Forecasting Oil and Gas Production and Consumption in Kingdom of Bahrain using Optimized Grey Forecasting Models

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Abstract:
Oil and Gas are the prime factors that play a vital role on any country's economy, irrespective of being exported or imported. In order to ensure the economic growth of any country, it is essential for it to forecast the future need of Oil and Gas and plan the production and export accordingly. In this paper, four different types of Grey Forecasting Models namely GFM, FAGFM, MFAGFM and RGFM are developed and used to predict the future requirements of Oil and Gas production in the Kingdom of Bahrain. The official data released through Annual Report by the National Oil and Gas Authority (NOGA) of Bahrain are taken for this research. The developed Grey Forecasting Models are employed to forecast 8 most significant factors presented in the annual reports from 2010 to 2017, namely Total Oil Production, Crude Oil Imported, Crude Oil Run to Refinery+Feedstock, Refinery Production, Local Sales, Aviation Jet-fuel, Petroleum Product Export and Total Gas Production for the year 2025. The results of simulation studies are encouraging to see that the Kingdom progressing towards achieving its Vision 2030. The accuracy of forecasts are assessed using the Average Relative Percentage Error (ARPE) performance measure.

Keywords: Grey Forecast Model (1,1), Rolling Grey Forecast Model (1,1), Grey Prediction, Forecast accuracy, Average Relative Percentage Error, Firefly Algorithm.

1. INTRODUCTION

The demand for Oil and Gas is continuously on their high across the globe for many decades in spite of the initiatives by countries on renewable and sustainable energies by pulling out oil from the power generation sector. The domestic economy of any country is directly or indirectly impacted by the import and/or export of oil and gas [1]. It has been reported in many studies that the Oil and Gas will continue dominating the energy market throughout the 21st century [2]. The oil is an internationally traded commodity but gas cannot not be traded internationally due to cost and means of transportation of it. [3]. It has been reported that the oil and gas markets will be different than the past and present [4] due to many factors including the geopolitics. However, the aim of any country's lawmakers needs to be always to maximize the social benefit out of its energy resources [5]. The future growth of source of crude oil published in 2013 by International Energy Agency (IEA) for the period of 2012-2035 shows that only the countries of Middle East will have the increasing growth [4]. It is stated in BP Statistical review of 2019 that Production of Oil and Gas by the Middle East is 33% and 17% respectively, of the world's production [6].

The Kingdom of Bahrain is the first country in the region of Middle East which discovered its first oil well in the early 1930's. The energy required for Bahrain is generated from its own Oil and Gas resources. The Economic Vision 2030 of Bahrain mainly focuses on sustainability, competitiveness and fairness through becoming a non-oil dependent economy, benefiting its people by its robust growth of economy, efficient and effective government with high quality policies and the thriving society [7]. The government and authorities have been developing and implementing plans and strategies in order to achieve this Vision by 2030. One of the key focusses of Vision 2030 is sustainability, which comprises of economic, environmental and social components [8]. One of the factors that dictates the economic growth of the country is its natural resources such as Oil and Gas, etc. . Hence, it is necessary to continuously monitor the Oil and Gas production, export and revenue gained through it during the past, present and future to ensure the economic growth. In order to keep a track of factors influencing the economy and foresee their future, there are many techniques employed. The related literature were surveyed and found that Grey System Theory has been extensively used for this and related purposes. They are presented briefly below.

Grey Models have been proposed to predict the pressure status of gas reservoir, gas well and oil reservoirs, oil production and gas production [9]. A special type of Grey Model (GM) called FSIGM has been employed to forecast the future oil consumption in China [10]. A time-delayed polynomial fractional order grey model has been used to allocate optimum oil-gas field to improve the production [11]. Various methods published for forecasting the consumption of Gas have been consolidated in the review [12]. In this research review, the methods of prediction, variables being predicted, the horizon of prediction and etc. used in the prediction methods have been reviewed in detail. Numerical structure and numeric value of seismic data are taken in to consideration to predict the condition of gas reservoir using Grey Models [13]. Gas consumption and fuel production in china have been forecasted using improved Grey model of prediction in [14] and [15] respectively. The former model uses the principle of new information priority and the later uses the generalized stepwise ratio. The trend and potency tracking method has been developed to model a Grey prediction Model

[16] and a non-parametric incremental learning algorithm [17] for the prediction of small size of data sets of manufacturing..

