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Electrical Energy Consumption Forecasting for Turkey Using Grey Forecasting Technics with Rolling Mechanism

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Abstract

The accuracy of electricity energy consumption prediction is an important issue effecting energy investment decisions as well as environmental policies. Although there are several forecasting techniques, selection of the most accurate technique is vital for energy planners. In this study, grey forecasting techniques with rolling mechanism (RM) have been used for modeling and predicting yearly net electrical energy consumption in Turkey. Three different grey models are generated to find the best model. The best grey model with RM is used for energy consumption forecasting from 2014 to 2030. Furthermore, the effect of RM is studied by comparing the obtained results with a Grey Model without RM. Results show nonhomogeneous Grey Model with RM improves forecasting accuracy.

***Keywords:** grey forecasting, rolling mechanism, electricity energy consumption*

1. Introduction

Worldwide energy consumption has been increasing due to the increase in human population, economic wealth, and industrialization in developing countries. Prediction of energy consumption plays a vital role in countries for policy makers and related organizations [1], [2]. The prediction of energy consumption is one of the major problem of the energy planning process. Turkey is an important regional policy maker in terms of energy due to its increasing energy appetite and strategic location [4]. Electricity market in Turkey is rapidly growing [3], [4]. Turkey was ranked as the first European country and the second in the world with respect to the increase in electrical energy consumption rates in the last decade [4]. Therefore, utilizing alternative techniques in order to obtain more accurate electricity consumption estimates is very important [3]. Recently, several new methods have been used to accurately predict the future electricity consumption. Kermanshahi and Iwamiya [5] discussed forecasting of peak electric loads in Japan using Artificial Neural Networks (ANN). They utilized gross national product, gross domestic product, population, number of household, number of air-conditioners, amount of CO_2 pollution, index of industrial production, oil price, amount of energy consumption, electricity price, average temperature, and maximum electricity power of the previous year as input variables in order to predict long-term load forecasting. Mohamed and Bodger [6] developed multiple linear regression analysis to forecast electricity consumption in New Zealand by using data related to gross domestic product, average price of electricity and population of during the period 1965–1999. Bianco et al. [1] proposed the trigonometric grey rolling with rolling mechanism and Holt–Winters exponential smoothing method for forecasting electric energy consumption of Romania. Zhang and Wang [7] developed a fuzzy wavelet neural network (FWNN) approach for forecasting annual electricity consumption. They used actual energy data from 1983 to 2003 to apply ANN approach. Feng et al. [8] proposed a Grey Model (GM) for the total energy, coal energy and clean energy consumption of China, respectively. In addition, several methods have been utilized to forecast

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electricity consumption in Turkey. The State Planning Organization and Ministry of Energy and Natural Resources of Turkey initiated the use of some simple techniques for energy forecasting [2]. Hamzaçebi and Kutay [9] studied on long-term energy consumption forecasting using ANN for Turkey. Akay and Atak [10] used GM with rolling mechanism (RM) to predict industrial and total electric energy consumption of Turkey using the data set between 1987-2004. Çunkaş and Taşkiran [11] predicted the electricity consumption of Turkey by using genetic algorithms. Kavaklioglu [12] used support vector regression methodology to model and predict Turkey's electricity consumption. Hamzacebi and Es [4] proposed an iterative optimized GM in order to predict total electric energy demand in Turkey for the 2013-2025 period.

Grey Models are simple and powerful forecasting tools for energy forecasting [4], [8], [10]. Yet, they have limited ability to model nonhomogeneous growth effects [13]. To cope with this, the above mentioned discrete Grey Models can be employed. In this study, three grey forecasting methods, (i) discrete grey model (DGM), (ii) optimized discrete grey model (ODGM) and non-homogeneous discrete grey model (NDGM), with RM are used for modeling and predicting electrical energy consumption of Turkey. Additionally, RM will be used to consider recent data in forecasting relying on the basic assumption that the future consumption values are better forecasted by using recent data rather than whole data set. Another important design parameter for GM with RM is the period length. To see the effect of length for rolling period on these three approaches, we conducted several experiments. Furthermore, aiming to prove merit of RM, the results obtained by the best method are compared with an NDGM without RM.

The main contribution of this study is to present effect of RM on various GMs as well as identify the best rolling period for Turkish demand on electricity.

Following the introduction section, a literature review is presented. The second section covers background and methodology while the third section is devoted to application. The results are reported and discussed in the fourth section while the last section concludes the work.

