Ethiopian energy consumption forecast

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A B S T R A C T

This Energy consumption forecast is vital and has a great economic impact. Mathematical models developed for energy forecast can also serve as inputs for further studies. This study is intended to develop an energy consumption forecast using the grey prediction model GM (1,1), based on the actual energy consumption data from the year 2008 to 2017. The models are developed for the total, solid biomass, oil products, and electrical energy consumption; and the accuracy for each model is ratified. These developed forecasting models were used to anticipate six-year Ethiopian consumption of major energy types. The outcomes of models for all four energy consumption types show an upward trend; simulating and forecasting are found suited with the grey system model with development coefficient values less than 0.3 for all selected energy forms.

1. Introduction

Ethiopia is among the least-developed nations in the world. About 34% of its population live below the poverty threshold. Access to modern energy resources and energy creation is at the lowest level, and is mainly reliant on biomass. The energy segments of the country are estimated to be 92.4% of waste and biomass, 5.7% oil and 1.6% hydro-power sources [1]. However, the World Bank report shows that the economy is among the fastest rising, with an annual growth rate of 9.8% since 2008. The country has also set a plan and is striving to realize its development till 2025 with climate resilient actions. The country's commitment to the climate issue was proven by taking the lead in delivering the Nationally Determined Commitment of all developed countries to the United Nations Framework Convention on Climate Change.

It is known that the social and economic growth of a country is mainly supported by energy, one of the strategic resources. As a nation occupied with an incredibly yearning and quick energy improvement program, Ethiopia has a feature of harvesting mainly of hydro based renewable energy and targeting to increase the electricity access from 26% in 2014 to 60% by 2040 [2]. The country's clean energy demand versus the supply gap creates an unsuitable and unhealthy living status; besides to this shortage of access to clean energy brings resemblance of the citizens to use biomass-based energy sources as a first choice. The dependence on biomass-based energy sources in-turn becomes a cause for deforestation and leads to soil erosion and fertility loss for which the economy of a country is hindered by. To minimize the environmental loads and improve the living status of the community, the energy sector should properly be managed with a forecast of short and long term strategy.

Forecasting is a technique which uses historical data as inputs to make informed estimates that are predictive in determining the direction of future trends; now a days it is becoming a powerful tool for policy makers in different sectors and industries. With this regard,

forecasting the energy consumption trend of Ethiopia is taken as the focus of this work for better decision-making process.

It is believed that energy consumption is an intricate scheme with vulnerable and limited helpful data, and hence its prediction is a troublesome issue. Issues related to economy, urbanization, industrialization and the environment make energy remain obscure to a great extent [3]. In the recent decades studies related to energy problems are getting due attention with a special focus on developing countries in which the energy system is evolving at a high level [4]. The study done on the energy demand-forecasting methods summarized and showed that different models such as regression, time series, grey model and some others can come up with better prediction accuracy [4-5]. However, these models have limitations of demanding 30 to 100 or more initial data/observations, it is therefore meaningful to find an efficient and feasible model for forecasting the pattern of an evaluated structure with scarce observations. In poor countries like Ethiopia, where proper data of a long-range of time and full information are not found, it is reasonable to use grey system theory in building forecasting models [6]. The grey forecasting theory which initially proposed by Deng [7] mainly addresses ambiguous problems with limited data and minimal knowledge. Now a day, grey system theory is getting a wider application in various manufacturing and service industries, education, and environment related fields [8-12]. Though lots of Grey model (GM) types are developed so far, its computational strength and ease to handle makes the first-order grey model be a favoured tool for different research works [13]. The GM(1,1) prediction model seems to obtain the lowest post-forecasting errors and it is more suitable to make a short-term prediction [14].

Procedures for the GM(1,1) model are briefly discussed by Xiao et al. [15] as the starting procedure called the whitening equation is a differential equation, preceded by discretising this differential equation so that the basic form is attained. Thereafter, evaluating the system parameters using the least-squares method, after that using the whitening equation and system parameters the data sequence is simulated and predicted. Just four or more samples are used in such a model to analyse the system's characteristics and evolution.