Other prediction models found in the recent literature on various fields of application are, Grey Wave Model for prediction of Trade volume of China [18], GM and Nonlinear Bernoulli Grey Model for Economic forecasting in Taiwan [19], Grey Predication Model to predict the emission of CO_2, consumption of energy and growth of economy in Brazil [20], Grey Model optimized by Genetic Algorithm (GA) for forecasting the trend and output of IC industry of Taiwan [21], Nonlinear Grey Bernoulli Model to forecast the rates of foreign exchange of major trading partners of Taiwan [22], Rolling Grey Model for prediction of production of Taiwan's semiconductor industry [23], GA based Grey model for forecasting the output of Taiwan's Opto-electronics industry [24], Hybrid Grey Forecast Model for forecasting the output values of Taiwan's Industrial Park [25], Grey and Verhulst models for prediction of rainfall and water level in dam in Thailand [26], Nonlinear Grey Bernoulli Model for predicting the pressure under the working surfaces in mines in China [27], Artificial Bee Colony optimized Rolling Grey Model for predicting the spontaneous combustion in coal stockpiles of an electric plan in China [28], improved grey model with modified background value for energy management in China [29] and Grey and Modified Grey prediction models for forecasting the generation and consumption of electricity in Bahrain [30].

It has been found from the literature survey that the use of Grey models have resulted a good forecast of future status from the past available data of any factor being considered. In this paper, four Grey Forecasting Models (GFM) namely a simple GFM, a Firefly Algorithm optimized GFM (FAGFM), a Modified Firefly Algorithm optimized GFM (FAGFM) and a Rolling GFM (RGFM) are developed to forecast the production of Oil and Gas in the Kingdom of Bahrain. The relevant data for the period of 2010 to 2017, published in the annual reports by National Oil & Gas Agency (NOGA) of Kingdom of Bahrain are used for this study [31].

The further contents of this paper are organized as follows. The proposed GFM, FAGFM, MFAGFM and RGFM are described in the following section which is followed by the data of NOGA from 2010 to 2017 being summarized. Then, the obtained results of proposed forecast models are presented with detailed analysis. Finally the paper is concluded with further possible scopes for extending this research.

2. GREY FORECASTING MODELS

Grey Forecast Models are extensively used for prediction of future values in almost all areas of technical research [32]. Grey Models (GM) are capable of handling the uncertainties and incompleteness existing in the available data [33]. The mathematical model of Grey Model is typically denoted as GM (m,n) with m representing the order of differential equation used to represent the model having n number of input variables in it [34]. One important fact always to be noted is that the GM can be used for forecasting the series of data containing only positive elements and at least 4 samples.

2.1 Grey Forecasting Model (GFM)

The most simple GFM can be represented as GFM (1,1), which is a first order model with single variable. The model of GFM (1,1) is derived as follows.

Considering an actual positive data series $X^{(a)}(n)$ represented as,

$$X^{(a)}(n)=\left(x^{(a)}(1),x^{(a)}(2),\ldots x^{(a)}(n)\right);\ n\geq 4 \tag{1}$$

An operation called Accumulation Generation (AG) is performed on the actual sequence in order to reduce the randomness present in it.

$$X^{(AG)}(m)=\sum_{i=1}^{m}x^{(a)}(i);\ m=1,2,\ldots n \tag{2}$$

The result of AG operation yields,

$$X^{(AG)}=\left(x^{(AG)}(1),x^{(AG)}(2),\ldots x^{(AG)}(n)\right) \tag{3}$$

Further, the mean sequence of $X^{(AG)}$ can be obtained as,

$$X_m^{(AG)}=\left(x_m^{(AG)}(1),x_m^{(AG)}(2),\ldots x_m^{(AG)}(n)\right) \tag{4}$$

Where, $x_m^{(AG)}(k)=\left(P\times x_m^{(AG)}(k)+(1-P)\times x_m^{(AG)}(k-1)\right),\quad k=2,3..n$ (5)

The value of P in equation (5) is usually taken as 0.5.

For the sequences presented in equations (1), (3) and (4), the GFM (1,1) can be represented as a differential equation of order 1 with time variable 't',

$$\frac{d}{dt}\left(X^{(AG)}\right)+g\,X^{(AG)}=h \tag{6}$$

Where, '*g*' is developing coefficient and '*h*' is grey input.

