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Comparison of Forecasting Energy Consumption in East Africa Using the MGM, NMGM, MGM-ARIMA, and NMGM-ARIMA Model

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Abstract: Forecasting energy demand is the basis for sustainable energy development. In recent years, the new discovery of East Africa's energy has completely reversed the energy shortage, having turned the attention of the world to the East African region. Systematic research on energy forecasting in Africa, particularly in East Africa, is still relatively rare. In view of this, this study uses a variety of methods to comprehensively predict energy consumption in East Africa. Based on the traditional grey model, this study: (1) Integrated the power coefficient and metabolic principles, and then proposed non-linear metabolic grey model (NMGM) forecasting model; (2) Used Auto Regressive Integrated Moving Average Model (ARIMA) for secondary modeling, and then developed a metabolic grey model-Auto Regressive Integrated Moving Average Model (MGM-ARIMA) and non-linear metabolic grey model-Auto Regressive Integrated Moving Average Model (NMGM-ARIMA) combined models. In terms of the prediction interval, the data for 2000–2017 is a fit to the past stage, while the data for 2018–2030 is used for the prediction of the future stage. To measure the effect of the prediction, the study used the average relative error indicator to evaluate the accuracy of different models. The results indicate that: (1) Mean relative errors of NMGM, MGM-ARIMA, and NMGM-ARIMA are 2.9697%, 2.0969%, and 1.4654%, proving that each prediction model is accurate; (2) Compared with the single model, the combined model has higher precision, confirming the superiority and feasibility of model combination. After prediction, the conclusion shows that East Africa's primary energy consumption will grow by about 4 percent between 2018 and 2030. In addition, the limitation of this study is that only single variable are considered.

Keywords: energy consumption forecasting; East Africa; power coefficient; linear and nonlinear model; new combined models

1. Introduction

Energy forecasting is the basis for countries and regions to develop energy development strategies and achieve sustainable energy using. Africa is rich in energy resources. In recent years, the new discovery of energy in East Africa has completely reversed the situation of energy shortage and put the energy industry on the track of rapid development. At the same time, the world has turned its attention to East Africa. However, most of the existing research on energy in Africa focuses on North Africa, Southern Africa and sub-Saharan Africa, which provides a gap for our research [1,2]. Therefore, a comprehensive analysis of East Africa's energy consumption by various methods will be helpful to the mastery of East Africa's energy in the future.

Taking East Africa as an example, this work forecasts the primary energy demand from 2018 to 2030 with the help of the primary energy consumption from 2000 to 2017 published by BP Statistical Review of World Energy 2018. Forecasting results will provide insights into rational allocation for existing resources in East Africa, which will be conducive to coping with future opportunities and challenges and formulating sustainable development strategies. In this paper, two categories and five methods are utilized to predict the primary energy demand in East Africa. First, NMGM (non-linear metabolic grey model) forecasting model is proposed by integrating the power coefficient and metabolic principles to grey model (GM) model. Then, based on the strategy of quadratic modeling, the combined metabolic grey model-Auto Regressive Integrated Moving Average Model (MGM-ARIMA) and non-linear metabolic grey model-Auto Regressive Integrated Moving Average Model (NMGM-ARIMA) models are developed. According to the forecasting results of various methods, the future energy consumption in East Africa will be more comprehensively reflected.

The structure of this paper is as follows: the second section mainly reviews the research on energy forecasting in Africa and the development and application of GM and ARIMA Model. The third section mainly explains the prediction principles and steps of the five methods. The fourth section shows the actual prediction process and related parameters. Fifth section summarizes the entire paper.

2. Literature Review

This section begins with a review and discussion of African energy forecasting studies. Then the development of Grey model and ARIMA model and related applications in recent years are discussed. Finally, based on the above analysis, this section gives a summary of the existing literature.

2.1. Review of Energy Research in Africa

For the whole of Africa, Mulugetta et al. [3] made an economic assessment of biodiesel and studied the energy transition [4]. Sanoh et al. [5] analyzed the optimal project for supplying electricity to national economies by using high voltage lines. Mentis et al. [6] assessed the potential of wind energy technology. Ouedraogo et al. [7] studied the long-term sustainable electricity supply and demand. In addition, other scholars have studied the issue of renewable energy technologies [8] and development [9]. Besides, energy research in Africa is generally carried out by region, i.e., North Africa, West Africa, East Africa, Central Africa, Southern Africa, and sub-Saharan Africa.

For North Africa, Tsikalakisa et al. [10] studied the best way of use solar energy in MENA countries [11]. Lacher et al. [12] discussed potential threats to energy security and the development of renewable energy plans. For West Africa, Gnansounoua [13] discussed the prospects for the development of the West African electric power industry. Lee and Leal [14] provided a systematic review of the energy planning (EP) activities being conducted in the Economic Community of West African States (ECOWAS). Ameyaw et al. [15] predicted and discussed the relationship between CO_2 Emissions and GDP in five West African countries. For East Africa, James [16] discussed energy transformation in rural. Tigabu et al. [17] analyzed technology innovation systems (TIS) by comparing Kenya with Rwanda. For middle Africa, Kenfack et al. [18] used Cameroon as an example to discuss renewable energy and energy efficiency in Central Africa.For Southern Africa, there are relatively few studies. Conway et al. [19,20] discussed the relevance between climate and water–energy–food. Then they studied hydroelectric plans in Southern and Eastern Africa.Rafeya et al. [21] studied the implications of the Medupi coal-fired power plant in South Africa Fant et al. [22] assessed the impact of climate change on wind and solar energy resources. For sub-Saharan Africa, Bazilian et al. [23] used long-term forecasting methods to forecast installed generation capacity. Esso [24] studied the relationship between threshold cointegration, causality, energy use and growth. Al-mulali [25] and Kivyiroab et al. [26] studied the relationship between energy consumption and CO2 emissions and economic growth, respectively. Asumadu-Sarkodie et al. [27] forecasted Nigeria's energy consumption by an econometric approach. Emodia et al. [28] explored the relationship between energy supply and demand and carbon emissions from 2010 to 2040. Another researcher studied the relationship between Nigeria's carbon dioxide emissions and GDP [29]. Wu et al. [30] predicted South Africa's carbon dioxide emissions. Lebotsa et al. [31] tested the forecasting model using South Africa's electricity consumption and made a prediction of short-term electricity demand. Sigauke et al. [32] predicted daily peak load demand in South Africa. Moreover, scholars have studied the price and income elasticity of South Africa's oil import demand [33], the economic growth and Electricity consumption [34].

In summary, a review of the literature on energy forecasting in Africa reveals that there is relatively more energy research in North Africa and sub-Saharan Africa and less systematic research on primary energy consumption projections in East Africa.

2.2. Review of Grey Model

The grey theory, first put forward by Professor Deng [35], is the theory that some of the information is unclear and has an uncertain phenomenon. The resulting Grey Model is commonly used in the field of prediction. Xie et al. [36] used grey model to predict China's energy demand and self-sufficiency rate. Mao [37] used GM (1,1) in vehicle fatality risk estimation and got accurate prediction. Jouini et al. [38] applied GM(1,1) model to forecast historical medical sensor data towards system preventive in smart home e-health for elderly person. Jiang et al. [39] applied grey model to the operating energy performance of air cooled water chillers. Although GM is widely used in forecasting, there is room for improvement. As for the GM model, the data obtained by the prediction are not fully utilized. Therefore MGM (grey model of metabolism) improved the grey model according to the principle of metabolic, added the latest predicted data into the original data for grey prediction again, and so on to obtain the predicted value of the target. At present, it is also commonly used in the field of prediction. Wang et al. [40] applied GM and MGM to forecast the consumption of coal in the US. Truong et al. [41] studied the feasibility of applying MGM (1,1) to real-time control of wave energy converters (WECs). Tang et al. [42] combined MGM with BP neural network to construct a tandem Grey Neural Network model for load forecasting of smart grid. Lee et al. [43] used MGM model and GM model to evaluate air quality in traffic tunnels. Wang et al. [44] applied MGM to forecast future energy consumption in China and India. Akay et al. [45] used Grey prediction with rolling mechanism (GPRM) to forecast the Turkey's total and industrial electricity consumption. Kumar et al. [46] used a variety of models to predict India's energy consumption. Among them, MGM was used to predict India's coal consumption. Despite the fact that MGM models are used more in energy prediction, they become inaccurate when the time series is nonlinear. By adding the power factor β to the MGM model, a new model, the non-linear metabolic grey model (NMGM), has been created. It is a nonlinear prediction method, which obtains both linear and nonlinear prediction results by proper adjustment of power coefficient, so that the results are more accurate. Today, energy forecasting is widely available. Wang et al. [47] established the NMGM model and applied it to the prediction of shale oil production in the United States and compared with other three model [48]. Later, NMGM served several times in the field of energy forecasting [49].