Different studies on Ethiopia's energy scenario have been done so far, some of which are done in the last few years focusing on access to sustainable energy [16], power sector development [17], residential electricity demand [18], Regional urban energy use trend [19], allocation of biomass energy sources [20] review on bigas technology [21], energy scenarios for sustainable strategies [22], and very few on energy demand projection using different approaches and tools. However, to the author's knowledge, there is no literature providing a comprehensive analysis of Ethiopian energy demand projections for different energy source types using the grey theory.

Such models would enable policy makers and energy planners to reconcile the energy supply with the projected growth in demand. With all above listed benefits and for its significant importance to counter-act against energy crisis, and structure the future energy demand recommended by Brinckerhoff [23], Ethiopian major energy types of consumption forecast is developed. It is a new work especially in East Africa for Ethiopia. The author believes that this paper will be a valuable input and have a better acceptance as it refers to the case of Ethiopia where the trend of having focus to energy is yet not developed. Besides to this such energy forecasting research could help other developing countries adopt it and have a related work on, for better energy planning and management.

2. Principles/Basics of the GM(1,1) Model

2.1 The Grey Model (1,1)

Grey systems theory has been grown up over almost thirty years of growth as a recently emerging scientific field with its own theoretical framework comprising of system analysis, measurement, simulation, estimation, decision-making, control, and optimization techniques. One of the fundamental pieces of this theory is the Grey model. This approach accepts grey module as its establishment sorting out apparently non continuous data sequences through data processing. Afterwards model values will be computed and obtained from the new sequentially built differential equations. Residual errors are possibly be found by taking the real measured value as a reference, and hence the model can be rectified and thus be conferred with a better degree of forecasting accuracy. There are numerous sorts of grey forecasting models, yet Grey Model (1,1) is the commonly utilized type, besides this different grey based models are risen up from it. Meanwhile GM(1,1) is characterized by differential conditions to portray the inner and evolving behaviour of the system predictability for extrapolation.

2.2 The Grey Model (1,1) Development

1. By having some equivalent time span sections of a case, ordered values are attained and are called as original numerical sequences $X^{(0)}$ (Eq. 1).

$$X^{(0)} = x^{(0)}(k)(k = 1,2,\ldots n) \qquad (1)$$

The arbitrator for randomness of the initial data is treated by generating the First-Order Accumulated Generating Operation (IAGO) from the original time sequence $X^{(0)}$, as Eqs. 2 and 3.

$$X^{(1)} = x^{(1)}(k)(k = 1,2,\ldots n) \qquad (2)$$

Where:

$$X^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \qquad (3)$$

Whenever $X^{(0)}$ values are non-negative, the $X^{(1)}$ sequence values will have an increasing trend, with an exception value of $X^{(0)}(1)=X^{(1)}(1)$.

2. First, we have to use quasi-smoothness sequence and quasi exponential law to verify that GM(1,1) can be built, if both are fulfilled at a time then the criteria is satisfied to build the model.

Quasi-smoothness sequence criterion is fulfilled for $\rho(k) \in [0,\epsilon]$, $k = 3,4,\ldots n$ and $\epsilon < 0.5$, and is represented as $X^{(1)}$.

$$\rho(k) = \frac{x^{(0)}(k)}{x^{(1)}(k-1)}, k = 2,3,\ldots,n-1 \qquad (4)$$

Quasi-exponential law criterion is fulfilled when $\sigma^{(1)}(k) \in [0,\epsilon]$, $k = 3,4,\ldots n$ and $\delta = b - a = 0 \cdot 5$, and then $X^{(1)}$ follows quasi-exponential law.

$$\sigma^{(1)}(k) = \frac{x^{(1)}(k)}{x^{(1)}(k-1)}, k = 2,3,\ldots,n-1 \qquad (5)$$

3. On the parameter sequence, make the least-squares estimation, $\hat{a} = [a,b]^T$, and attain Eqs. 6-9.

$$\hat{a} = (B^T B)^{-1} B^T Y \qquad (6)$$

Where

$$B = \begin{bmatrix} -Z^{(1)}(2) - Z^{(1)}(3)\ldots -Z^{(1)}(10) \\ 1 \quad 1 \quad \ldots \quad 1 \end{bmatrix} \qquad (7)$$

$$Z^{(1)}(k) = \delta x^{(0)}(k) + \delta x^{(0)}(k-1) \qquad (8)$$

Where $\delta = 0.5$

$$Y = [x^{(0)}(2), x^{(0)}(3), \ldots x^{(0)}(n)] \qquad (9)$$

Where $x^{(0)}(k) + az^{(1)}(k) = b$, the grey model (1,1) differential equation is basic forecasting equation.