2. Grey Theory for Forecasting

Grey Theory (GT) is related to systems including uncertain and imperfect information [10]. Grey Theory (GT) is originally developed by Ju-Long[14] as a system characterizing vagueness and incompleteness of the relations among system components. GT has become an influential method of solving problems in highly uncertain environments [15]. In information research field, deep or light colors represent clear or ambiguous information, respectively. Black represents that the researchers have no knowledge of system and white indicates that the information is completely clear. Colors between black and white indicate systems that are not clear, such as social, economic or weather systems [16].

The Grey Model (GM) is a forecasting approach relying on GT [8]. The most widely used grey prediction model is GM (1,1). The GM (1,1) uses a first order differential equation to characterize an unknown system [19]. GM (1,1) has three basic operations: accumulated generating operator (AGO), inverse accumulating operator (IAGO) and grey model (GM) [15]. Grey prediction with rolling mechanism (GPRM) is a variant of GM (1,1) Grey-forecasting model that adopts the essential part of Grey system theory [20]. The steps of GM(1,1) are described as follows [13], [19]:

Let $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n), n \geq 4$ be a sequence of original data. Using AGO operator, new time series sequence $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)$ are obtained as:

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \tag{1}$$

Then, GM (1,1) is established by a first-order grey differential equation:

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

Here a is the development coefficient and b is driving coefficient.

Theorem 1: Let $X^{(0)}$, and $X^{(1)}$ be the same as above. But $X^{(0)}$ is non-negative. If

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \tag{3}$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \dots\dots & .. \\ -z^{(1)}(n) & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \dots\dots \\ x^{(0)}(n) \end{bmatrix} \tag{4}$$

and,

$$z^{(1)}(k) = 0.5\left(x^{(1)}(k) + x^{(1)}(k-1)\right) k = 2,.,n \tag{5}$$

then

$$\frac{dX^1}{dt} + aX^1 = b \tag{5}$$

is referred to as a whitenization equation of the GM(1,1) model in (2).

Theorem 2: Let *B, Y*, and â be the same as in Theorem 1. If $\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y$ then, grey forecasting equation blow is obtained by grey differential equation.

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \quad for\ k = 1,2,\dots,n \tag{6}$$

Here, $\hat{x}^{(1)}(k+1)$ shows the forecast of x at time *k+1*. The initial condition is given as;

$$x^{(1)}(1) = x^{(0)}(1) \tag{7}$$

Final step is applied as follows in order to acquire forecasted values;

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1-e^{a})\left(x^{(0)}(1) - \frac{b}{a}\right) e^{-ak} \quad for\ k = 1,2,\dots,n \tag{8}$$

Rolling Mechanism for GM(1,1) model

In GM(1,1), the entire data set is used for forecasting. However, using only recent data is recommended to increase forecasting accuracy [10]. To avoid the accumulation of historical data, while also keeping a constant number of data points and adopting the recent data for model construction, the rolling GM(1,1) model was presented to modify the traditional GM(1,1) [21]. In GM with RM, $x^{(0)}(k+1)$ is forecasted by implementing GM(1,1) to the original sequence $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(k))$ where *k* < *n*. Then, procedure is repeated, but the new forecasted data $x^{(0)}(k+1)$ is added to the end of data, and the first data of the previous sequence, $x^{(0)}(1)$, is extracted from the model. This procedure creates a new sequence of $x^{(0)} = (x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(k+1))$. So, following GM (1,1), the predictive value of $x^{(0)}(k+2)$ can be obtained. This is called the rolling GM(1,1) [10], [16], [21]. Here, the length of the sequence, *k*, is an important parameter effecting the forecasting accuracy which we focus on in this work.

The above described GM is named as continuous grey model and has a limited range of applicability on a data with total exponential growth as presented in [13]. Hence, this work focuses on three extensions of basic grey model providing better performance on this type of data.

First Extension: *Discrete Grey Model*

Considering the fact above, a discrete version of the model, $\hat{x}^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2$, is proposed, Discrete Grey Model (DGM), aiming to remedy limitations of continuous approach [13].

Following the same idea in Eq. (3), least square estimates for the two parameters satisfy:

$$\hat{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} = (B^T B)^{-1} B^T Y \tag{9}$$

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

Letting $x^{(1)}(1) = x^{(0)}(1)$, the estimate of the *(k+1)*th observation is given as $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$.