Furthermore, other researchers have enhanced the Grey model. For instance:Lee et al. [50] combined genetic programming with grey model to improve the grey model. Bahrami et al. [51] used PSO (particle swarm optimization) algorithm to improve the grey model and used the model to forecast the short-term electric load. Ding et al. [52] improved grey model byalterable weighted coefficients and rolling mechanism. Chen [53] investigates forecasting by using novel nonlinear grey bernoulli model (NGBM). Xu et al. [54] proposed a adaptive grey model with buffered rolling method. Zeng et al. [55] proposed a new multivariate grey model by combining multivariate grey model with univariate grey model. Li et al. [56] used BP (Back Propagation) to improve the NMGM model. To sum up, after years of development, the grey model has been optimized in more and more ways, and the prediction effect has become better and better.

2.3. Review of ARIMA Model

ARIMA Model is recognized as Autoregressive Integrated Moving Average Model and abbreviated as ARIMA. It is a famous time series prediction method proposed by Box and Jenkins in the early 1970s [57]. The basic idea of the ARIMA model is to process the data sequence formed by the predicted object into a random sequence over time, which is roughly described by a precise mathematical model.

Once identified, the model can predict future values from the past and present values of the time series. Nowadays, ARIMA model is applicable to ecological, economic, energy and other aspects of time series prediction. In terms of ecology, Kumar et al. [58] applied ARIMA to the prediction of atmospheric pollutants (Ozone, carbon monoxide, nitric oxide, nitrogen dioxide) and could effectively predict short-term atmospheric pollutants. Nieto et al. [59] used four models to predict PM10 concentration, including ARIMA. Aasim et al [60] proposed combined repeated wavelet transform and ARIMA to forecast short-term wind speed. S. Swain et al. [61] applied ARIMA to forecast Monthly Rainfall. On the economic front, Nyangarika et al. [62] used the modified ARIMA model to predict oil prices. Prasad et al. [63] applied ARIMA model to the prediction of India's total export value. Hossain et al. [64] used ARIMA to forecast the prices of motor, mash and mung. For energy, Edigera et al. [65] used ARIMA to forecast Turkey's primary energy consumption and found that the ARIMA forecasting of the total primary energy demand appears to be more reliable than the summation of the individual forecasts. Musaylh et al. [66] used ARIMA to forecast short-term electricity demand in Australia. Jiang [67] take advantage of ARIMA to calculate China's coal consumption and price from 2016 to 2030. Mehedintu et al. [68] used five single methods to predict the share of renewable energy consumption in total consumption in 2020, including ARIMA model. It can be seen that ARIMA model is widely used, and the accuracy of prediction results is also accepted by researchers. Because the application of ARIMA model has been paid a lot of attention, so many researchers have made optimization and improvement of the ARIMA model. For instance, Wang et al. [69] combined ARIMA with MNGM to establish the MNGM-ARIMA model that produced more accurate forecasting results. Ludlow and Enders [70] found that a non-linear time-series can be represented by a deterministic time-dependent coefficient model without first specifying the nature of the non-linearity. Chen et al. [71] proposed a nonlinear ARIMA model based on SVR (support vector regression). Zhang et al. [72] combined EEMD and ARIMA to establish the EEMD-ARIMA model to predict hotel daily occupancy rate, which has obvious advantages in short-term prediction Celestino et al. [73] combined ARIMA and SVM models for the remaining useful life of aircraft engines forecasting. Lee et al. [74] combined ARIMA model with genetic programming to improve both models and commit the effectiveness of the new model. Baraka and Sadegh [75] proposed a hybrid ARIMA-ANFIS (Adaptive Neuro Fuzzy Inference System) algorithm which based on three different pattern. Dindarloo [76] compared ARIMA and ANN (Artificial Neural Network). Daz-Roblesa et al. [77] combined ARIMA with ANN (Artificial Neural Network) to predict particulate matter in urban areas. Wang et al. [78] combined ARIMA with ANN to forecast shale gas monthly production in Pennsylvania and Texas of the United States and compared with single model and the result of application shows the advantages of this method. Zhang et al. [79] improved MEEMD-ARIMA model by using PE. Matyjaszek et al. [80] used the full time series, GRNN (generalized regression neural network) models to improve ARIMA model. These improvements make ARIMA's predictions more convincing.

Although GM and ARIMA model have been widely used in real life, there is still room for improvement. Therefore, the model needs to be strengthened to get more accurate predictions. At present, there are roughly three improved methods. First, put together a few single models to predict and compare prediction accuracy, and finally put the results together to show or select the most accurate model. Secondly, the theory of single model is improved. For example, the MGM model, the NMGM model. Third, the combination of more than two models complements the advantages to achieve more accurate results.

Based on this, this study has the following contributions: (1) From the existing research, it was found that the systematic prediction of energy resources in East Africa is a gap. This study predicts primary energy demand in East Africa from 2018 to 2030. The forecasting results will be helpful for a comprehensive understanding of the current energy situation in East Africa and for the prospects of energy development.

(2) For more accurate prediction, various prediction methods have been developed and used in this study. On the one hand, NMGM (non-linear metabolic grey) forecasting model was proposed

by integrating the power coefficient and metabolic principles to GM model. On the other hand, the improved grey model and ARIMA model are combined by the strategy of secondary modeling, thus resulting in MGM-ARIMA and NMGM-ARIMA models.

3. Method

This section will detail the operation of five models used to predict primary energy consumption in East Africa one by one. Five are MGM, NMGM, ARIMA MGM-ARIMA, and NMGM-ARIMA, of which the latter two models are combinations of the first three models. The relevant formulas and steps will be presented. In addition, a formula for measuring the prediction accuracy of the five models is attached at the end of this section.

For ease of understanding, Table 1 presents the meaning of the relevant symbols in the formulas.

Table 1. Meaning of the symbols in the formula.

Notation	Explanation	Notation	Explanation
$X^{(0)}(k)$	Raw sequence	ε_t	Error term of initial data
$X^{(1)}(k)$	Once accumulated sequence	θ_i	Harmonic parameter
$\hat{X}^{(0)}(k)$	Prediction of Raw sequence	B	Matrix of data and constants
$\hat{X}^{(1)}(k)$	Prediction of 1-AGO sequence	d	Order of the data sequence
t	Time sequence	p	Order of auto -regression
D	Matrix of data and constants	q	Order of moving average
C_n	Matrix of data	$E^{(0)}(1)$	Initial residual sequence
a	Constant parameter	$E^{*(0)}(1)$	Predicted residual sequence
b	Constant parameter	$X_t^*(i)$	Corrected forecasts
β	Power coefficients	n	Sample size
Y_t	Initial data sequence	$y(i)$	Fitting value
Y_t^*	Predicted data sequence	$x(i)$	Truth value
μ	Constant term		

3.1. MGM Model

MGM model is a shorthand for metabolic grey model. This method uses the obtained data sequence to establish the grey differential equation. The objective is to obtain the law of these data and predict the future data. Assume that the original data sequence is: $X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \ldots, X^{(0)}(n)\}$. In most cases, the original data's rules are not obvious, and cannot be directly used for modeling. For the sake of getting a more stable time series data, we accumulate it and get the once accumulated sequence (1-AGO): $X^{(1)} = \{X^{(1)}(1), X^{(1)}(2), X^{(1)}(3), \ldots, X^{(1)}(n)\}$. Among them, $X^{(1)} = \sum_{i=1}^{m} X^{(1)}(i), k = 1,2,3\ldots n$.

After that, the following differential equation is established by means of the obtained cumulative sequence:

$$\frac{dX}{dt} + aX^{(1)}(t) = b \tag{1}$$

For differential Equation (1), the cumulative matrix D, constant term C_n and the values of 'a' and 'b' are obtained by using the least square method. The construction results are as follows:

$$D = \begin{bmatrix} -\frac{1}{2}\left(X^{(1)}(1) + X^{(1)}(2)\right) & 1 \\ -\frac{1}{2}\left(X^{(1)}(2) + X^{(1)}(3)\right) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left(X^{(1)}(n-1) + X^{(1)}(n)\right) & 1 \end{bmatrix} \tag{2}$$

$$C_n = \begin{bmatrix} X^{(0)}(2) & X^{(0)}(3) & \cdots & X^{(0)}(n) \end{bmatrix}^{\mathrm{T}} \tag{3}$$

$$\left[\begin{array}{c} a \\ b \end{array}\right] = \left(D^T D\right)^{-1} D^T C_n \quad (4)$$

Put the calculated value of "a" and "b" into the Equation (1) to get the result. Since the results are also cumulative sequences, the predicted values are obtained by cumulative subtraction.