4. Finding formulas for whitenization and time response for $x^{(1)}$, and developing Grey Model(1,1) prediction shown as Eqs. 10-12.

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \qquad (10)$$

$$\hat{X}^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)} + \frac{b}{a} \qquad (11)$$

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1) \qquad (12)$$

Where $-a$ represents the development coefficient, b represents grey action quantity, $\hat{X}^{(1)}$ describes the simulative value of $X^{(1)}$, and $\hat{X}^{(0)}$ describes the simulative value of $X^{(0)}$.

As a result, $x^{(1)}(1) = x^{(0)}(1)$, make I-AGO on $\hat{X}^{(1)}$, $\hat{X}^{(0)}$ can be obtained. Eqs. 10-12 are representations for the GM(1,1) model mathematical expressions.

2.3 The Grey Model (1,1) Precision Verification

The developed model through the above procedures can be ratified using different techniques. Posterior error, Residual error and Degree of grey association are among the most commonly applied methods to check and confirm the accuracy of Grey Model(1,1). With the recommendation of Huang et al. [24] and Lian et al. [25], this research prefers to use 'Posterior error' for model accuracy checking. The following are steps implemented in checking models.

Step 1: Finding for an average ($\bar{X}$) and root-mean-square error (S_1^2) for initial order values by Eqs. 13 and 14.

$$\bar{X} = \frac{1}{n}\sum_{k=1}^{n} X^{(0)}(k) \qquad (13)$$

$$S_1^2 = \frac{1}{n}\sum_{k=1}^{n} (X^{(0)}(k) - \bar{X})^2 \qquad (14)$$

Step 2: Finding for an average ($\bar{\epsilon}$) and root-mean-square error (S_2^2) of deviation errors (residual errors)

First we have to find the absolute residual, $\epsilon(k) = |X^{(0)}(k) - \hat{X}^{(0)}(k)|, k = 1,2,3 \cdots n$

$$\bar{\epsilon} = \frac{1}{n}\sum_{k=1}^{n} \epsilon^{(0)}(k) \qquad (15)$$

The residual variance S^2_2 is then find from Eq. 16.

$$S_2^2 = \frac{1}{n}\sum_{k=1}^{n} (\epsilon^{(0)}(k) - \bar{\epsilon})^2 \qquad (16)$$

Step 3: Finding for mean square deviation ratio C and small error probability p

$$C = \frac{s_2}{s_1} = \sqrt{\frac{s_2^2}{s_1^2}} \qquad (17)$$

The common formula used to verify the forecasting accuracy is Eq. 18.

$$P = p\{|\epsilon(k) - \bar{\epsilon}| < 0 \cdot 6745 S_1\} \qquad (18)$$

As can be seen from Table 1, the accuracy classes indicate that as p worth higher, probability of leading to a minor error gets larger; thus, when the C value is small, the p value becomes large; hence prediction accuracy

becomes nice. If C and p maintain within a permissible range, we can use Grey Model (1,1) for prediction.

Table 1

Model Evaluation Indicators (Adapted from ref. [5])

Precision Category	Posterior mean square deviation ratio, C	Small error probability, p
Best (1st)	<0.35	>0.95
Good (2nd)	0.35 - 0.5	0.95-0.8
Poor (3rd)	0.5 - 0.65	0.8-0.7
Very Poor (4th)	>0.65	<0.7

3. Energy Consumption Prediction with the Grey Model (1,1)

Using the procedures and steps described in section 2.2 GM(1,1) model for electric, oil products, solid biomass and total energy consumption have developed for the country based on the data of year 2008-2017 adopted from the Knoema library catalog [1]. With these the original sequence $X^{(0)}$ shown in Table 2 has developed.

In this case, we use the consumption of electric energy as an example to illustrate how these models are built and measured.