Writing the equation (6) in a difference equation form,

$$X^{(a)}(k)+g\,X_m^{(AG)}(k)=h \tag{7}$$

By employing the least squares method, the estimates of model parameters can be obtained as,

$$\begin{bmatrix} g \\ h \end{bmatrix} = \left[B^T B\right]^{-1} B^T Y; \text{ where } B = \begin{bmatrix} -x_m^{(AG)}(2) & 1 \\ -x_m^{(AG)}(3) & 1 \\ . & . \\ . & . \\ . & . \\ -x_m^{(AG)}(n) & 1 \end{bmatrix} \text{ and } Y = \begin{bmatrix} x^{(a)}(2) \\ x^{(a)}(3) \\ . \\ . \\ . \\ x^{(a)}(n) \end{bmatrix} \tag{8}$$

Solving the equation (6) to obtain the forecasted output at the instant '*k*' yields,

$$\hat{x}^{(AG)}(k) = \left(x^{(a)}(1) - \frac{h}{g}\right) \times e^{(-g \times (k-1))} + \frac{h}{g}, \qquad k = 2,..n \tag{9}$$

It is to be noted that,

$$x^{(AG)}(1) = x^{(a)}(1) \tag{10}$$

The equation (9) gives the forecasted AG value at the instant 'k'. In order to get the actual forecasted data at '*k*', Inverse of AG (IAG) operation has to be performed as,

$$x^{(a)}(k) = x^{(AG)}(k) - x^{(AG)}(k-1) \tag{11}$$

Therefore, the actual forecasted value at '*k*', can be obtained by using equation (9) in equation (11) as,

$$\hat{x}^{(a)}(k) = \left(1 - e^{g}\right) \times \left(x^{(a)}(1) - \frac{h}{g}\right) \times e^{-g(k-1)} + \frac{h}{g} \tag{12}$$

2.2 Rolling Grey Forecasting Model (RGFM)

In actual cases of prediction, usually the oldest data has relatively least impact on the future values. Hence, by using the latest data and ignoring the oldest data to compensate it, the accuracy of forecasting can be improved further [24]. This ensures maintaining the same number of data points being used for the forecast. This method of modifying the GFM is termed as Rolling GFM (RGFM).

Building a RGFM is described as follows.

For the given actual data sequence of size '*n*', the forecasted data at '*n+1*' can be obtained as,

$$\hat{x}^{(a)}(n+1) = \left(1 - e^{g}\right) \times \left(x^{(a)}(1) - \frac{h}{g}\right) \times e^{-g(n)} + \frac{h}{g} \tag{13}$$

In order to build a RGFM, the first data point in the actual data sequence is removed and the forecasted data point at '*n+1*' is appended at the last [24], thereby ensuring that there is no change in the size of the data sequence, as shown in equation (14).

$$X_{R1}^{(a)}(n) = \left(x^{(a)}(2), \ldots x^{(a)}(n), \hat{x}^{(a)}(n+1)\right) \tag{14}$$

Then, this new data sequence in (14) is used as the actual data to forecast the data at '*n+2*', as given in (15).

$$X_{R2}^{(a)}(n) = \left(x^{(a)}(3), .. \hat{x}^{(a)}(n+1), \hat{x}^{(a)}(n+2)\right) \tag{15}$$

This process can be stopped when reaching the required number of instants for which the forecast is needed. This idea of RGFM is depicted in Figure 1.

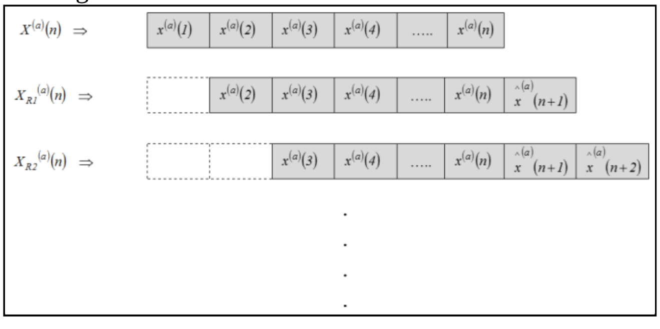


Figure 1: Rolling Grey Forecast Model

2.3 *Firefly Algorithm optimized Grey Forecast Model (FAGFM)*

Yet another way to improve the accuracy of forecast is to find the optimum value of 'P' that is used in the equation (5), which is usually set as 0.5. There are researches which address on selecting an appropriate value for '*P*' using different methodologies [21-24, 28-29]. Optimization algorithms such as Genetic Algorithms (GA) [21, 24] and Artificial Bee Colony Algorithm [28] have also been employed for choosing an optimum value of 'P' with the objective of minimizing the forecasting error.

Firefly Algorithm (FA) is a popular and well-received method of swarm intelligence, introduced by Yang [35]. FA is capable of dealing with non-linear and multi model problems of optimization with faster convergence than its counterparts [36] and searching globally in the spaces of large dimensions [37]. The flashing light emitted by the fireflies is used as a communication signal by them to attract their prey, matting partner and means for warning others. The intensity of this flashing light increases when the square of distance decreases and thereby the attractiveness too. This phenomenon is utilized to formulate the objective function of FA optimization [36-37]. Three parameters are used to control the performance of FA, namely the randomization parameter, absorption coefficient and the attractiveness. The algorithm of FA is presented in Figure 2.