The forecast is calculated as follows:

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1)(k = 2, 3, 4 \cdots n) \quad (5)$$

3.2. NMGM Model

The NMGM model is called the nonlinear metabolic grey model, which is a nonlinear prediction method and an improvement of MGM. The difference between NMGM and MGM is the addition of power factor "β". When the data is non-linear, MGM becomes inaccurate. Therefore, by properly adjusting the power coefficient, the results will be more accurate when considering linearity and nonlinearity. In general, grey predictions are calculated using 4 to 10 data, and here are five data for convenience. Suppose the original time series data is: $X = \{X(1)\, X(2)\, \cdots\, X(n)\}$. The steps of the calculation are as follows:

i. Extract 5 pieces of data from the original data:

$$X^{(0)} = \{X^{(0)}(i) X^{(0)}(i+1) X^{(0)}(i+2) \cdots X^{(0)}(i+4)\}\ i = (1, 2, \cdots n-4) \quad (6)$$

ii. Get the cumulative sequence:

$$X^{(1)} = \{X^{(1)}(1) \quad X^{(1)}(2) \quad \cdots \quad X^{(1)}(n)\} \quad (7)$$

Based on (7), get the linear addition sequence:

$$Z^{(1)}k = \frac{1}{2}(X^{(1)}(k-1) + X^{(1)}(k)) \quad (8)$$

iii. On the basis of (7) and (8), the differential equations of NMGM are as follows:

$$X^{(0)}(k) + a(z^{(1)}(k))^{\beta} = b \quad (9)$$

$$\frac{dX^{(1)}}{dt} + a(X^{(1)}(t))^{\beta} = b \quad (10)$$

After the differential equations are listed, the following equations are used to solve them:

$$D = \left[\begin{array}{cc} -\left(z^{(1)}(2)\right)^{\beta} & 1 \\ -\left(z^{(1)}(3)\right)^{\beta} & 1 \\ \vdots & \vdots \\ \left(z^{(1)}(n)\right)^{\beta} & 1 \end{array}\right] \quad (11)$$

$$C_n = \left[\begin{array}{cccc} X^{(0)}(2) & X^{(0)}(3) & \cdots & X^{(0)}(n) \end{array}\right]^T \quad (12)$$

$$\beta = \left[\begin{array}{c} a \\ b \end{array}\right] = \left(D^T D\right)^{-1} D^T C_n \quad (13)$$

Referring to the fourth-order Runge–Kutta, the equation is

$$\frac{dX}{dt} = F(t, X) \quad (14)$$

$$\begin{cases} L_1 = F(t_n, X_n) \\ L_2 = F(t_n + \frac{h}{2}, X_n + \frac{h}{2}L_1) \\ L_3 = F(t_n + \frac{h}{2}, X_n + \frac{h}{2}L_2) \\ L_4 = F(t_n + h, X_n + hL_3) \\ X_{n+1} = X_n + \frac{h}{6}(L_1 + 2L_2 + 2L_3 + L_4) \end{cases} \tag{15}$$

iv. The cumulative sequence of the predicted value can be obtained from the iii, and the predicted values are obtained by deducting it. The formula is as follows:

$$\hat{X}^{(0)}(k+1) = \hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k) \tag{16}$$

3.3. ARIMA Model

The principle of ARIMA is to transform the non-stationary time series into stationary time series, and then return its lag value and random error term and establish a model. In fact, ARIMA model consists of auto-regressive (AR) model and moving average (MA) model. On the one hand, AR can describe the relationship between the current value and the historical value. On the other hand, the historical time data of the variable itself can also be used to estimate and predict itself. The MA model is devoted to the accumulation of error terms from the regression model, which can effectively eliminate the random fluctuations in the prediction.

The p-order autoregressive formula AR (p) is:

$$Y_t^* = \mu + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t \tag{17}$$

Where the ε_t is the error term.

The q-order moving average formula is MA(q) for:

$$Y_t^* = \varepsilon_t - \theta_1 Y_{t-1} - \theta_2 Y_{t-2} - \cdots - \theta_p Y_{t-p} \tag{18}$$

By combining AR (p) and MA (q), the autoregressive average moving formula ARMA (p, q) is obtained as follows:

$$Y_t^* = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \theta_0 \varepsilon_t - \theta_1 Y_{t-1} - \theta_2 Y_{t-2} - \cdots - \theta_p Y_{t-p} + \mu_t \tag{19}$$

Firstly, aiming to meet the requirement of stability, the order in which the time series becomes smooth is denoted as "d". Secondly, the two specific parameters related to AR and MA are "p" and "q". "P" is called autoregressive term, and "q" is called moving average term. Therefore, the ARIMA model can be written as ARIMA (p, d, q). In addition, set the original time series as $Y_t = [Y^{(0)}(1)\, Y^{(0)}(2) \cdots Y^{(0)}(n)]$. The forecast result is $Y_t^* = [Y^{(1)}(1)\, Y^{(1)}(2) \cdots Y^{(1)}(n)]$. In the process of solving the Equation (19), it is found that Y_t^* can be represented by Y_t, the specific formula is as follows:

$$Y_t^* = (1-B)^d Y_t \tag{20}$$

$$B = \begin{bmatrix} -\frac{1}{2}\left(Y^{(1)}(1) + Y^{(1)}(2)\right) & 1 \\ -\frac{1}{2}\left(Y^{(1)}(2) + Y^{(1)}(3)\right) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left(Y^{(1)}(n-1) + Y^{(1)}(n)\right) & 1 \end{bmatrix} \tag{21}$$

3.4. MGM-ARIMA and NMGM-ARIMA Model

Based on three single MGM, NMGM, and ARIMA models, this study conducted a combination of models and proposed MGM-ARIMA and NMGM-ARIMA. The principle is to use the MGM and

NMGM for initial forecasting, and then recalibrate the error series by ARIMA, so as to reduce the error and get more accurate prediction results. Therefore, the prediction steps for combining models include three parts. First of all, the predicted value is obtained and then the error is corrected and new error sequence is obtained. Finally, the novel predicted value can be obtained by subtracting the predicted value obtained by MGM from the new relative error time series.

For ease of understanding, set the error series to be: $E^{(0)} = \{E^{(0)}(1)\,E^{(0)}(2)\,\cdots\,E^{(0)}(2)\}$

The corrected error is: $E^{*(0)} = \{E^{*(0)}(1)\,E^{*(0)}(2)\,\cdots\,E^{*(0)}(n)\}$

Figure 1 shows this process.

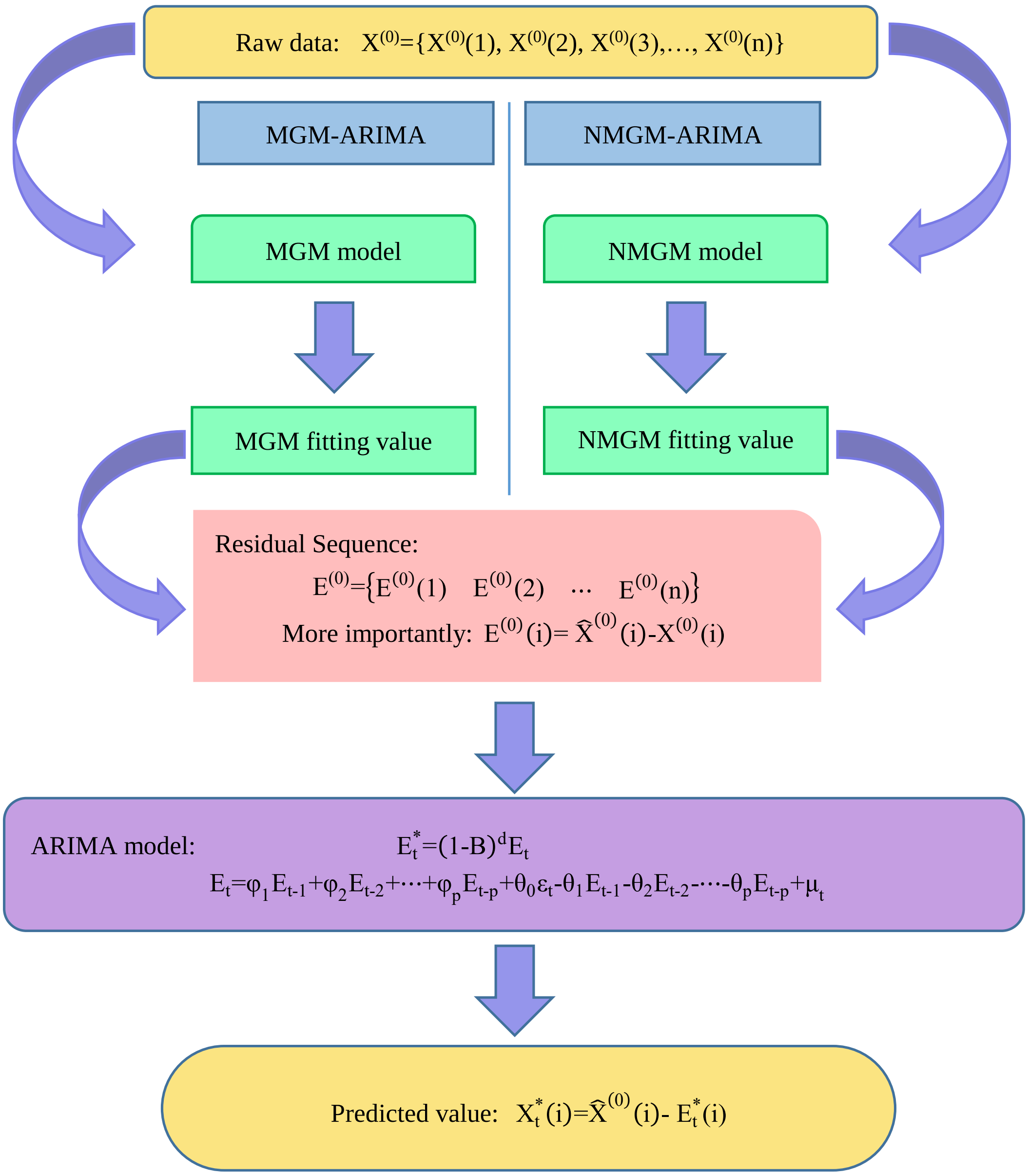

Figure 1. The Forecasting Process of metabolic grey model-Auto Regressive Integrated Moving Average Model (MGM-ARIMA) and non-linear metabolic grey model (NMGM)-ARIMA.