Table 2

Electric, oil products, solid biomass and total energy consumption data of Ethiopia from 2008 to 2017, (Unit: kilo-tons of oil equivalent (ktoe))

Year	Electrical energy	Oil products energy	Solid biomass energy	Total energy
2008	268	1795	27798	29870
2009	279	1800	28442	30547
2010	330	1904	29248	31513
2011	379	2084	30077	32645
2012	454	2206	30900	33699
2013	524	2545	31718	34966
2014	616	3049	32554	36469
2015	764	2989	33257	37263
2016	738	3453	34022	38537
2017	814	3803	34891	39865

The electrical energy consumption of Ethiopia from 2008 to 2017 is determined by using Eq. 1, when n=10, as follows.

$$X^{(0)} = x^{(0)}(1) + x^{(0)}(2), \ldots, x^{(0)}(10)$$

Similarly, IAGO values for $X^{(0)}$ are determined from Eq. 2 as follows.

$$X^{(1)} = x^{(1)}(1) + x^{(1)}(2), \ldots, x^{(1)}(10)$$

Based on Eq. 2 and the quasi-smoothness on $X^{(1)}$, we can achieve values for the following.

$$\sigma(3) \approx 1 \cdot 60; \sigma(4) \approx 1 \cdot 43; \sigma(5) \approx 1 \cdot 36;$$

$$\sigma(6)1 \cdot 31; \sigma(7) \approx 1 \cdot 28; \sigma(8) \approx 1 \cdot 27;$$

$$\sigma(9) \approx 1 \cdot 20; \sigma(10) \approx 1 \cdot 19;$$

When $k < 3, \rho(k) < 0 \cdot 5, \sigma(k) \in [1, 1 \cdot 5], \xi = 0.5, X^{(1)}$ meets the two criteria for the quasi-smoothness sequence and quasi-exponential order, it is possible to define GM(1,1). It is also possible to determine the immediate adjacent average value using Eq. 8.

$$Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(10))$$
$$= (408, 712, 1067, 1483, 1972, 2542, 3232, 3983, 4759)$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdot & \\ \cdot & \\ \cdot & \\ -z^{(1)}(9) & 1 \end{bmatrix} = \begin{bmatrix} -408 & 1 \\ -712 & 1 \\ -1067 & 1 \\ -1483 & 1 \\ -1972 & 1 \\ -2542 & 1 \\ -3232 & 1 \\ -3983 & 1 \\ -4759 & 1 \end{bmatrix}$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdot \\ \cdot \\ \cdot \\ x^{(0)}(10) \end{bmatrix} = \begin{bmatrix} 279 \\ 330 \\ 379 \\ 454 \\ 524 \\ 616 \\ 764 \\ 738 \\ 814 \end{bmatrix}$$

Then, the sequence of parameters could be further defined as follows.

$$\hat{a} = [a, b]^T = (B^T B)^{-1} B^T Y = \begin{bmatrix} -0.1287 \\ 256.0588 \end{bmatrix}$$

$$a = -0.1287$$

$$b = 256.0588$$

We get the GM(1,1) model according to Eq. 11 as follows.

$$\hat{X}^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)} + \frac{b}{a}$$

$$\hat{X}^{(1)}(k) = (268 - 256.0588/(-0.1287)) \\ * e^{-(-0.1287)(k-1)} \\ + 256.0588/(-0.1287)$$

$$\hat{X}^{(1)}(k) = 2258 * e^{(-0.1287)(k-1)} - 1990$$

The simulative value of $X^{(1)}$ can be found to be as follows.

$$\hat{X}^{(1)} = (x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(10))$$

$$= (268,578,931,1332,1788,2307,2897,3568,4332,5200)$$

Based on Eq. 12, an inverse accumulated generating operation on $\hat{x}^{(1)}$, enables attain the simulative value of $x^{(0)}$ as follows.

$$\hat{X}^{(0)} = (x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(10))$$

$$= (268,310,353,401,456,519,590,671,763,868)$$

Using 'posterior error' method described in section 2.3 and Eqs. 13-18, the electric energy consumption model is examined and can get the following.

