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Forecasting the Generation and Consumption of Electricity and Water in Kingdom of Bahrain using Grey Models

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Abstract: Generation and consumption of Electricity and water are the key factors impacting the economy of any nation. Forecasting the future need of electricity and water can help the nation to plan its economy and future growth. This motivates to pursue a research to develop an efficient method to forecast the future need of Electricity and Water. In this paper, two Grey Models have been developed and employed to forecast the expected amount of generation and consumption of Electricity and Water in Kingdom of Bahrain by 2025. The past data of generation and consumption have been taken from the official statistics of Electricity and Water Authority of the Kingdom. The developed Grey Model and Modified Grey Model are used to forecast various factors such as Fuel Oil Consumption for Electricity Generation, Natural Gas Consumption for Electricity Generation, Electricity Consumption, Average Daily Production of Desalinated Water & Abstraction of Ground Water, Average Daily Water Consumption and Population for the year 2025. The results of experiments clearly show that the Kingdom is progressing towards achieving its Vision 2030. The accuracy of forecast is ensured by ensuring the least Mean Relative Percentage Error in forecasting.

Keywords: Grey Model (1,1), Modified Grey Model (1,1), Grey Prediction, Mean Relative Percentage Error, Forecast accuracy

1. Introduction

The need for energy has been continuously going up across the world because of the developments happening all around in the human lifestyle, industrial development, commercial use, advancements in communication facilities and etc. One of the key factors that directly influences the nation's economy is the electricity [1]. Also, it is a very well-known fact that the per capita income of a nation has a direct relation with the usage of per capita energy [2]. Therefore, the economic growth of any nation depends directly on the consumption of energy. For the countries located near the tropical areas such as Gulf Cooperation Council (GCC) countries, the energy demands are dictated considerably by the consumption of electricity by the residential usage [3].

In the Kingdom of Bahrain, the need for water is also equally in high demand as the need for electricity due to the rapid developments and increased population in the recent years [4]. The Electricity and Water Authority (EWA) has been taking intensive efforts to cater and cope with the fast raising demand of electricity and water of Kingdom of Bahrain. In the EWA Statistics of year 2018 [5], it has been reported that there has been an increase of 10.88% in production of electricity from the year 2014 to 2018. To accentuate the Bahrain Economic Vision 2030 of reducing the overconsumption of electricity and water and becoming less dependent on oil, the government has been effectively exercising the Government Action Plan.

One of the useful and effective methods to increase the productivity of energy is to accurately forecast the future demand of electricity and water [6]. It is obvious that the poor forecast of electricity and water demand will eventually lead to either waste of resources due to excess production or outage of supply of electricity and water. Since the demand of electricity is usually uncertain due to the factors such as climate changes, etc., the forecast for long term will not yield any useful information [1]. Also, the simple statistical treatment of data of consumption of electricity are not found to be feasible all the times [7]. Hence, it is inevitable to device an effective and accurate forecasting model for prognosticating the electricity and

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water demands for the short term future based on the most recent and limitedly available data.

There have been a lot of attempts made to forecast the consumption of electricity using difference types of forecast models and reported in literature. The most popular forecast models include simple Autoregressive Integrated Moving Average (ARIMA) model [2], Method of Multiple Linear Regression Analysis [8], Functional Vector Autoregressive State Space model [9], Wrapper Feature Selection and Multinomial Logistic Regression [10], Spatial Econometrics [11], Time-varying Weighted Average method using High-order Markov chain model [12], Seasonal Auto-Regressive Integrated Moving Average method and Support Vector Machines method [13], Kalman filter [14], Univariate Autoregressive model [15], Artificial Neural Network model [16,17] and Neuro-Fuzzy model [18]. Researchers have accomplished the forecast of electricity consumption in various countries including Lebanon [15], Taiwan [16], Australia [19], Spain [20], New Zealand [21], Jordan [22], China [12, 23], Sri Lanka [24], Canada [25], Turkey [26], Ghana [27] and Italy [28].

Besides these all forecast models, another and most lionized model widely used for forecasting the time series is the Grey Model [29]. In many applications, The Grey Models have been proved to be better in forecasting from the uncertain data which are partially known. Grey models have been successfully employed in almost all fields including environment, meteorology, agriculture, transportation, ecology, geology, medicine, tourism, Education, military, and all technical sciences [30, 31].