3.5. The Comparison of Five Models and Formulas for Measuring Accuracy

Based on the interpretation of these five methods, the conclusions shown in Table 2 are derived. Besides, mean absolute per error (MAPE) is used to measure the accuracy of the model. The formula is Equation (22).

Table 2. The comparison of five models.

	Difference		Feature	
	Principle	**Data trend**	**Advantages**	**Disadvantages**
MGM	Differential equation Model	Linear	Sample; Does not need regularity and large numbers; Add metabolic principle to the modeling of GM model	Cannot reflect the non-linearity of data series
NMGM	Differential equation Model	Non-Linear	Sample; Does not need regularity and large numbers; Add metabolic and none-linear principles to the modeling of GM model	The Positive and negative fluctuations of the error are too large
ARIMA	Differential auto regressive moving average Model	Linear	The mathematical requires only endogenous variables without resorting to exogenous variables	Determination of model parameters is complicated; Non-linear relationship cannot be reflected; Require timing data to be stable
MGM-ARIMA	Cover two principle of MGM and ARIMA	Linear	Use ARIMA model to correct the fluctuations of NMGM model; Wider application range	Non-linear relationship cannot be reflected; More steps than a single model
NMGM-ARIMA	Cover two principle of NMGM and ARIMA	Cover Linear and Non-Linear	Use ARIMA model to correct the fluctuations of NMGM model; Combine linearity with None-linearity; Wider application range	The effects of multiple variables on predictors cannot be considered; More steps than a single model
Similarity		Forecast period: Short and Medium term The number of variables: Univariate		

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{y(i)-x(i)}{x(i)} \tag{22}$$

Accordingly, the predicted goodness can also be calculated based on the relative error. The formula is as follows:

$$\text{Goodness} = 1 - \text{APE} = 1 - \frac{|\text{Prediction-True value}|}{\text{True value}} \tag{23}$$

4. Empirical Results and Discussion

Figure 2 shows the primary energy consumption in East Africa and the growth rates from 2000 to 2017 (data from the BP Statistical Review of World Energy 2018). The data demonstrates that the overall trend in primary energy consumption in East Africa is increasing. Since 2008, the overall trend has remained relatively stable.

Built on the explanation of Figure 2. This section mainly demonstrates the prediction process of the five models, MGM, NMGM, ARIMA, MGM-ARIMA, and NMGM-ARIMA, the generation of relevant parameters and the fitting data. In addition, after the fitting results are obtained, the accuracy of the five models is analyzed and compared with the original data. Then make a forecast of the energy consumption of East Africa from 2018 to 2030.

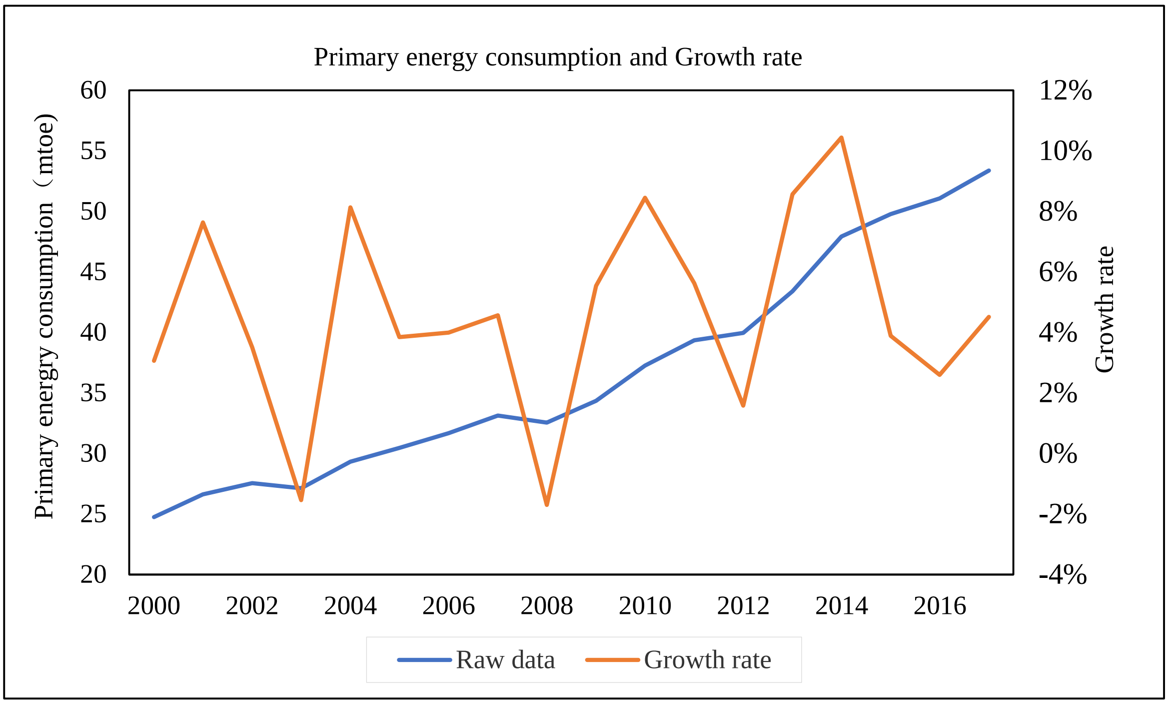

Figure 2. Primary energy consumption (Unit: mtoe) and growth rate in East Africa from 2000 to 2017.

4.1. Forecasting Process of MGM Model

Using the raw data, first step adds up to a cumulative time series. As shown in Figure 3, the cumulative processing of the data becomes more stable.

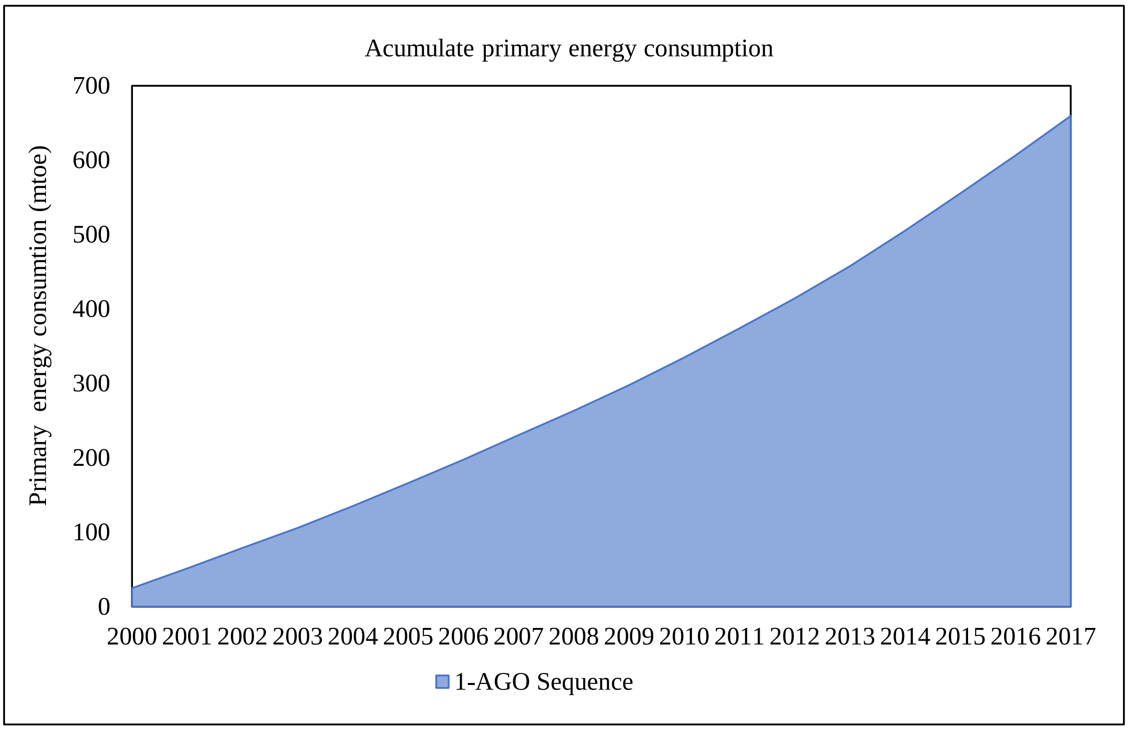

Figure 3. 1-AGO Sequence of primary energy consumption in Eastern Africa.