$$\bar{X} \approx 517; S_1^2 \approx 38453 \cdot 44; \bar{\epsilon} \approx -3.4; S_2^2 \approx 1475 \cdot 35$$

Mean square deviation ratio is then given as under.

$$C = \frac{S_2}{S_1} \approx 0 \cdot 0.2 < 0.35;$$

Small error probability: $P = P\{|\epsilon(k) - \bar{\epsilon}| < 0 \cdot 6745 S_1\} = 1$

Table 3

Predicted energy in (ktoe) & deviations of Ethiopian electric energy utilization (1ktoe is equivalent to 11.63kWh)

S. No.	Year	Original quantity $x^{(0)}(k)$	Simulated quantity $\hat{X}^{(0)}(k)$	Absolute Error $\epsilon(k) = x^{(0)}(k) - \hat{x}^{(0)}(k)$	Relative Error $\Delta k = \frac{|\epsilon(k)|}{x^{(0)}(k)}$
1	2008	268	268	0	0%
2	2009	279	310	-31	11.1%
3	2010	330	353	-23	6.87%
4	2011	379	401	-22	5.83%
5	2012	454	456	-2	0.48%
6	2013	524	519	5	0.98%
7	2014	616	590	26	4.2%
8	2015	764	671	93	12.2%
9	2016	738	763	-25	3.44%
10	2017	814	868	-54	6.66%
				Average error	5.17%
				Model accuracy	94.83%

Using Table 1, precision of the established model is in a 2nd precision level, where it can qualify to be used for making prediction. Calculated values are shown in Table 3. Based on Ghalehkhondabi et al. [26], mid-long-term forecasting can be done using grey system as long as the development coefficient $-a$ is < 0.3. This implies that the model can be utilized to forecast the country's

electric energy utilization for the year 2020-2025. Findings from numerical manipulations using Eq. 6-9 in section 3, the development coefficient for the model becomes $-a = 0.1287 < 0.3$, and is given as under.

$$\hat{X}^{(0)} = (x^{(0)}(11), x^{(0)}(12), \ldots, x^{(0)}(18))$$

$$= (987,1123,1277,1453,1652,1879,2137,2431)$$

With a similar approach Grey Model (1,1) of the oil products, bio-fuels and the total energy consumption of Ethiopia for the years 2020 to 2025 has developed as the output results and are shown in Tables 2, 3, 4 and 6. The fitting curves of each prediction models are also indicated in Figs. 1, 3, 5 and 7.
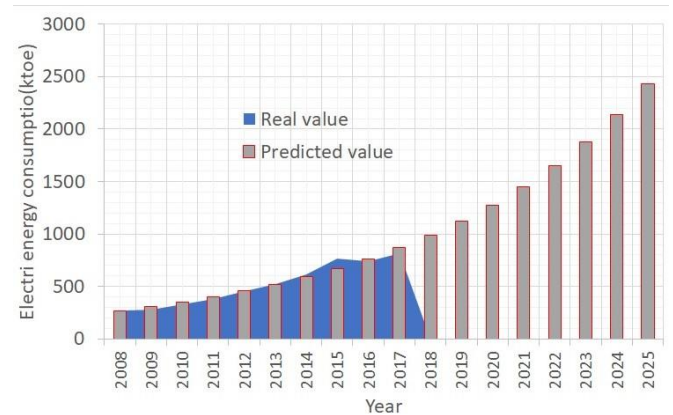

Fig. 1. Ethiopian electric energy utilization forecast

Table 4

Predicted energy in (ktoe) & deviations of Ethiopian oil-products energy utilization (1ktoe is equivalent to 11.63kWh)

