a result, it suffers from a chronic crisis in the electricity supply for many years.

1.3. Objectives

Our main objectives are given below:

- To know about the Grey prediction method GM (1,1) to predict time series data
- Comparing the simulated result from grey prediction method GM (1,1) with ARIMA(1,1,1) and EWMA.

2. Literature Review

The simple grey prediction method needs only a few samples and shows high accuracy. Grey theory was first applied to predicting electricity loads by Morita in 1995 [2]. Since then, much more research has been undertaken which has greatly enriched the application of grey theory to electricity prediction. In view of the problem that traditional GM (1,1) model has a low modeling accuracy for seasonal time series, scholars, after conducting much research, proposed using quarterly time series. There are two main approaches employed. Wang et al. [3] presented indices for seasonal adjustment and introduced a parameter to deal with nonlinear quarterly data series. Zhang et al. [4] used particle swarms to optimize the parameters of their model and reduced the fluctuations in the original series by utilizing the K-nearest neighbor algorithm to further improve the prediction accuracy. Bao et al. [5] combined the GM (1,1) model with linear regression and constituted the data (which had a large degree of 'jumping') into independent sequences. The aberrant and corresponding values were fitted and predicted by employing the GM (1,1) model, and the unchanged values were fitted and predicted using a linear regression model. This nicely overcomes the defects of the linear and GM (1,1) models. Sun et al., using a quarterly-average method, proposed a method employing a dynamic seasonal index. In their work, calculated runoff states were used to enhance the smoothness of the original data in combination with a Markov chain. This improved the GM (1,1) model and produced highly accurate predictions for the generation ability of small hydropower stations. Qian et al. [6] applied an accelerated translation transformation to the original data and thus changed a non-monotonic oscillatory sequence into a monotonic sequence. As a result, the modeling and forecasting processes were subject to reduced fitting errors. The other approach employed, is to improve the model itself and to increase adaptation of the model. By utilizing particle swarms and neural networks, Wu et al. and Huang et al. [7] optimized and improved the development and coordination coefficients of the GM (1,1) model, respectively.

3. Methodology

Grey Information System and GM (1,1) Models

The forecasted values of the original raw data $\hat{x}^{(0)}$ can be computed based on the (1-IAGO), one time inverse accumulated generating operation. The predicted values can be expressed as follows:

$$\hat{x}^{(0)}=(\hat{x}^{(0)}(1),\hat{x}^{(0)}(2),\ldots\ldots,\hat{x}^{(0)}(n))$$

where:

$$\hat{x}^{(0)}(1)=x^{(0)}(1) \tag{3.1}$$

$$\hat{x}^{(0)}(k)=\hat{x}^{(1)}(k)-\hat{x}^{(1)}(k-1),\ \ k=2,3,\ldots\ldots,n$$

Moreover, Equation (9) can be expressed as follows:

$$\hat{x}^{(0)}(k)=(x^{(0)}(1)-\frac{\hat{a}}{\hat{b}})e^{-\hat{a}(k-1)}.(1-e^{-\hat{a}}),\ k=2,3,\ldots\ldots,n \tag{3.2}$$

Exponential Weighted Moving Average Model

$$Yi=\alpha\times Xi+\alpha\times(1-\alpha)\times Xi-1+\alpha\times(1-\alpha)2\times Xi-2+\cdots+\alpha\times(1-\alpha)i-1\times Y1, \tag{3.3}$$

Where, $Y1=X1$

According to (3.2), an example of the forecasted result of the month 12 is:

$Y_{12}=\alpha\times X_{12}+\alpha\times(1-\alpha)\times X_{11}+\alpha\times(1-\alpha)2\times X_{10}+\cdots+\alpha\times(1-\alpha)^{11}\times X_1$

ARIMA Model

ARIMA model can be expressed as ARIMA (p,d,q), where p is the order of the auto-regression process, d is the order of the difference, and q is the order of the moving-average processes.