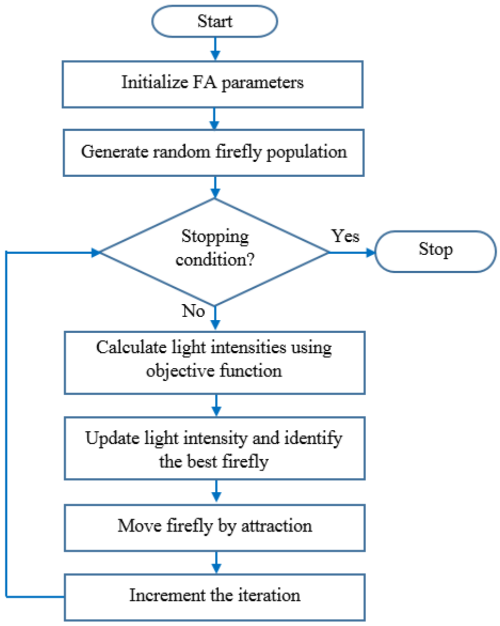


Figure 2: Firefly Algorithm Flow chart

In the proposed FAGFM, FA is used to find the optimum value of '*P*' for which the forecasting error will be minimum. The Average of Relative Percentage Error (ARPE), given in equation (16) is considered as Objective function for FA to minimize.

$$ARPE = \frac{1}{n}\sum_{m=1}^{n}\left|\frac{x^{(a)}(m) - \hat{x}^{(a)}(m)}{x^{(a)}(m)}\right| \times 100\% \quad (16)$$

Where, $\frac{x^{(a)}(m) - \hat{x}^{(a)}(m)}{x^{(a)}(m)}$ is Relative Error (RE).

The other parameters of FA considered in this research are listed in Table 1.

TABLE 1: FIREFLY ALGORITHM PARAMETERS

Number of Fireflies	500
Randomization parameter	0.8
Attractiveness	0.5
Light absorption coefficient	1
Total number of Evaluations	100

2.4 *Modified Firefly Algorithm optimized Grey Forecast Model (MFAGFM)*

In the basic GFM described earlier, the parameter 'P' is taken as 0.5 to find the background value in Equation (5). This means that the average of two consecutive values are taken as '*P*', irrespective of the nature and amount of change from the former value to the later one. Hence, in the proposed FAGFM, the optimum value of 'P' is found using the FA with an objective function of minimizing the ARPE. Here again, the optimum value of '*P*' is used in common for the whole data sequence without concerned about the nature and amount of change between two consecutive values of the data. In order to improve the forecasting accuracy further, in this section, a novel Modified Firefly Algorithm optimized Grey Forecast Model (MFAGFM) is proposed, Here, instead of using a single optimum value of '*P*' across the whole input data, the novel idea of using individual optimum '*P*' values is used by finding '*P*' for each couple of consecutive values in the given input data. This newly proposed approach is explained below.

For the mean sequence $X_m^{(AG)}$ given in Equation (5), the optimum values of '*P*' found by FA are represented as,

$$P=(P_1,P_2,\ldots P_{n-1}),\quad 0<P<1 \tag{17}$$

The obtained optimum values of '*P*' using FA are used to find the background value as,

$$x_m^{(AG)}(k)=\left(P_{(k-1)}\times x_m^{(AG)}(k)+\left(1-P_{(k-1)}\right)\times x_m^{(AG)}(k-1)\right),\quad k=2,3..n \tag{18}$$

This method of using individual optimum values of '*P*' improves the forecast accuracy further than using a single optimum '*P*' value for the whole input data.

3. National Oil & Gas Agency (NOGA) Data of Kingdom of Bahrain

The National Oil & Gas Authority of Bahrain is a government organization established in 2005 in order to look after all affairs related to Oil and Gas related businesses in the Kingdom. NOGA publishes the annual report every year in its official website www.noga.gov.bh. The data pertaining to the production of Oil and Gas and their consumption, have been extracted from these published annual reports from the year 2010 to the latest available annual report of the year 2017. The various factors that are extracted for consideration in this research are namely Total Oil Production (TOP), Crude Oil Imported (COI), Crude Oil Run to Refinery+Feedstock (CORRF), Refinery Production (RP), Local Sales (LS), Aviation Jet-Fuel (AJF), Petroleum Product Export (PPE) and Total Gas Production (TGP). The extracted data of these eight factors for the period of 2010 to 2017 are consolidated and presented in Table 2. There are few slight differences found in the entries in the published annual reports, in such cases the latest entries are considered.