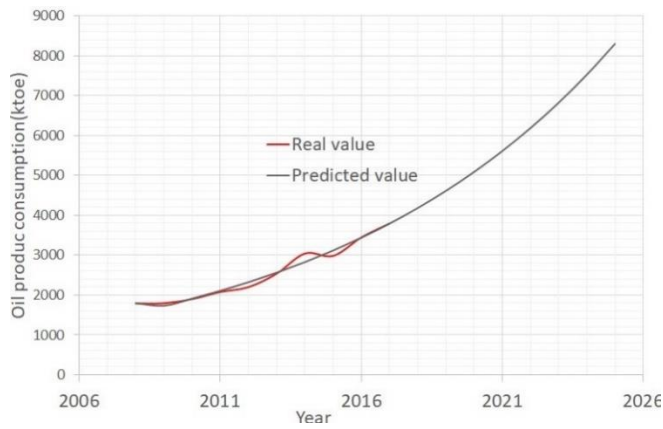| S. No.	Sample years	Real value $x^{(0)}(k)$	Prediction Value $\hat{X}^{(0)}(k)$	Absolute error $\epsilon(k) = x^{(0)}(k) - \hat{x}^{(0)}(k)$	Relative error $\Delta k = \frac{|\epsilon(k)|}{x^{(0)}(k)}$
1	2008	1795	1795	0	0%
2	2009	1800	1731	69	3.81%
3	2010	1904	1909	-5	0.28%
4	2011	2084	2106	-22	1.04%
5	2012	2206	2322	-116	5.27%
6	2013	2545	2561	-16	0.64%
7	2014	3049	2825	224	7.36%
8	2015	2989	3115	-126	4.22%
9	2016	3453	3436	17	0.51%
10	2017	3803	3789	14	0.37%
				Mean deviation	2.35%
				Precision	97.65%

Fig. 2. Ethiopian oil products energy consumption forecast

Table 5

Predicted energy in (ktoe) & deviations of Ethiopian solid biomass energy utilization (1ktoe is equivalent to 11.63 kWh)

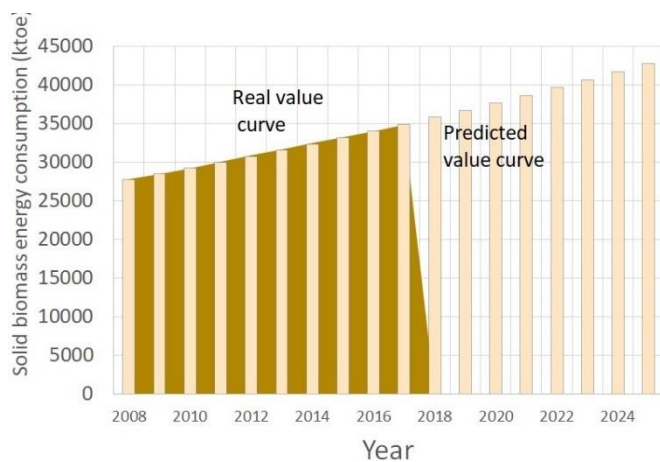| S. No.	Sample Years	Real Value $x^{(0)}(k)$	Prediction Value $\hat{X}^{(0)}(k)$	Absolute error $\epsilon(k) = x^{(0)}(k) - \hat{x}^{(0)}(k)$	Relative Error $\Delta k = \|\epsilon(k)\|x^{(0)}(k)$
1	2008	27798	27798	0	0%
2	2009	28442	28569	-127	0.45%
3	2010	29248	29301	-53	0.18%
4	2011	30077	30051	26	0.09%
5	2012	30900	30821	79	0.26%
6	2013	31718	31610	108	0.34%
7	2014	32554	32419	135	0.41%
8	2015	33257	33250	7	0.02%
9	2016	34022	34101	-79	0.23%
10	2017	34891	34974	-83	0.24%
			Mean deviation		0.22%
			Precision		99.78%

Fig. 3. GM (1,1) model forecast for Ethiopian solid biomass energy consumption

Table 6

Predicted energy in (ktoe) & deviations of Ethiopian total energy utilization (1ktoe is equivalent to 11.63 kWh)