Let $\{X_t\}$ be the time series. Do the stationary improvement to it as

$$Y_t = (1- L)^d X_t$$

So the series $\{Y_t\}$ are stationary and can be expressed by ARIMA (p, q) model, which is a linear combination of past values of Y_t and errors ε_t . The L is called as the delay operator of one-step. And there is

$$L^k Y_t = L Y_{t-k+1} = Y_{t-k}$$

The L^k is called as the delay operator of k-step.
If Y_t can be expressed as

$$Y_t = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots - \theta_q\varepsilon_{t-q} \quad (3.4)$$

The Y_t satisfy the q-order of the moving-average model, which is also called as MA(q) model.
If Y_t can be expressed as

$$Y_t - \varphi_1 Y_{t-1} - \varphi_2 Y_{t-2} - \ldots - \varphi_p Y_{t-p} = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots - \theta_q\varepsilon_{t-q} \quad (3.5)$$

The Y_t satisfy the p-order of the auto-regression and the q-order of the moving-average model, which is also called as ARMA (p,q) model.

Model Accuracy Examination

Table 3.1: Accuracy Measures

Acronyms	Definition	Formula
ARE	Absolute Relative Error	$\frac{\lvert x^{(0)}(k) - \hat{x}^{(0)}(k)\rvert}{x^{(0)}(k)}$
MAPE	Mean Absolute Percentage Error	$\frac{1}{n}\sum_{k=1}^{n}\frac{\lvert x^{(0)}(k)-\hat{x}^{(0)}(k)\rvert}{x^{(0)}(k)}*100\%$

Where $x^{(0)}(k)$ is the original value at time k.

Table 3.2: The values of the MAPE

MAPE	≤10%	(10%-20%)	(20%-50%)	>50%
Forecasting ability	High	Good	reasonable	Weak

4. Data Analysis

Table 4.1: Electricity Demand of Bangladesh

Year	Electricity Demand (MW)
2010	4606
2011	4890
2012	6066
2013	6434
2014	7356
2015	7817
2016	11405
2017	12644
2018	14014

Source: PSMP/2017

The comparison of the predictive accuracy for the above three forecasting model is presented in the table. The mean absolute percentage error (MAPE) is utilized which measures the predicting accuracy of model using a statistical method as defined earlier.

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The above table explains that the showing of the ARIMA (1,1,1) is better than GM(1,1) and EWMA. The MAPE value of electricity demand data (2010-2018) for GM (1,1),EWMA and ARIMA(1,1,1) is 22%,27%,16% respectively. The above results show that ARIMA (1,1,1) has higher accuracy of forecasting than other forecasting models. Moreover, according to the grade values of the MAPE criteria, GM (1,1) model is categorized in reasonable category and ARIMA(1,1,1) model is categorized in good category.

Year	Actual Electricity Demand	GM(1,1)		EWMA		ARIMA(1,1,1)	
		value	ARE	value	ARE	value	ARE
2010	4606	4606	0	4606	0	3891.32	.155
2011	4890	5097.02	.0423	4606	.0581	5503.14	.125
2012	6066	6225.52	.0263	4662.8	.2313	6739.94	.111
2013	6434	7603.87	.1818	4943.44	.2317	7782.62	.209
2014	7356	9287.38	.2626	5241.552	.2874	8701.24	.183
2015	7817	11343.64	.4512	5664.4416	.2754	9531.72	.219
2016	11405	13855.14	.2148	6094.95328	.4656	10295.44	.097
2017	12644	16922.72	.3384	7156.962624	.4339	11006.28	.129
2018	14014	20669.45	.4749	8254.370099	.4109	11673.94	.167
MAPE(%)		**0.22**		**0.27**			**0.16**

Table 4.2: Prediction Values and Performance Evaluation of Actual Values,GM(1,1), EWMA and ARIMA (1,1,1) For Part of Years of Study (2010-2018).