In the second step, the accumulated sequence is used to establish the differential equation, and as mentioned in Equation (4), the parameters "a" and "b" are calculated by the least square method, as shown in Table 3.

Table 3. The value of MGM Parameters in 2005-2030.

	2005	2006	2007	2008	2009	2010	2011
a	−0.0281	−0.0386	−0.0495	−0.0405	−0.0239	−0.0228	−0.0423
b	25.4265	25.4278	25.4351	27.5843	29.7357	30.746	30.15
	2012	2013	2014	2015	2016	2017	2018
a	−0.0649	−0.0495	−0.0479	−0.0695	−0.0744	−0.0511	−0.035
b	29.2509	32.4913	34.6235	34.3844	35.9062	41.2347	45.5445
	2019	2020	2021	2022	2023	2024	2025
a	−0.035	−0.0364	−0.035	−0.0357	−0.0357	−0.0353	−0.0355
b	47.056	48.4787	50.5573	52.2065	54.1031	56.1414	58.1107
	2026	2027	2028	2029	2030		
a	−0.0353	−0.0353	−0.0354	−0.0353	−0.0353		
b	60.2676	62.4286	64.6446	66.9892	69.4027		

Next, this study used the values of parameters "a" and "b" obtained and EXCEL to obtain the fitting value and predicted value.

4.2. Forecasting Process of NMGM Mode

As described in the method, the actual operation process of NMGM's prediction is generally divided into two steps. In the first step, the five data of the original time series are operated to get the fitting value from 2000 to 2017 through the cycle. The second step is to use the data from 2013 to 2017 to get the predicted value for 2018, and then put the predicted value of 2018 into the original data, namely metabolism. In other words, the predicted value needs to be used as the known data and used for prediction to get the predicted value of 2018 to 2030.

As mentioned above, a series of power coefficient "β" values can be obtained by using Matlab R2018b, the same goes for a and b. as shown in Table 4. "β", "a" and "b" values in the table can be used to obtain the fitting values and predicted values.

Table 4. The value of NMGM Parameters in 2005–2030.

Year	**β**	**a**	**b**	**Year**	**β**	**a**	**b**
2005	1	−0.0281	25.4256	2018	1.023	−0.0305	45.642
2006	1	−0.0386	25.4278	2019	1.434	−0.0028	48.44
2007	0.131	−16.8519	−0.223	2020	0.962	−0.0508	47.8173
2008	1	−0.0405	27.5843	2021	1.274	−0.0078	51.3491
2009	0.001	−2.1175	−2.095	2022	0.95	−0.059	51.3057
2010	0.151	−6.5919	19.9396	2023	1.19	−0.0135	55.1413
2011	1	−0.0423	30.15	2024	0.959	−0.0583	55.7161
2012	1	−0.0649	29.2509	2025	1.142	−0.0185	59.7007
2013	0.001	−4.8584	−4.8429	2026	0.973	−0.0551	60.8656
2014	1	−0.0479	34.6235	2027	1.112	−0.0228	64.9779
2015	1	−0.0695	34.3844	2028	0.987	−0.0517	66.715
2016	0.621	−0.7374	30.7245	2029	1.092	−0.0263	70.9873
2017	0.001	−6.3232	−6.3056	2030	0.999	−0.0489	73.2918

4.3. Forecasting Process of ARIMA Model

ARIMA model requires smooth raw data. To stabilize the data, the unit root test, autocorrelation function (ACF) and partial autocorrelation function (PACF) can be the tool. In this work, Eviews 7 was used to obtain the order of the difference required, that is, the value of "d". As shown in Table 5, the first-order difference is performed on the original data. If the test value is less than three critical values, data series pass the square root test. Therefore, the value of "d" is determined to be 1.

Table 5. Square root test results of first-order difference.

		t-Statistic	Prob.*
Augmented Dickey-Fuller Test Statistic		**−4.8604**	**0.0080**
Test critical values:	1% level	−4.7284	
	5% level	−3.7597	
	10% level	−3.3250	

Since the value of "d" is 1, the autocorrelation function diagram and partial autocorrelation function diagram are drawn by using Eviews 7, as shown in Figure 4. The autocorrelation function graph and partial correlation function diagram of the original time series under the difference of order 1 show that neither of the two functions has the characteristic of 0 after a certain order, and neither of them has the property of censoring, but has the property of trailing. According to the model selection rules, ARIMA model should be selected for prediction.

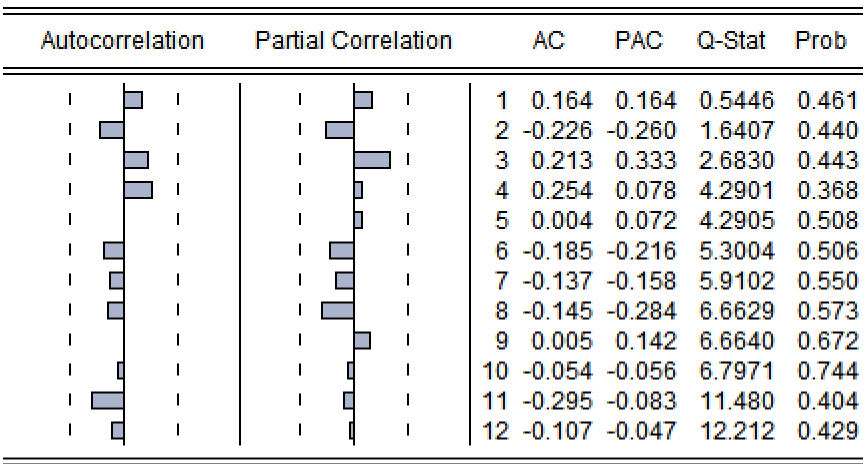

Figure 4. Autocorrelation (AC) and partial autocorrelation (PAC) coefficients.

Next step requires to determine the values of "p" and "q" parameters, aiming to minimize the error of the prediction results. In this step, ARIMA modeler of time series model in IBM SPSS statistics is used to model. In order to obtain more accurate fitting value, the optimal model with high fitting accuracy is selected by referring to the following principles: First, the higher the fixed value R2 is, the better the fitting degree is; Second, the larger the decision coefficient R2 is, the better the fitting degree of the model is; Third, the larger the root mean square error (RMSE) is, the greater the degree of data dispersion is, the worse the fitting degree of the model is, the lower the reliability is. Fourth, the smaller the maximum absolute prediction error MAPE is, the better the fitting degree of the model is. After repeated experiments, the final selected ARIMA (11,1,2). The data required for judgment is shown in Table 6.

Table 6. Parameters of the goodness of fit for the ARIMA (11,1,2) Model.

Model	Number of Predictors	Model Fit Statistics			
		Stationary R-Squared	R-Squared	RMSE	MAPE
ARIMA (11,1,2)	1	0.643	0.993	2.13	1.59

4.4. Forecasting Process of MGM-ARIMA Model

The first step of MGM-ARIMA is to obtain the residual by subtracting the original data from the fitted values obtained from MGM model. After calculation, the fitting values, original data and absolute errors of MGM are shown in Table 7.

Table 7. Relative error based on MGM fitting.

Year	Raw Data	Fitting Value Obtained by MGM	Residual
2000	24.7252	24.7252	0.0000
2001	26.6129	26.4917	0.1212
2002	27.5444	27.2467	0.2977
2003	27.1190	28.0232	0.9042
2004	29.3231	28.8218	0.5012
2005	30.4504	29.6432	0.8072
2006	31.6666	31.4755	0.1911
2007	33.1097	33.4884	0.3787
2008	32.5465	34.4190	1.8725
2009	34.3482	33.8933	0.4549
2010	37.2472	34.8381	2.4091
2011	39.3385	38.0948	1.2437
2012	39.9579	42.0569	2.0990
2013	43.3790	42.6155	0.7634
2014	47.9040	44.9973	2.9066
2015	49.7643	50.5590	0.7947
2016	51.0530	54.2879	3.2349
2017	53.3564	54.4711	1.1147

In the second step, the ARIMA model is used to correct the residual. Firstly, the difference is used to stabilize the relative error. The square root test results are shown in Table 8. We found that the zero-order difference of the relative error has already passed the square root test, so the original error is stable without difference, that is, "d" is 0.

Table 8. Square root test of zero order differential of MGM relative error.

Augmented Dickey–Fuller Test Statistic		t-Statistic	Prob.*
		−6.4376	**0.0005**
Test critical values:	1% level	−4.6679	
	5% level	−3.7332	
	10% level	−3.3103	

Based on the above analysis, the autocorrelation function diagram and part of autocorrelation function diagram are drawn by using "d" value through Eviews 7, as shown in Figure 5. It can be seen that under the first-order difference of the original time series, the autocorrelation function graph and the partial correlation function graph neither has the characteristics of zero after a certain order, nor has the truncation property, but has the trailing property. According to the model selection rules, ARIMA model is selected.