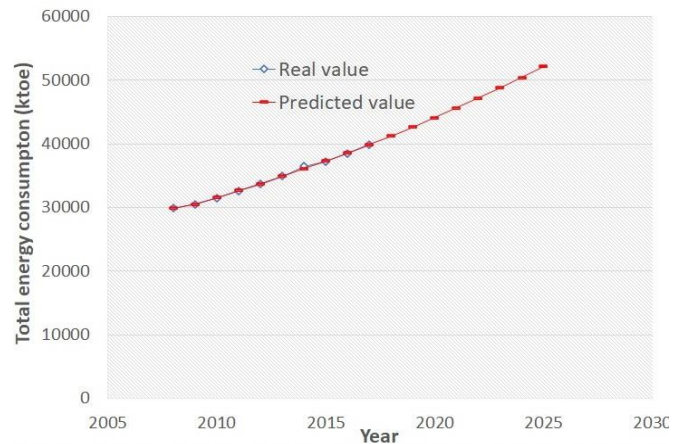| No.	Sample Years	Real Value $x^{(0)}(k)$	Prediction Value $\hat{X}^{(0)}(k)$	Absolute error $\epsilon(k) = x^{(0)}(k) - \hat{x}^{(0)}(k)$	Relative error $\Delta k = \|\epsilon(k)\|x^{(0)}(k)$
1	2008	29870	29870	0	0%
2	2009	30547	30548	-1	0.004%
3	2010	31513	31588	-75	0.24%
4	2011	32645	32662	-17	0.05%
5	2012	33699	33773	-74	0.22%
6	2013	34966	34922	44	0.13%
7	2014	36469	36110	359	1.0%
8	2015	37263	37339	-76	0.20%
9	2016	38537	38609	-72	0.19%
10	2017	39865	39922	-57	0.14%
			Mean Deviation		0.216%
			Precision		99.78%

Fig. 4. Total energy consumption forecast of Ethiopia developed with Grey Model (1,1)
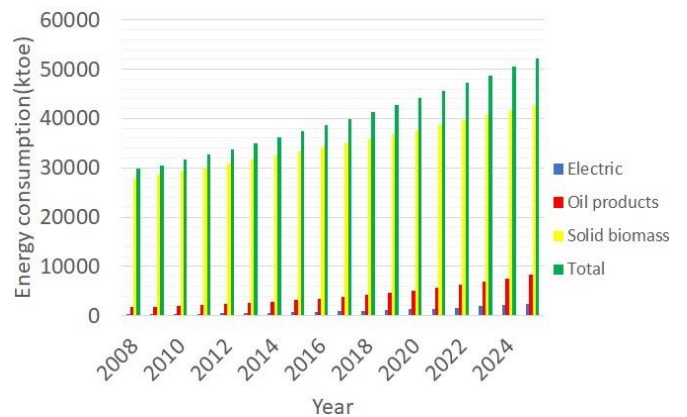

Fig. 5. Ethiopian energy consumption trend

Based on the utilization data of each energy types from the year 2008 to 2017, prediction models of the country's electric, oil, solid biomass and total energy respectively are developed for the coming six years as shown below.

$$X_1^{(1)}(k) = 2259e^{0.1287(k-1)} - 1990$$

$$X_2^{(1)}(k) = 16833e^{0.0979(k-1)} - 15038$$

$$X_3^{(1)}(k) = 1115587e^{0.02529(k-1)} - 1087789$$

$$X_4^{(1)}(k) = 897982e^{0.03345(k-1)} - 868112$$

4. Conclusion

In this study, electricity, oil products, solid biomass, and total energy consumption prediction of Ethiopia from 2020 to 2025 were made based on the grey model. Accordingly, the following conclusions are drawn.

The stimulative accuracy level of the forecasting models examined through the \posterior error" method found for electric, oil products, solid biomass and total energy are: 94.83%, 97.65%, 99.78% and 99.78 respectively. These stimulative accuracy level values except for electric energy consumption model all lie in the first precision level range. However, all the developed models met the standards for mid to long term prediction.

In comparison to the 2017 (last actual data used), findings indicate that electric, oil products, solid biomass, and the total energy consumption rise averagely at a rate of 24.83%, 14.75%, 2.84% and 3.86% respectively every single year. This rising pattern could possibly be due to the rapid population growth and the country's strive to attain the second growth and transformation plan. The findings from the forecast indicate that the country's energy structure seems to mainly depend on solid biomass energy sources followed as a secondly consumed energy of oil products.

The overall level of accuracy is higher as more initial data is acquired. In general, these prediction results can be used as references in providing information to the policy makers, and other concerned governmental and non-governmental sectors in charge, especially in establishing and adjusting the energy consumption structure in relation to the environmental and economic values.

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