TABLE 2: OIL AND GAS STATISTICS (IN MILLION BARRELS)

	2010	2011	2012	2013	2014	2015	2016	2017
TOP	66.376	69.452	63.302	72.122	73.882	73.556	73.943	71.958
COI	85.658	79.263	80.164	78.583	76.015	78.711	76.682	80.179
CORRF	97.472	94.531	97.464	97.410	97.280	97.767	95.031	96.258
RP	99.362	96.026	101.103	99.962	100.233	100.987	97.617	99.031
LS	9.486	8.787	9.442	9.814	10.057	10.480	10.672	10.992
AJF	4.951	4.604	4.372	3.124	3.070	3.388	3.377	3.471
PPE	85.603	82.529	86.596	87.183	87.861	87.637	82.503	91.983
TGP	556.644	552.093	591.684	679.474	728.426	751.615	743.803	758.03

4. Forecasting the Production and Consumption of Oil and Gas in Kingdom of Bahrain

The models of GFM (1,1), FAGFM (1,1), MFAGFM (1,1) and RGFM (1,1) have been built and simulated for forecasting the values of the listed factors of Table 2. The forecasted values of these factors for the years 2011 to 2017 are obtained and compared with their actual values to access the accuracy of forecasts. The APRE given in equation (16) is found for this purpose. Further, the forecasted values for the years 2020 to 2025 are obtained and presented in the next section.

5. Results and Discussion

The obtained results of forecasts by GFM (1,1), FAGFM (1,1), MFAGFM (1,1) and RGFM (1,1) are compiled and presented in Table 3.

TABLE 3: FORECASTED RESULTS OF GREY FORECASTING MODELS

Year	TOP					COI				
	Actual	Forecast				Actual	Forecast			
		GFM	FAGFM	MFAGFM	RGFM		GFM	FAGFM	MFAGFM	RGFM
2010	66.376	66.376	66.376	66.376	66.376	85.658	85.658	85.658	85.658	85.658
2011	69.452	68.016	68.557	69.452	68.016	79.263	78.957	78.911	79.263	78.957
2012	63.302	69.042	69.585	70.328	69.04	80.164	78.809	78.761	78.941	78.809
2013	72.122	70.084	70.629	71.215	70.081	78.583	78.661	78.611	78.621	78.661
2014	73.882	71.141	71.689	72.113	71.136	76.015	78.513	78.461	78.302	78.513
2015	73.556	72.214	72.765	73.022	72.208	78.711	78.366	78.312	77.984	78.366
2016	73.943	73.304	73.856	73.943	73.296	76.682	78.219	78.163	77.668	78.219
2017	71.958	74.409	74.964	74.876	74.4	80.179	78.072	78.014	77.353	78.072
ARPE (%)		**2.97**	**2.70**	**2.44**	**2.97**		**1.32**	**1.33**	**1.29**	**1.32**
2018		75.532	76.089	75.82	71.958		78.010	77.865	77.039	77.926
2019		76.671	77.231	76.776	75.532		77.867	77.717	76.726	77.779
2020		77.828	78.389	77.744	76.67		77.724	77.568	76.415	77.633
2025		**83.878**	**84.449**	**82.771**	**83.865**		**77.014**	**76.832**	**74.877**	**76.906**

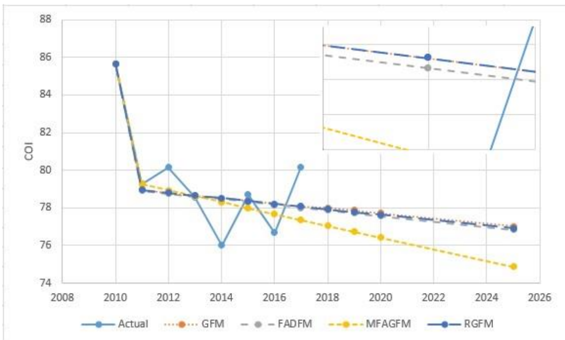
Year	CORRF					RP				
	Actual	Forecast				Actual	Forecast			
		GFM	FAGFM	MFAGFM	RGFM		GFM	FAGFM	MFAGFM	RGFM
2010	97.472	97.472	97.472	97.472	97.472	99.362	99.362	99.362	99.362	99.362
2011	94.531	96.463	96.447	96.692	96.463	96.026	98.955	99.017	99.419	98.955
2012	97.464	96.487	96.473	96.619	96.487	101.103	99.063	99.122	99.354	99.063
2013	97.41	96.511	96.498	96.547	96.51	99.962	99.171	99.226	99.289	99.171
2014	97.28	96.534	96.523	96.475	96.534	100.233	99.280	99.331	99.225	99.28
2015	97.767	96.558	96.549	96.402	96.558	100.987	99.388	99.436	99.16	99.388
2016	95.031	96.582	96.574	96.33	96.582	97.617	99.497	99.541	99.096	99.497
2017	96.258	96.606	96.599	96.258	96.606	99.031	99.606	99.647	99.031	99.605
ARPE (%)		**0.99**	**0.99**	**0.95**	**0.99**		**1.36**	**1.35**	**1.28**	**1.36**
2018		96.630	96.625	96.186	96.63		99.714	99.752	98.967	99.714
2019		96.654	96.651	96.114	96.654		99.823	99.857	98.902	99.823
2020		96.677	96.676	96.042	96.678		99.932	99.963	98.838	99.932
2025		**96.797**	**96.803**	**95.683**	**96.798**		**100.480**	**100.492**	**98.516**	**100.48**