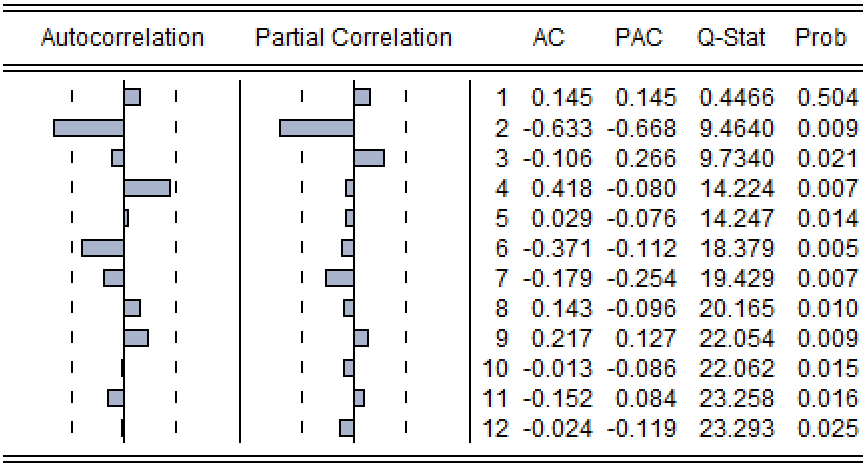

Figure 5. Autocorrelation (AC) and Partial Autocorrelation coefficients (PAC) of MGM-ARIMA.

To get more accurate results, the ARIMA model of time series model in data mining and analysis tool IBM SPSS statistics is used to model, and after continuous testing, MGM-ARIMA (3, 0, 9) model is selected, and the required data is shown in Table 9. For comparison, we put the relative error of MGM and corrected error into Figure 6. Figure 6 shows that the relative error of MGM becomes smoother after correction by the ARIMA model, indicating that the MGM-ARIMA model is more accurate than the MGM model.

Table 9. Parameters of the goodness of fit for the MGM-ARIMA (3,0,9).

Model	Number of Predictors	Model Fit Statistics			
		Stationary R-Squared	**R-Squared**	**RMSE**	**MAPE**
MGM-ARIMA (3,0,9)	1	0.703	0.703	1.697	73.033

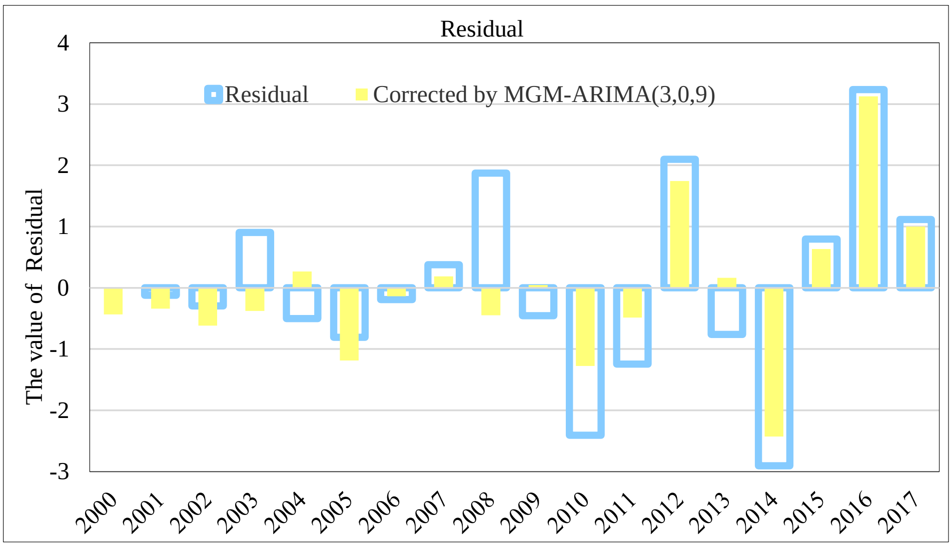

Figure 6. Comparison between the residual of MGM fitting results and the corrected residual.

4.5. Forecasting Process of NMGM-ARIMA Model

As shown in the method, the NMGM-ARIMA model is like the prediction process of the MGM-ARIMA model. Therefore, the prediction process is as follows: first step is to obtain the NMGM-ARIMA residual time series. The fitting value, raw data, and residuals of NMGM are calculated as shown in Table 10.

Table 10. Residual based on NMGM model.

Year	Raw Data	Fitting Value Obtained by NMGM	Residual
2000	24.7252	24.7252	0.0000
2001	26.6129	26.4926	−0.1203
2002	27.5444	27.2482	−0.2962
2003	27.1190	28.0253	0.9063
2004	29.3231	28.8246	−0.4985
2005	30.4504	29.6467	−0.8037
2006	31.6666	31.4718	−0.1948
2007	33.1097	32.5918	−0.5179
2008	32.5465	34.4112	1.8647
2009	34.3482	33.4706	−0.8776
2010	37.2472	34.3667	−2.8805
2011	39.3385	38.0857	−1.2528
2012	39.9579	42.0644	2.1065
2013	43.3790	41.3733	−2.0057
2014	47.9040	44.9876	−2.9164
2015	49.7643	50.5522	0.7879
2016	51.0530	53.2581	2.2051
2017	53.3564	52.8345	−0.5219

In the second step, ARIMA is used to correct the residuals. First, the difference makes the residual stable. The residual of first-order differential has passed the square root test, that is, "d" for 1. Square root test results as shown in Table 11.

Table 11. Square root test of first order differential of NMGM residual.

Augmented Dickey-Fuller Test Statistic		t-Statistic	Prob.*
		−5.4485	**0.0037**
Test critical values:	1% level	−4.8001	
	5% level	−3.7912	
	10% level	−3.3423	

Based on the above analysis, "d" value is used to draw autocorrelation function and partial autocorrelation function. As shown in Figure 7, the autocorrelation function and partial correlation function graphs of the original time series under first order difference show that the two functions are not truncated after a certain period but have tailing property.

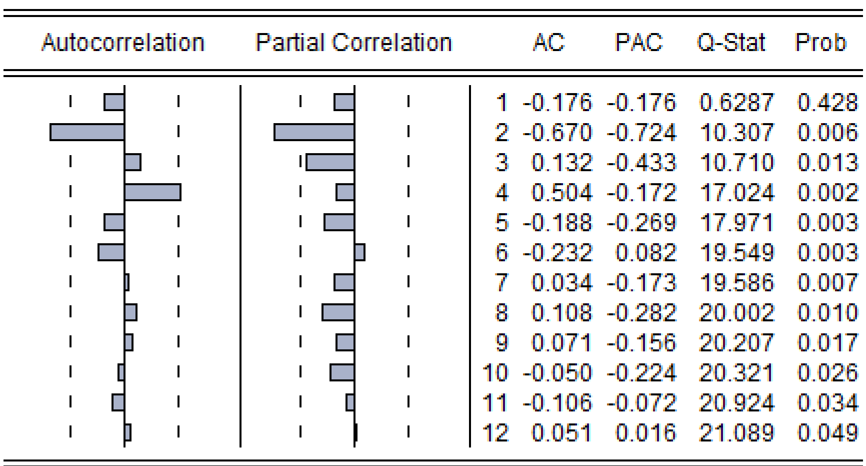

Figure 7. Autocorrelation (AC) and Partial autocorrelation coefficients of NMGM-ARIMA.

Analogous to MGM-ARIMA, in order to obtain more accurate results, the ARIMA modeler of the time series model in IBM SPSS statistics was used for modeling. After continuous testing, the NMGM-ARIMA (4,1,1) model was finally selected, and the required data was determined in Table 12. To facilitate comparison, we put the residual of NMGM and the corrected error into Figure 8. Figure 8 shows that the residuals of NMGM becomes more stable after the correction of ARIMA model.

Table 12. Parameters of the goodness of fit for the NMGM-ARIMA (4,1,1).

Model	Number of Predictors	Model Fit Statistics			
		Stationary R-Squared	R-Squared	RMSE	MAPE
NMGM-ARIMA(4,1,1)	1	0.752	0.496	1.374	89.307

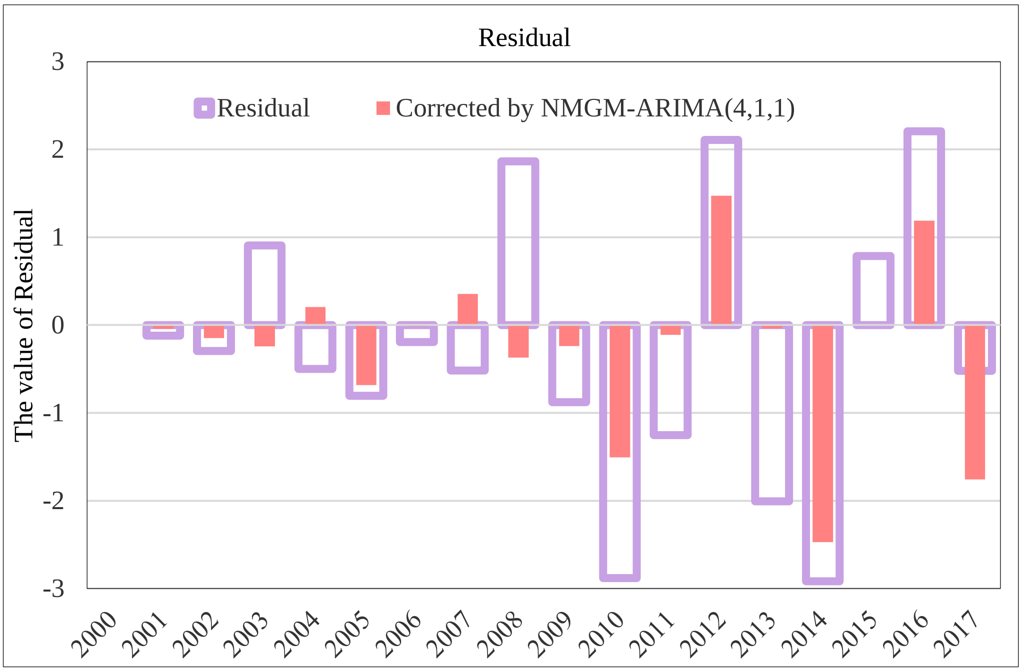

Figure 8. Comparison between the residual of NMGM fitting results and the corrected residual.