Second Extension: *Optimized Discrete Grey Model*

Liu and Lin [13] analyzed different choices of the initial value, $\hat{x}^{(1)}(1)$, and concluded that different initial values lead to different results, where a small change in the initial value might create different simulation sequences. To eliminate this effect, they suggested adding a small adjustment, β_3, to $x^{(1)}(1)$ so that the deviation caused by the initial value can be cancelled. Having this idea, the following model can be constructed:

$$\begin{cases} \hat{x}^{(1)}(k+1) = \beta_1 \hat{x}^{(1)}(k) + \beta_2 \\ \hat{x}^{(1)}(1) = x^{(1)}(1) + \beta_3 \end{cases} \tag{10}$$

where β_1, β_2, and β_3 are model parameters to be determined, and $\hat{x}^{(1)}(1)$ is the basis of iteration. This model is referred to the *optimized grey model with fixed starting point*, ODGM [13].

As before, β_1 and β_2 will be determined with Eq. 10. The optimal value of β_3 is obtained by minimizing the sum of squared errors of estimation (MSE) [13]:

$$\beta_3 = \frac{\sum_{k=1}^{n-1}[x^{(1)}(k+1) - \beta_1 x^{(1)}(1) - \frac{1-\beta_1^k}{1-\beta_1}\beta_2]\beta_1^k}{1 + \sum_{k=1}^{n-1}(\beta_1^k)^2} \tag{11}$$

Similar to DGM**,** $x^{(1)}(1) = x^{(0)}(1)$ and the estimate of the *(k+1)*th observation is given as:

$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$.

Third Extension: *Non-homogeneous Discrete Grey Model (NDGM)*

The Grey prediction models described above relies on the assumption that the original data, $X^{(0)}$, satisfies the law of homogeneous exponential growth, that is $x^{(0)}(k) \approx ac^k, k = 1,2, \dots, n$. NDGM expands the model to handle non-homogeneous samples as follows [13]:

$$\begin{cases} \hat{x}^{(1)}(k+1) = \beta_1 \hat{x}^{(1)}(k) + \beta_2 k + \beta_3 \\ \hat{x}^{(1)}(1) = x^{(1)}(1) + \beta_4 \end{cases} \tag{12}$$

where β_1, β_2, and β_3 are to be determined by the method of least squares estimate.

$$\hat{\beta} = [\beta_1, \beta_2, \beta_3]^T = (B^T B)^{-1} B^T Y \tag{13}$$

Similar to the previous model, B, and Y are defined as follows:

$$B = \begin{bmatrix} x^{(1)}(1) & 1 & 1 \\ x^{(1)}(2) & 2 & 1 \\ \vdots & \vdots & \vdots \\ x^{(1)}(n-1) & n-1 & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \dots \dots \\ x^{(1)}(n) \end{bmatrix} \tag{14}$$

Estimation of the fourth parameter, β_4, is done with an optimization model without any constraint so that the sum of squared errors is minimized. That is, $\min_{\beta_4} \sum_{k=1}^{n} [\hat{x}^{(1)}(k) - x^{(1)}(k)]^2$, [13]. Solving this model leads to

$$\beta_4 = \frac{\sum_{k=1}^{n-1} [x^{(1)}(k+1) - \beta_1^k x^{(1)}(1) - \beta_2 \sum_{j=1}^{k} j \beta_1^{k-j} - \frac{1-\beta_1^k}{1-\beta_1} \beta_3] \beta_1^k}{1 + \sum_{k=1}^{n-1} (\beta_1^k)^2} \tag{15}$$

Performance criterion

In the literature several performance measures are used to compare the quality of forecasting methods. Mean Absolute Percentage Error (MAPE) is a very common indicator and also used by this work. MAPE is defined as [3];

$$\mathrm{MAPE}(\%) = 100 \times \frac{\sum_{k=1}^{N} \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right|}{N} \tag{16}$$

3. APPLICATION

The above mentioned three methods are modified by embedding the RM. Additionally, a parameter analysis is conducted to identify the best rolling period length. To identify the best method, the historical data is simulated with three Grey models. The data related to Turkey's electrical energy consumption between 1970-2013 reported by Turkish Statistical Institute (TURKSTAT), and depicted in Figure 1 [22].

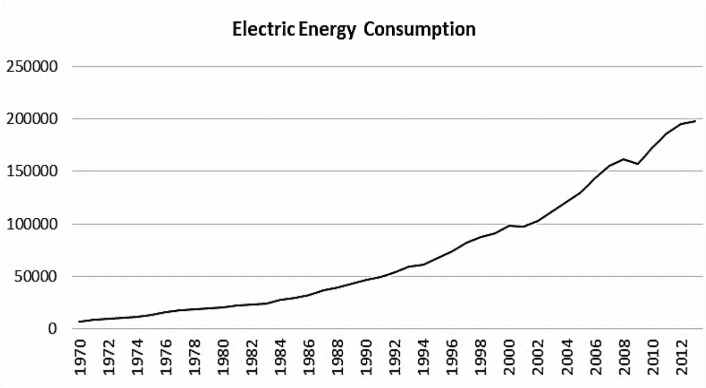

Fig. 1: Turkey's electrical energy consumption from 1970 to 2013

4. Results and Discussion

Using the data from 1970 to 2013 three Grey Models are generated and tested for different k values where *k= 4, 5, 6,..., 25*. Applying the three variants of GM with various rolling lengths we obtained the following MAPE values given in Figure 2.