Though there have been a lot of attempts made by researchers around the world to forecast electricity demand, it is found from the present literature survey that there has been no attempts so far to perform this forecast for Kingdom of Bahrain. This motivated us to develop a Grey Model to forecast the future generation and consumption of Electricity and Water in Bahrain for the first time. In this paper, a simple Grey Model (GM) and a Modified Grey Model (MGM) are employed to forecast the future demand of electricity and water based on the relevant recent past data of the Kingdom of Bahrain [5]. The data published by the Electricity and Water authority of the Kingdom in its official website are taken for the studies.

The rest of the contents of this paper is organized as follows. The section 2 describes the development of Grey Model and Modified Grey Model. In the section 3, the official data data of EWA are summarized. The results of forecast of water and electricity using Grey models are presented in the section 4 with necessary analysis. Finally the paper is concluded with the possible scopes for future research in the section 5.

2. Grey Forecast Models

The Grey models are represented by differential equations with time changing amplitude, which are capable of dealing with the problems of uncertainty with the available incomplete and least amount of data [33, 34]. The general form of representing a Grey Model is using GM (x, y), where x is the order of differential equation being used and y is the number of input variables employed in it.

A. Grey Model (GM)

The most common GM is of first order with one variable. Hence it is denoted as GM (1,1). There are two important facts to be kept in mind always that the Grey Models can be used only for non-negative data series and at least 4 samples are needed to accomplish the forecast process successfully.

The three essential steps involved in modeling a GM (1,1) forecast model are namely (i) Operation of Accumulated Generation (AG), (ii) Building of GM by mean operation and (iii) Reverse operation of Accumulated Generation (RAG).

Let an actual sequence of available data $'g'$ be denoted as,

$$g^{(a)} = \left(g^{(a)}(1), g^{(a)}(2), \ldots. g^{(a)}(n)\right) \text{ with } n \geq 4 \qquad (1)$$

In order to lessen the randomness in $g^{(a)}$, the operation of AG is performed as,

$$g^{(AG)}(m) = \sum_{i=1}^{m} g^{(a)}(i) \quad with \quad m = 1,2,3 \ldots n \qquad (2)$$

Upon performing the Operation of Accumulated Generation (AG), the actual data sequence $g^{(a)}$ becomes as,

$$g^{(AG)} = \left(g^{(AG)}(1), g^{(AG)}(2), \ldots. g^{(AG)}(n)\right) \qquad (3)$$

The GM (1,1) can be represented in the form of a differential equation of order 1 as,

$$\frac{d}{dt}\left(g^{(AG)}\right) + p\; g^{(AG)} = q \qquad (4)$$

Where, t is time variable.

From equation (4), the GM (1,1) can be discretized and represented in the form of difference equation as,

$$g^{(AG)}(m) + p\; H^{AG}(m) = q \qquad (5)$$

Where, p is the coefficient of development, q is the factor of coordination and $H^{AG}(m)$ called as background value of GM which is evaluated as,

$$H^{(AG)}(m+1) = \frac{g^{AG}(m+1) + g^{AG}(m)}{2}, m = 1,2, \ldots n-1 \qquad (6)$$

The estimates of p and q can be obtained using the method of least squares as,

$$[p, q]^T = \left[D^T D\right]^{-1} D^T E \qquad (7)$$

Where, D is the Data matrix.

$$D=\begin{bmatrix} -H^{AG}(2) & 1 \\ -H^{AG}(3) & 1 \\ . & . \\ . & . \\ . & . \\ -H^{AG}(n) & 1 \end{bmatrix}$$

and $E=\left[g^{(a)}(2) \quad g^{(a)}(3) \quad . \quad . \quad . \quad g^{(a)}(n)\right]^T$ (8)

The equation of for $g^{(AG)}$ can be solved at the instant '*m*' and the solution can be written as,

$$\hat{g}^{(AG)}(m)=\left(g^{(a)}(1)-\frac{q}{p}\right)exp(-p(m-1))+\frac{q}{p} \quad (9)$$

Therefore, the forecasted actual values at the given instant $(m+1)$ can be obtained from (9) as,

$$\hat{g}^{(a)}(m+1)=(1-exp(p))\left(g^{(a)}(1)-\frac{q}{p}\right)exp(-pm), \quad (10)$$
$$m=1,2,\ldots n$$

At the instance of (m+r), the forecasted value can be written as,

$$\hat{g}^{(a)}(m+r)=(1-exp(p))\left(g^{(a)}(1)-\frac{q}{p}\right)exp(-p(m+r-1))$$

(11)