Year	LS					AJF				
	Actual	Forecast				Actual	Forecast			
		GFM	FAGFM	MFAGFM	RGFM		GFM	FAGFM	MFAGFM	RGFM
2010	9.486	9.486	9.486	9.486	9.486	4.951	4.951	4.951	4.951	4.951
2011	8.787	9.030	9.158	9.161	9.03	4.604	4.248	4.166	3.599	4.248
2012	9.442	9.346	9.483	9.49	9.346	4.372	4.022	3.944	3.553	4.02
2013	9.814	9.672	9.819	9.831	9.672	3.124	3.807	3.733	3.508	3.805
2014	10.057	10.011	10.167	10.184	10.01	3.07	3.604	3.533	3.464	3.601
2015	10.48	10.361	10.528	10.55	10.36	3.388	3.412	3.344	3.42	3.408
2016	10.672	10.723	10.901	10.929	10.723	3.377	3.230	3.166	3.377	3.225
2017	10.992	11.098	11.287	11.321	11.098	3.471	3.058	2.996	3.334	3.225
ARPE (%)		**1.03**	**1.38**	**1.53**	**1.04**		**8.99**	**9.38**	**8.82**	**8.38**
2018		11.486	11.687	11.728	11.486		2.895	2.836	3.292	3.471
2019		11.887	12.101	12.149	11.886		2.740	2.684	3.251	2.895
2020		12.303	12.53	12.585	12.301		2.594	2.541	3.209	2.74
2025		**14.610**	**14.914**	**15.014**	**14.596**		**1.973**	**1.931**	**3.012**	**1.969**

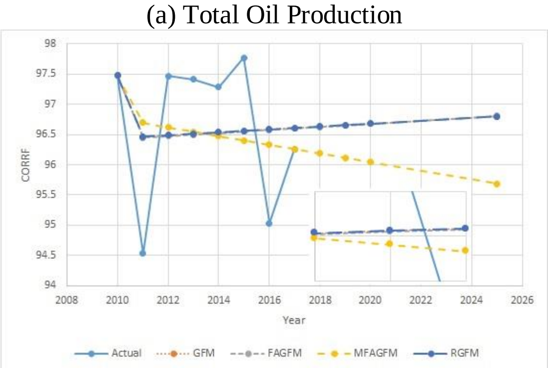
Year	PPE					TGP				
	Actual	Forecast				Actual	Forecast			
		GFM	FAGFM	MFAGFM	RGFM		GFM	FAGFM	MFAGFM	RGFM
2010	85.603	85.603	85.603	85.603	85.603	556.644	556.644	556.644	556.644	556.644
2011	82.529	84.421	84.418	85.836	84.421	552.093	588.214	600.579	601.259	588.214
2012	86.596	85.141	85.138	86.506	85.141	591.684	618.306	631.786	632.898	618.306
2013	87.183	85.868	85.865	87.181	85.868	679.474	649.938	664.615	666.202	649.937
2014	87.861	86.600	86.597	87.861	86.6	728.426	683.187	699.151	701.259	683.187
2015	87.637	87.339	87.336	88.547	87.339	751.615	718.138	735.48	738.16	718.138
2016	82.503	88.084	88.081	89.238	88.084	743.803	754.877	773.697	777.003	754.876
2017	91.983	88.835	88.833	89.934	88.835	758.03	793.495	813.9	817.89	793.495
ARPE (%)		**2.18**	**1.95**	**1.94**	**2.18**		**4.02**	**4.41**	**4.46**	**4.02**
2018		89.227	89.59	90.636	89.593		834.089	856.193	860.928	834.088
2019		89.995	90.355	91.343	90.357		876.760	900.682	906.231	876.509
2020		90.770	91.126	92.056	91.127		921.613	947.484	953.919	921.182
2025		**94.747**	**95.08**	**95.705**	**95.076**		**1182.739**	**1220.599**	**1232.742**	**1180.074**

The actual values and forecasted values of all factors are compared and shown graphically in Figures 3 (a) to (h). The forecasted values from 2020 to 2025 are also included in these figures. Where ever needed, a portion of plot is magnified and shown as subplot to show the difference in forecasted results of all models.