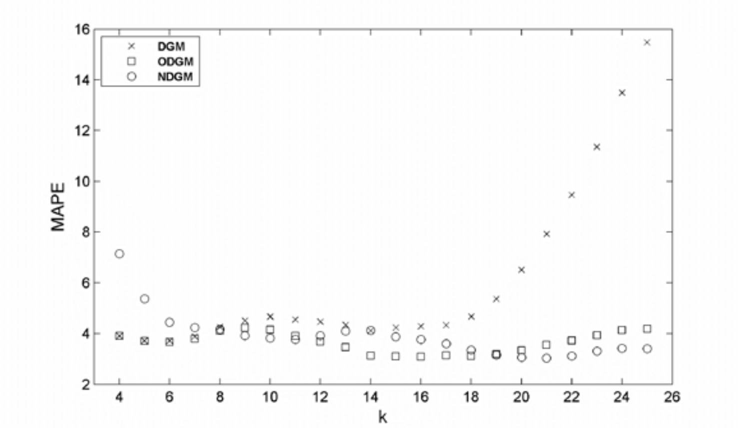

Fig. 2: Comparison of MAPE values obtainted with three methods for different *k* values

Table 1: Performance measures and best rolling period length for three models

	Best MAPE values and corresponding *k's*	
Method	*MAPE (%)*	*k*
DGM	3.7088	6
ODGM	3.0879	16
NDGM	3.0365	21

Looking more carefully to the results, we conclude that DGM and ODGM give more accurate forecasts than NDGM for short periods (*k* values ranging from 4 to 7) whereas the accuracy of the latter increases as *k* increases. This is due to relative complexity of NDGM compared to the other two methods as it requires more data to capture the underlying dynamic. Table 1 presents *k* and MAPE values for each method. We can conclude that the obtained models are highly accurate tools for making forecast based on the underlying data set as MAPE values are in the range of 3.0365% - 3.7088%. As expected, NDGM is the most precise forecasting method among the three. However, a longer rolling period is necessary. Thus, we can conclude that NDGM is the most competitive forecasting tool among the three.

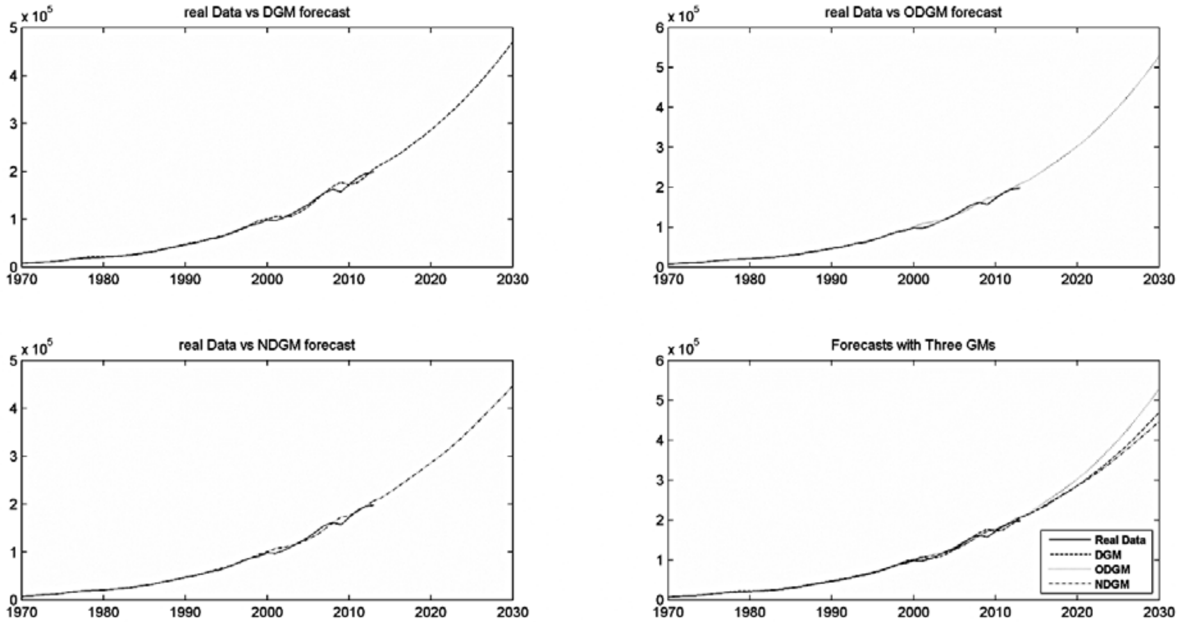

Fig. 3: Comparison of the forecasts with three methods and real data between 1970 and 2030