B. Modified Grey Model (MGM)

It is attempted to improve the forecast accuracy of simple Grey Model presented above. Hence, the continuous differential equation of GM given in equation (10) is modified by replacing the exponential function ($exp(-p)$) by a ratio of Taylor series, as given below. The resulting GM is termed as Modified Grey Model-MGM(1,1).

$$exp(-p)=\frac{exp\left(-p/2\right)}{exp\left(p/2\right)}=\frac{1-\frac{p}{2}+\frac{p^2}{8}+\ldots}{1+\frac{p}{2}+\frac{p^2}{8}+\ldots} \quad (12)$$

Ignoring the higher order terms in equation (12) can result,

$$exp(-p)==\frac{1-\frac{p}{2}}{1+\frac{p}{2}}=\frac{(2-p)}{(2+p)} \quad (13)$$

Substituting the approximation in equation (13) on equations (9) and (10) yields the forecasted sequence and RAG operated sequence as equation (14) and equation (15) respectively.

$$\hat{g}^{(AG)}(m+1)=\left(g^{(a)}(1)-\frac{q}{p}\right)\left(\frac{2-p}{2+p}\right)^m+\frac{q}{p},$$
$$m=1,2,..n$$

(14)

$$\hat{g}^{(a)}(m+1)=\left(1-\frac{2+p}{2-p}\right)\left(g^{(a)}(1)-\frac{q}{p}\right)\left(\frac{2-p}{2+p}\right)^m, \quad (15)$$
$$m=1,2,\ldots n$$

The equation (15) gives the forecasted results of MGM, which is expected to be better than the simple GM [35, 36].

3. ELECTRICITY AND WATER STATISTICS OF KINGDOM OF BAHRAIN

The Electricity and Water Authority (EWA) of Kingdom of Bahrain publishes the statistics every year in its official website www.ewa.bh [5]. From the published statistical reports, data of various important factors related to generation and consumption of electricity and water, have been extracted for the period of seven years from 2012 to 2018 and taken for consideration in this research. The factors taken for consideration are listed in Table I.

TABLE I. FACTORS FROM EWA STATISTICS

Sl.No.	Factor	Acronym	Unit
1	Fuel Oil Consumption for Electricity Generation	FOC-EG	M^3
2	Natural Gas Consumption for Electricity Generation	NGC-EG	Million Nm^3
3	Electricity Consumption	EC	Million KWh
4	Average Daily Production of Desalinated Water & Abstraction of Ground Water	ADPW	Million Imperial Gallon/Day
5	Average Daily Water Consumption	ADWC	Million M^3
6	Population	POP	Count

The extracted data of factors listed in Table I are consolidated and presented in Table II, for the period of 7 years from 2012 to 2018. When there are slight differences in the data across the reports of each year, the data of the latest year's report are taken in to account.

TABLE II. EXTRACTED DATA FROM EWA STATISTICS

Year	FOC-EG	NGC-EG	EC	ADPW	ADWC	POP
2012	5,672	4,673	12,644	148.58	144.77	1,254,952
2013	1,231	5,158	13,350	153.41	149.96	1,295,757
2014	3,285	5,614	15,186	160.05	156.62	1,338,261
2015	3,816	5,429	16,552	159.88	155.17	1,382,467
2016	1,389	4,888	16,270	157.95	155.04	1,428,169
2017	934	5,613	16,559	159.04	155.70	1,494,090
2018	853	5,377	17,241	157.39	157.04	1,573,597

4. Forecasting the Consumption of Electricity and Water in Kingdom of Bahrain

The models of GM(1,1) and MGM (1,1) are developed and deployed for forecasting the values of factors listed in Table I for the years 2019, 2020 and 2025. The accuracy of prediction is assessed using one of the most popular performance measures which is the Mean Relative Percentage Error (MRPE).

The Relative Error (RE) for each prediction is measured as,

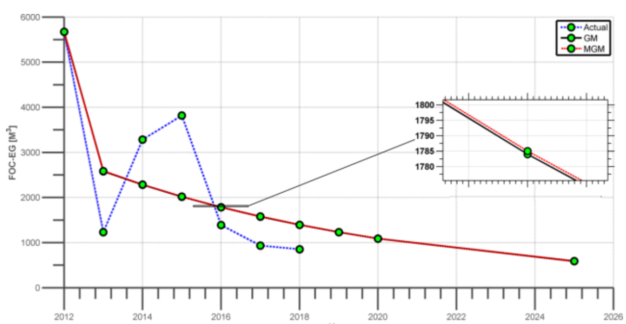
$$RE_m = \frac{g^a(m) - \hat{g}^a(m)}{g^a(m)} \tag{16}$$