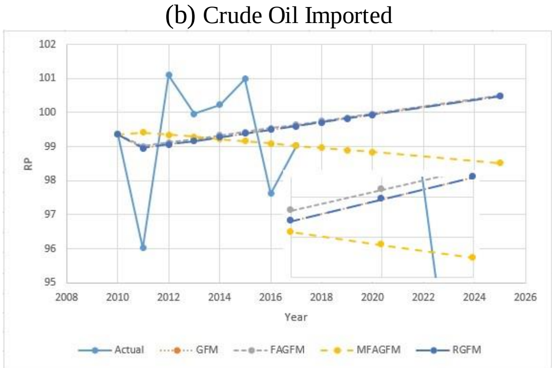
(a) Total Oil Production



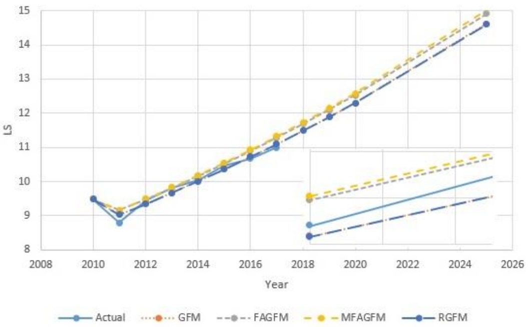
(b) Crude Oil Imported



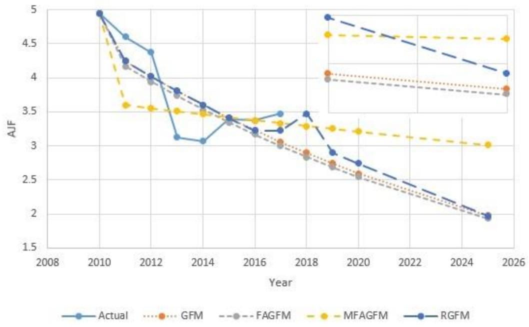
(c) Crude Oil Run to Refinery + Feedstock



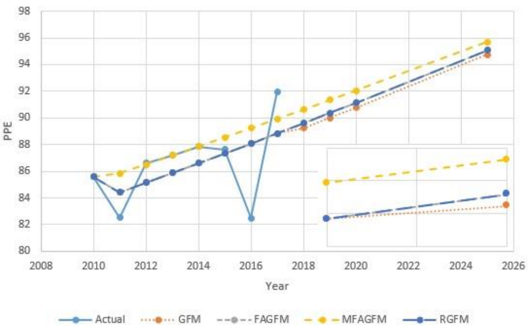
(d) Refinery Production



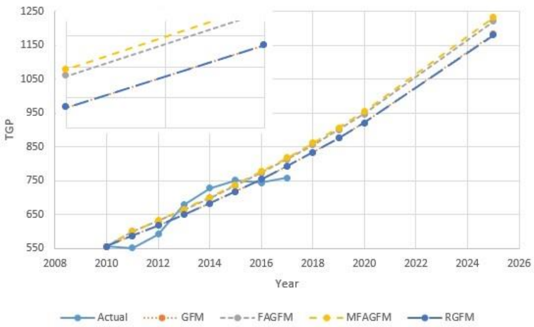
(e) Local Sales



(f) Aviation Jet-fuel



(g) Petroleum Product Export



(h) Total Gas Production

Figure 3: Actual and Forecasted data from 2010 to 2025

From the above figures it is found that the forecasting ability of proposed MFAGFM is more accurate than the other forecasting models namely GFM, FAGFM and RGFM, when the input data has more fluctuations. However, when the mean of fluctuation is close to zero (figure f), the ARPE has increased and thereby the accuracy of forecast has decreased compared to the other models. When the input data has less fluctuations (figures e and h), the MFAGFM performs much closer to the other models. The values of ARPEs in Table 3 also proves that the MFAGFM is more promising for the data which are changing drastically over the period time.

The RGFM results show that it performs much better than the other three models, when the fluctuations in input data is less or mean of fluctuation is close to zero. Hence it can be inferred from the results that the proposed MFAGFM is better for forecasting the data which is more fluctuating and the RGFM is effective when the data has less fluctuations and/or the average of fluctuations is close to zero.

In order to show the accuracy of forecast, the ARPE performance measure is found for all the four GFMs and shown in Figure 4.