The forecasted values with three methods with best k values given in Table 1 are depicted in Figure 3. ODGM considers the exponential growth in the data set and provides generously optimistic estimates. NDGM gives a cautious forecast and delivers moderate results. As mentioned before GM based models, in general, demonstrate a good performance for data set with exponential growth where we can see that NDGM results with the best fit to the real data due to its flexibility with additional two model parameters compared to DGM.

Table 2: Forecasted values for three DGMs with RM (10^6 kWh)

Year	DGM	ODGM	NDGM
2014	214828.02	217670.50	213598.34
2015	224159.89	230528.41	224950.10
2016	234189.41	244375.99	236779.48
2017	246508.62	258032.12	248938.58
2018	260461.19	272107.55	261130.71
2019	272202.51	286951.70	273381.76
2020	286424.70	302716.67	285968.90
2021	301343.32	319460.30	298448.31
2022	316527.19	337850.49	312219.11
2023	332339.05	358101.84	326981.70
2024	349588.30	379693.86	342552.21
2025	367283.52	400744.96	358904.68
2026	385882.88	423529.18	376097.17
2027	405558.80	448179.86	393459.99
2028	426249.92	474126.83	410604.26
2029	447856.58	500371.44	427901.22
2030	470661.82	528945.63	447688.42

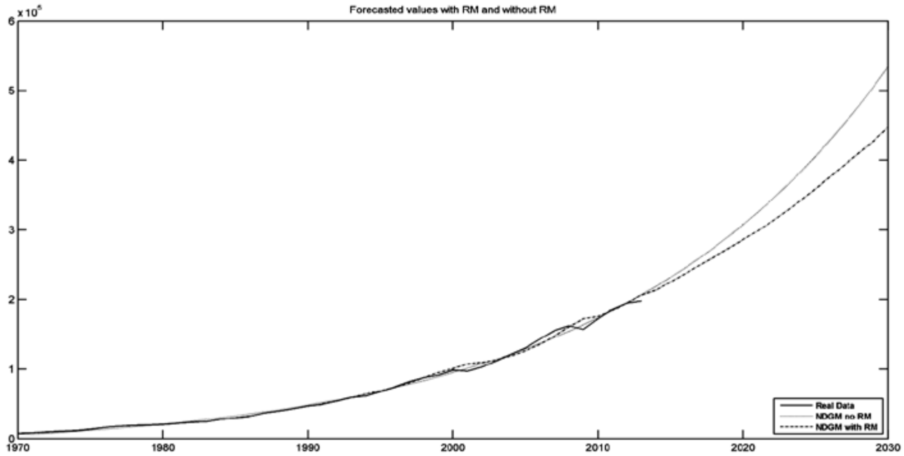

Fig. 4: Comparison of NDGM with and without RM

Another question that lies on the focal point of this work is whether RM increases the forecasting accuracy. To answer this, another NDGM model without RM is generated by using the whole data set. This model delivered a MAPE value of 6.3810 %. The result of this experiment obviously highlights the positive effect of RM embedded into NDGM. Figure 4 visualizes the forecasts obtained by NDGM with and without RM. As seen in the figure, NDGM with RM captures the recent downward fluctuations and gives a forecast of 447688.42 [10^6 kWh] in year 2030 whereas NDGM without RM forecasts the electricity demand as 534186.31 [10^6 kWh].

Conclusion

In recent years energy consumption is increasing due to increase in world population, living standards, industrialization in developing countries. Turkey is one of the fastest developing countries in the world in terms of increase in energy consumption. Thus, a precise forecast in energy planning process is very important for policy makers. This paper applies three different GM based approaches with an embedded rolling mechanism, DGM, ODGM, and NDGM, on Turkey's electrical energy demand. As the results of conducted experiments indicate, the length of the rolling horizon is highly important parameter to be optimized. The results show that DGM and ODGM are successful forecasting tools if the rolling period is short. However, NDGM captures the nonhomogeneous effects on the data better than other GM based methods and outperforms the others if rolling period is long.

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