Further, the MRPE measure is found as,

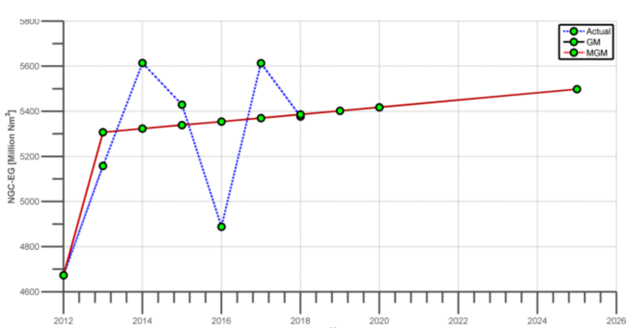
$$MRPE = \frac{1}{n}\sum_{m=1}^{n}\left|RE_m\right| \times 100\% \tag{17}$$

5. Results and Discussion

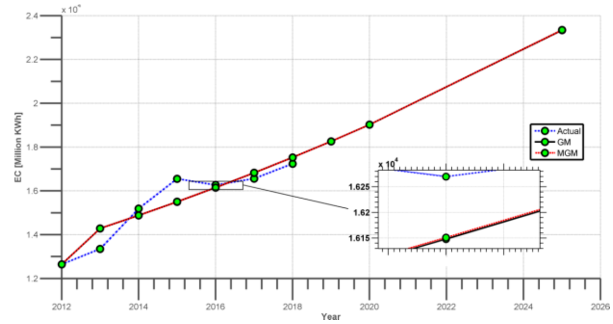
The results of experiments using GM (1,1) and MGM (1,1) are consolidated in Table III and Table IV respectively. The Actual and forecasted values by GM and MGM presented in Table III and Table IV are graphically shown in Figure 1.



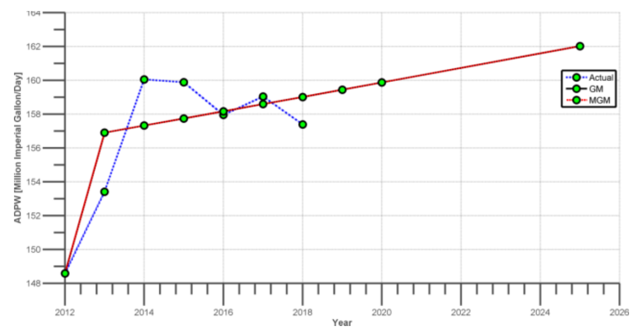
(a) Fuel Oil Consumption for Electricity Generation



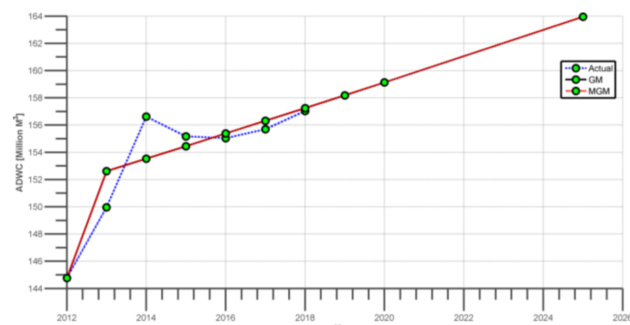
(b) Natural Gas Consumption for Electricity Generation



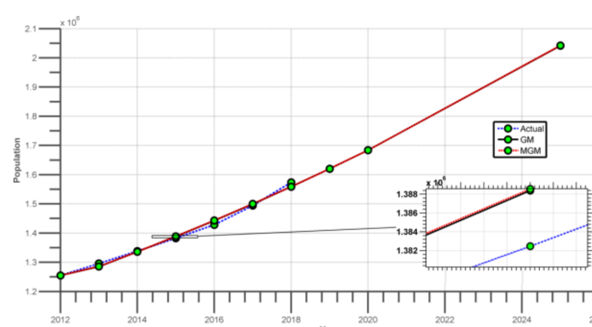
(c) Electricity Consumption



(d) Average Daily Production of Desalinated Water & Abstraction of Ground Water



(e) Average Daily Water Consumption



(f) Population

Figure 1. Actual and Forecasted data from 2012 to 2025

Though there are small differences in few of the forecasts of GM and MGM, they are not visible in the figures. This is due to the large range of scale of the plot. Hence, a part of the plot is magnified and shown inside the plot to show the difference.