4.6. Comparison of Fitting Results by Multiple Model

This section compares the accuracy of the five models and analyzes the performance of the five models, as well as the advantages of the combined model over the single model. Table 13 shows the fitting results of five models. Figures 9 and 10 shows our comparative results.

Table 13. Fitting results of five models (Unit:mtoe).

Year	Raw Data	MGM Fitting Value	NMGM Fitting Value	ARIMA (11,1,2) Fitting Value	MGM-ARIMA (3,0,9) Fitting Value	NMGM-ARIMA (4,1,1) Fitting Value
2000	24.7252	24.7252	24.7252	24.7252	24.2885	24.7252
2001	26.6129	26.4917	26.4926	25.5111	26.2707	26.5720
2002	27.5444	27.2467	27.2482	27.5392	26.9254	27.3952
2003	27.1190	28.0232	28.0253	27.9491	26.7398	26.8756
2004	29.3231	28.8218	28.8246	28.1713	29.5874	29.5278
2005	30.4504	29.6432	29.6467	31.4469	29.2630	29.7684
2006	31.6666	31.4755	31.4718	31.0226	31.5284	31.6552
2007	33.1097	33.4884	32.5918	32.9752	33.2940	33.4650
2008	32.5465	34.4190	34.4112	34.5129	32.0962	32.1749
2009	34.3482	33.8933	33.4706	34.8919	34.3922	34.1104
2010	37.2472	34.8381	34.3667	37.2656	35.9700	35.7398
2011	39.3385	38.0948	38.0857	39.1968	38.8543	39.2275
2012	39.9579	42.0569	42.0644	39.7740	41.7028	41.4293
2013	43.3790	42.6155	41.3733	43.2524	43.5410	43.3391
2014	47.9040	44.9973	44.9876	48.0133	45.4742	45.4348
2015	49.7643	50.5590	50.5522	49.3779	50.3979	49.7744
2016	51.0530	54.2879	53.2581	51.2035	54.1787	52.2417
2017	53.3564	54.4711	52.8345	53.3972	54.3555	51.5983

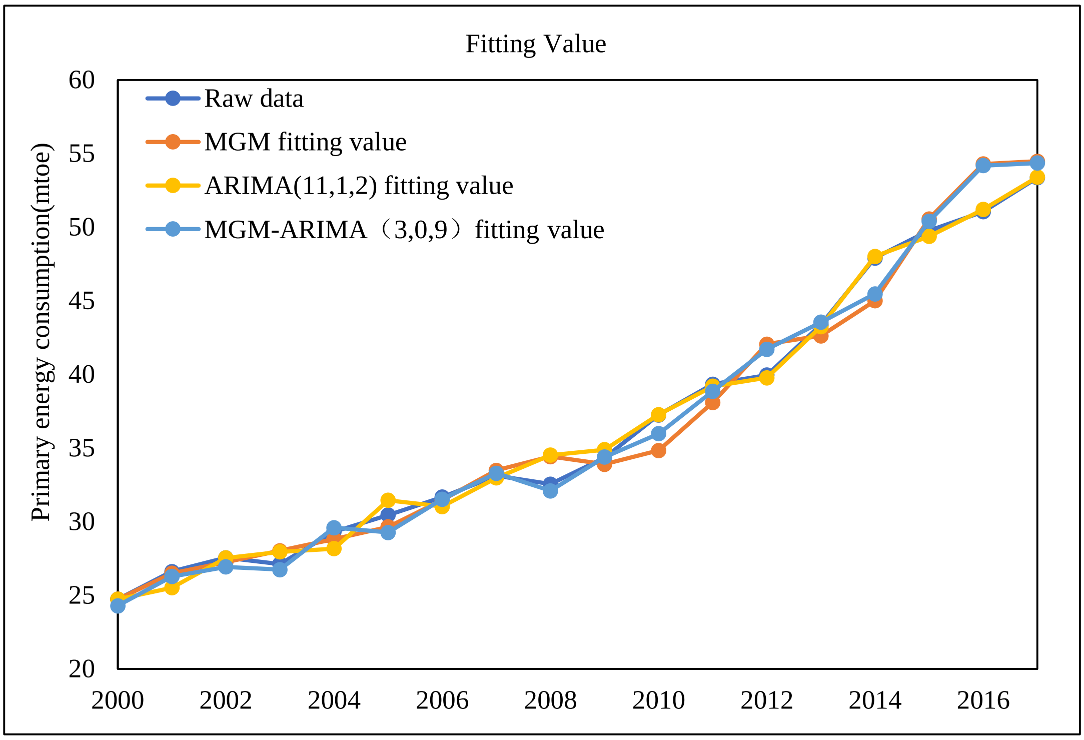

Figure 9. Comparison of MGM and MGM-ARIMA.

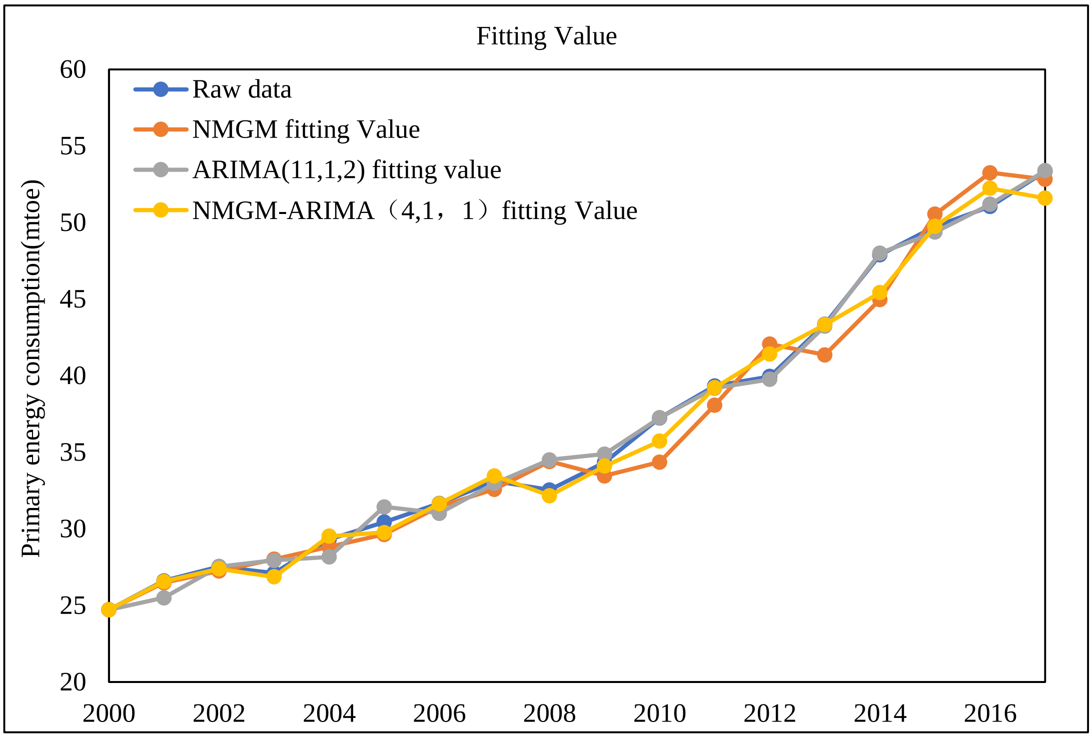

Figure 10. Comparison of NMGM and NMGM-ARIMA.

It can be seen roughly from Figures 7 and 8 that the deviation of MGM and NMGM is reduced after being corrected by ARIMA model at some points, which shows that it is reasonable and effective to use ARIMA to correct MGM and NMGM. In other words, the combined model is more accurate than the single model. As can be seen from Figure 9, there are not many differences between the absolute fit of the five models and the raw data. In order to see the accuracy of the five models more accurately, we explain them using formulas. First of all, as mentioned in the Method part, the MAPE of five models is calculated by using Excel. As show in Table 14, firstly, the accuracy of NMGM-ARIMA is the highest, followed by MGM-ARIMA and ARIMA, and finally MGM and NMGM; secondly, the combined model does improve the accuracy of a single grey model. Thirdly, criteria of MAPE is shown as Table 15, which is also the standard of the acceptability of the forecasting error. And the MAPE of the five models is lower than 5%, which shows that the five models are quite reliable.