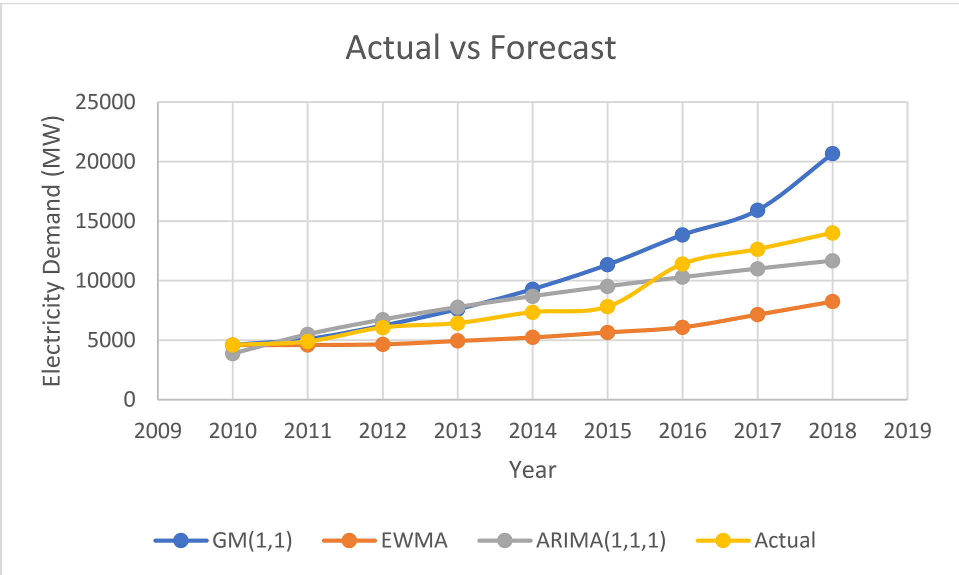

Figure 4.1: The comparison between the real values and the forecasted results by the three propose models.

5. Result Analysis

The appropriate curves are displayed in the following figure. The forecasting results clearly point out that the values predicted by these models are very close to the original values of the electricity demand in Bangladesh from (2010-2018). As we can see from the table and figure ARIMA (1,1,1) displays a preferable performance in trained forecasting.

There are some limitation in these methods that can be eliminated by adding some factors. In this paper, we use the traditional GM(1,1) model . The prediction formula in the traditional GM(1,1) model can't predict the seasonal fluctuations in the time series. To address this issue, various modifications have been made to the GM(1,1) to improve its prediction accuracy. EWMA model can't give the accurate value for short period of time series. It produces forecasts that lag behind the actual trend. That means, it can't handle trends well. Exponential smoothing is best used for forecasts that are short-term and in the absence of seasonal or cyclical variations. Comparatively, ARIMA is better in short term time prediction method. If we use seasonal factor, then the mentioned models give better accuracy.

6 Conclusion

The main objective of this paper is to forecast the yearly electricity demand in Bangladesh from (2010-2018). Three models are used as an attempt to select the most appropriate fit. There a prediction grey model GM (1,1), an exponential weighted moving average(EWMA) model, and a Box-Jenkins ARIMA model. The result show that the ARIMA (1,1,1) model exhibits good forecasting ability according to the MAPE criteria.

The analysis recognizes that the ARIMA (1,1,1) model has good prediction results than the exponential weighted moving average(EWMA) and GM (1,1) models based on the MAPE. However, we can note that although prediction ARIMA (1,1,1) is not widely applied in the forecasting of electricity demand. In addition, the empirical results assert the importance of the ARIMA (1,1,1) application.

The seasonal factor can be added in traditional grey forecasting model GM (1,1) to get better result and higher accuracy. Seasonal Autoregressive integrated moving average (SARIMA) can be used to forecast electricity demand for getting higher accuracy.

7. References

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