The obtained results are with least Relative Errors and Mean Relative Percentage Error in all factors being considered except the FOC-EG. The forecasted percentage change in all the six factors being considered for the year 2025 are shown in Figure 2.

TABLE III. FORECASTED RESULTS OF GM (1,1)

Year	FOC-EG			NGC-EG			EC			ADPW			ADWC			POP		
	Actual	Predicted	RE	Actual	Predicted	RE	Actual	Predicted	RE	Actual	Predicted	RE	Actual	Predicted	RE	Actual	Predicted	RE
2012	5,672	5,672	0	4,673	4,673	0	12,644	12,644	0	148.58	148.58	0	144.77	144.77	0	1,254,952	1,254,952	0
2013	1,231	2,581	-1.097	5,158	5,307	0.028	13,350	14,282	-0.07	153.41	156.9	-0.023	149.96	152.62	-0.02	1,295,757	1,285,327	0.008
2014	3,285	2,282	0.305	5,614	5,323	-0.054	15,186	14,879	0.02	160.05	157.32	0.017	156.62	153.53	0.02	1,338,261	1,335,862	0.002
2015	3,816	2,018	0.471	5,429	5,339	-0.017	16,552	15,500	0.064	159.88	157.74	0.013	155.17	154.45	0.005	1,382,467	1,388,385	-0.004
2016	1,389	1,784	-0.284	4,888	5,354	0.087	16,270	16,148	0.008	157.95	158.16	-0.001	155.04	155.38	-0.002	1,428,169	1,442,972	-0.010
2017	934	1,577	-0.688	5,613	5,370	-0.045	16,559	16,823	-0.016	159.04	158.59	0.003	155.7	156.31	-0.004	1,494,090	1,499,705	-0.004
2018	853	1,394	-0.634	5,377	5,386	0.002	17,241	17,526	-0.017	157.39	159.01	-0.01	157.04	157.24	-0.001	1,573,597	1,558,669	0.01
MRPE (%)	49.72			3.39			2.76			0.97			0.71			0.54		
2019		1,233			5,402			18,258			159.44			158.18			1,619,952	
2020		1,090			5,418			19,021			159.87			159.13			1,683,644	
2025		589			5,498			23,341			162.02			163.95			2,041,693	

TABLE IV. FORECASTED RESULTS OF MGM (1,1)

Year	FOC-EG			NGC-EG			EC			ADPW			ADWC			POP		
	Actual	Predicted	RE	Actual	Predicted	RE	Actual	Predicted	RE	Actual	Predicted	RE	Actual	Predicted	RE	Actual	Predicted	RE
2012	5,672	5,672	0	4,673	4,673	0	12,644	12,644	0	148.58	148.58	0	144.77	144.77	0	1,254,952	1,254,952	0
2013	1,231	2,584	-1.099	5,158	5,307	-0.029	13,350	14,284	-0.07	153.41	156.9	-0.023	149.96	152.62	-0.02	1,295,757	1,285,489	0.008
2014	3,285	2,285	0.304	5,614	5,323	0.052	15,186	14,881	0.02	160.05	157.32	0.017	156.62	153.53	0.02	1,338,261	1,336,038	0.002
2015	3,816	2,019	0.471	5,429	5,339	0.017	16,552	15,503	0.063	159.88	157.74	0.013	155.17	154.45	0.005	1,382,467	1,388,573	-0.004
2016	1,389	1,785	-0.285	4,888	5,354	-0.095	16,270	16,151	0.007	157.95	158.16	-0.001	155.04	155.38	-0.002	1,428,169	1,443,175	-0.011
2017	934	1,578	-0.69	5,613	5,370	0.043	16,559	16,825	-0.016	159.04	158.59	0.003	155.7	156.31	-0.004	1,494,090	1,499,924	-0.004
2018	853	1,395	-0.64	5,377	5,386	-0.002	17,241	17,528	-0.017	157.39	159.01	-0.01	157.04	157.24	-0.001	1,573,597	1,558,904	0.009
MRPE (%)	49.78			3.39			2.77			0.97			0.71			0.54		
2019		1,233			5,402			18,261			159.44			158.18			1,620,203	
2020		1,090			5,418			19,024			159.87			159.13			1,683,913	
2025		588			5,498			23,346			162.02			163.95			2,042,069	