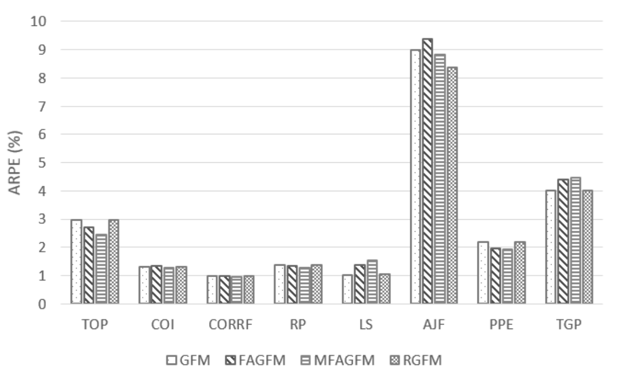


Figure 4: Average Relative Percentage Error of forecasts

The criteria for evaluation of performance of the proposed models is given in Table 4 [21, 24, 30]. Referring to the Table 4 shows that forecasts of all the four proposed GFMs are excellent in their forecasting ability, because the ARPE for all the GFMs are less than 10%.

TABLE 4: CREITERIA FOR EVALUATION OF FORECASTING ABILITY

Range (%)	Forecasting ability
0 ≤ ARPE ≤ 10	Excellent
10 < ARPE ≤ 20	Good
20 < ARPE ≤ 50	Reasonable
50 < ARPE	Poor

The evaluated ARPE values of results of experiments are presented in Figure 4. This figure shows that the simple GFM and the RGFM are efficient in dealing with the TGP data which is in sigmoidal nature and LS data which has least changes over the years.s The proposed MFAGFM is most accurate among all in forecasting the data, such as TOP, COI, CORRF, RP, AJF and PPE, which are continuously changing (both increase and decrease) in nature. But it is relatively less accurate for the LS data which has very less changes over the years. For the data which are continuously decreasing (AJF), the RGFM model is a suitable one for forecasting with least ARPE.

The overall forecasted changes in the NOGA data for the year 2025 are obtained in percentage and presented in Figure 5.

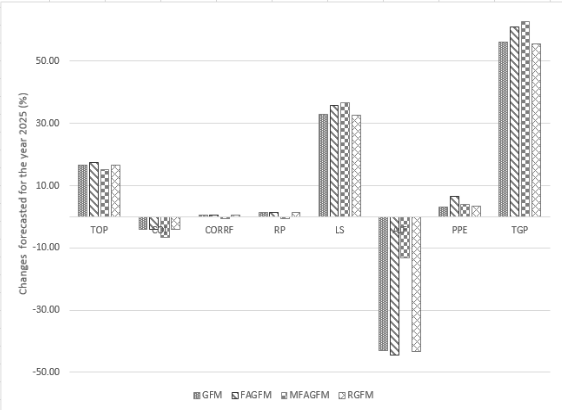


Figure 5: Forecasted percentage change from 2018 to 2025

Figure 5 shows that there will be approximately 60% increase in Total Gas Production expected by the year 2025. Other large increases forecasted are the Local sales which is nearly 35 % and the Total Oil Production which is nearly 15 %. Other factors such as Total Oil Production, Crude Oil Run to Refinery + Feedstock, Refinery Production and Petroleum Product Export are expected to increase by a mere amount. On the other hand, it is forecasted that the Aviation Jet Fuel demand will decrease by around 13% and the Crude Oil Import will decrease by about 4%.

6. CONCLUSION

Four different Grey Forecast Models namely a simple GFM, a Firefly Algorithm Optimized GFM, a Modified Firefly Algorithm Optimized GFM and a Rolling GFM are proposed for forecasting the future demand of Oil and Gas production and consumption in the Kingdom of Bahrain. Relevant data published by the National Oil and Gas Authority, Kingdom of Bahrain, for the period of 2010 to 2017 are taken for this research. Eight most influential factors have been considered for the forecasts. The forecasting performance of the proposed GFMs are evaluated against the standard criteria using the Average Relative Percentage Error of forecast and all the four models are found to be excellent in forecasting accuracy. It has been found that the data being considered in this research are of different natures such as slightly varying, highly varying, only increasing, only decreasing and both increasing and decreasing for the given period. The proposed GFM and RGFM are found to be most accurate for the data which are sigmoidal and least changing in nature. The optimized GFMs namely FAGFM and MFAGFM are more accurate in forecasting continuously changing (increasing and decreasing) data. The RGFM is a best model for continuously decreasing data. Being the first team pursuing research to attempt forecasting such most significant data of the Kingdom of Bahrain, the obtained excellent performance of the GFMs encourages to look for avenues for further modifications to build a generalized forecasting model which can efficiently forecast data of all natures.

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