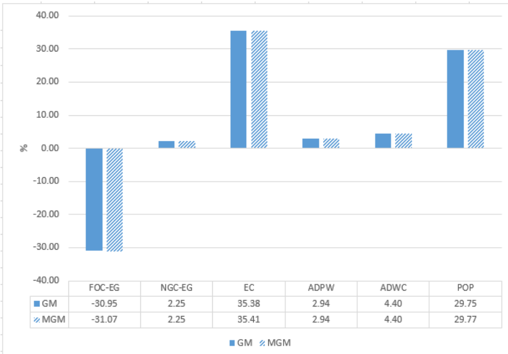


Figure 2. Change in percentage of factors forecasted for the year 2025

The results of forecasts show that the GM and MGM models exhibit almost same values, except few values. Hence, the attempt to improve the GM by replacing the exponentiation term in the equation for forecast by Taylor series expansion has not resulted considerable improvement in forecasting.

From Figure 2 it is evident that the Fuel Oil Consumption for Electricity Generation (FOC-EG) is expected to fall by approximately 31% in the next 5 years. This is a good sign of the Kingdom's progress towards its goal of oil independent economy. The Natural Gas Consumption for Electricity Generation (NGC-EC) is expected to be slightly increased by 2%, in spite of the population increase of 30% and 35% increase in Electricity Consumption (EC). This is again another good sign of progress. Referring to the Average Daily Production of Desalinated Water & Abstraction of Ground Water (ADP-W), it is forecasted to be increased by 3% in the year 2025. On the other hand, it is forecasted that the Average Daily Water Consumption (ADWC) will increase by 4.4 %.

Further, the Mean Relative Percentage errors of GM and MGM are graphically presented in Figure 3. As seen in the Figure 3, the difference in MRPE of GM and MGM is almost negligible. Hence, it tends to modify the MGM further to improve the forecast accuracy. This is one of the scopes for further research.

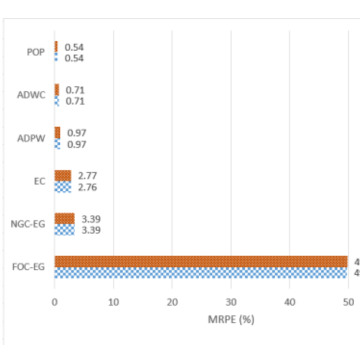


Figure 3. Mean Relative Percentage Error

The forecasts of proposed Grey Models are validated by evaluating their effectiveness. The error measure MRPE of all forecasts are referred for this purpose. The criteria for evaluation [37, 38] is presented in Table V.

TABLE V. CRITERIA TO ASSESS THE EFFECTIVENESS OF FORECAST

MRPE	Effectiveness of forecast
Less than 10 %	Most accurate forecast
Between 10 to 20 %	Good
Between 20-50 %	Reasonable
Greater than 50 %	Poor and inaccurate

As seen in Table V, any forecast with MRPE less than 10 % are accepted as most accurate forecast. Hence all factors except the FOC-EG are to be accepted as most accurate forecasts by both GM and MGM. The FOC-EG can be accepted as reasonable forecasts by both models since the MRPE are less than 50%. The increase in MRPE only for FOC-EG is due to the fact that the data has a sudden increasing and then decreasing trends.

6. Conclusion

A simple Grey Model (GM) and its modified model (MGM) are developed and used to forecast the Fuel Oil Consumption for Electricity Generation, Natural Gas Consumption for Electricity Generation, Electricity Consumption, Average Daily Production of Desalinated Water & Abstraction of Ground Water, Average Daily Water Consumption and Population of Kingdom of Bahrain for the year 2025. Relevant data from the year 2012 to 2018 are extracted from the statistics released by Electricity and Water Authority (EWA) of the Kingdom. The accuracy of forecasted data is assessed by the Mean Relative Percentage Error (MRPE) measure. The forecasted results clearly show that the Kingdom's progress of shifting towards the global competitive economy from the oil dependent economy.

It is found from these experiments that modifying the exponential term in forecast equation of GM to build MGM has not yielded encouraging results in terms of forecast accuracy. Also, both models exhibit relatively large MRPE for forecasting the FOC-EG data which cannot be accepted as an accurate forecast. Hence, it is found that these models are relatively less capable of dealing with the data which has suddenly increasing and decreasing trends. However, as a first group of researchers attempted to forecast EWA data of Kingdom of Bahrain, it motivates to extend this research further to improve the accuracy of forecast by modifying these Grey Models by employing techniques such as Optimization algorithms, Artificial Neural Networks, etc.

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