Table 14. Error of Five Models.

	MGM	MGM-ARIMA(3,0,9)	ARIMA(11,1,2)	NMGM	NMGM-ARIMA(4,1,1)
MAPE	2.8216%	2.0969%	1.5013%	2.9697%	1.4654%

Table 15. Criteria of mean absolute per error (MAPE).

MAPE (%)	Forecasting Power
<10	Excellent
10–20	Good
20–50	Reasonable
>50	Incorrect

Finally, the prediction errors of each model are calculated by formula (22). The accuracy of the five models is shown in Figure 11. As can be seen from the chart, although the accuracy of all models varies every year, it still exceeds 90%. This shows that these five models are very accurate and can be used for prediction.

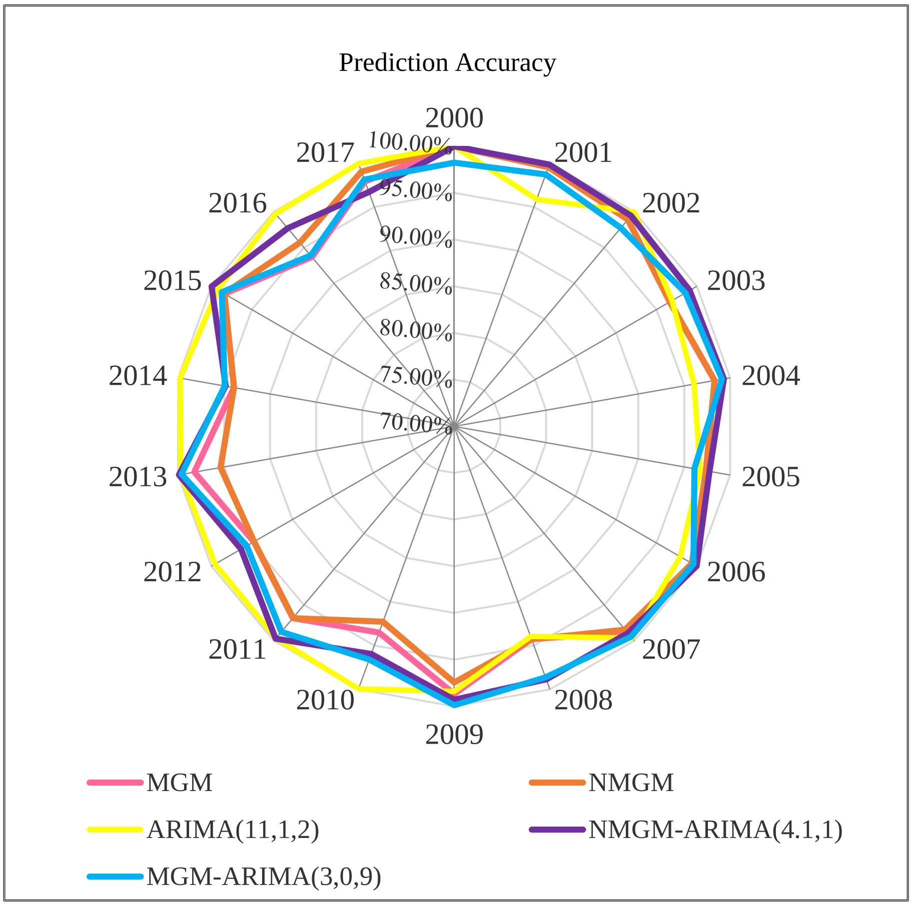

Figure 11. Goodness of fit for Five Models at different time points.

4.7. Prediction Results

From the above analysis, the prediction results obtained by these five models have high accuracy. In this paper, the primary energy consumption in East Africa from 2018 to 2030 can be predicted Table 16 shows the forecast results of the five models. Figure 12 shows the predicted results of the five models.

Table 16. Primary energy forecast results for East Africa (Unit: mtoe).

	MGM	NMGM	ARIMA(11,1,2)	MGM-ARIMA(3,0,9)	NMGM-ARIMA (4,1,1)
2018	55.0936	55.1227	55.7106	56.5922	58.0108
2019	57.0484	57.7738	57.6927	56.8401	58.3880
2020	59.2440	59.9616	59.5321	57.2969	58.8521
2021	61.2762	62.9231	61.4511	60.0575	63.6027
2022	63.5449	65.5126	64.7580	64.2203	67.7430
2023	65.8450	68.7909	70.1049	66.1489	69.6403
2024	68.1709	71.7930	73.7653	66.7320	71.3927
2025	70.6477	75.4205	76.2181	69.0905	76.1446
2026	73.1826	78.8638	80.8147	72.9075	80.6821
2027	75.8097	82.8894	85.9204	75.8358	83.8636
2028	78.5456	86.8177	88.5782	77.5107	86.9145
2029	81.3472	91.3016	90.4780	79.7870	92.0956
2030	84.2788	95.7718	94.2071	83.3983	97.3364

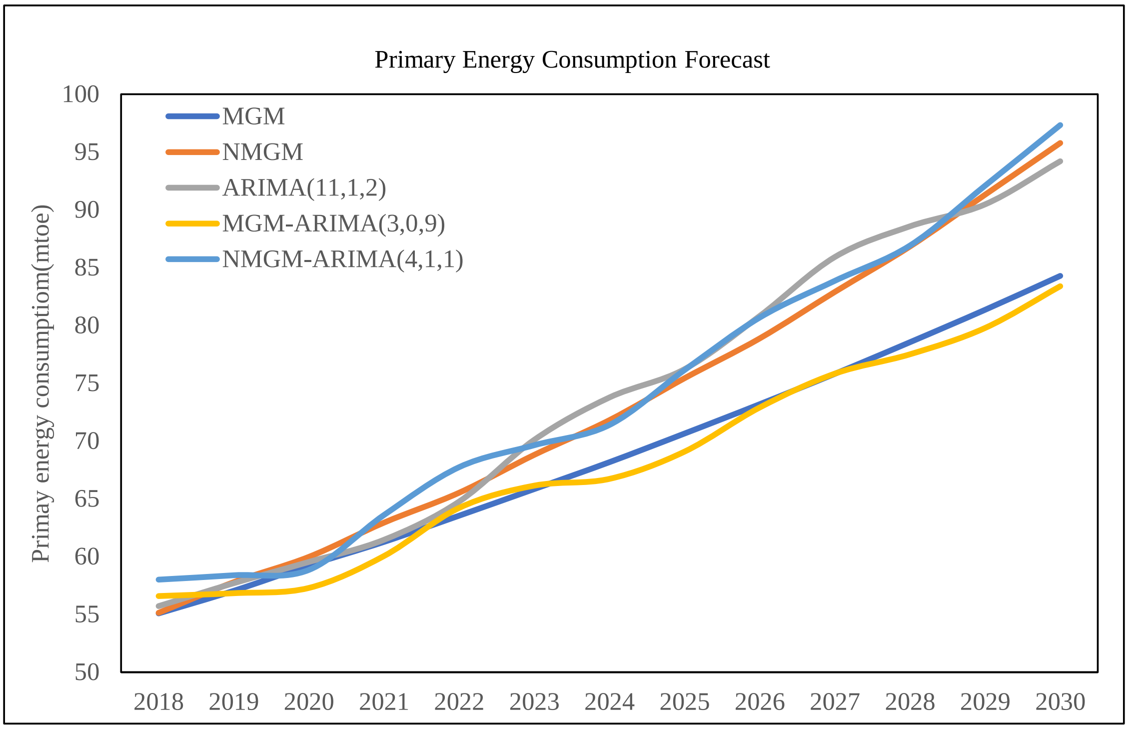

Figure 12. Outcomes of five models for predicting future primary energy consumption in East Africa.

5. Conclusions

In this paper, the primary energy demand of East Africa in the next 13 years is predicted by virtue of BP Statistical Review of World Energy 2018. The main conclusions (findings) are as follows:

(1) In this study, five methods (MGM, NMGM, ARIMA, MGM-ARIMA, and NMGM-ARIMA) are used to fit the primary energy consumption of East Africa from 2000 to 2017. On the one hand, the average relative errors of the five models are 2.8216%, 2.9697%, 1.5013%, 2.0969%, and 1.4654%, respectively. The average relative errors of the five models are all less than 3%. This shows that the five models are suitable for prediction and can produce reliable prediction information. On the other hand, compared with MGM and NMGM models, the average relative errors of models after ARIMA correction decreased from 2.8216%, 2.9697% to 2.0969%, 1.4624%, which showed the advantages of the combined model respectively.

(2) This work studies the future trend of primary energy consumption in East Africa. According to the fitting results of five models, future average growth rate of primary energy demand in East Africa is about 4% in the future. In short, this means that the demand for primary energy in East Africa will continue to increase from 2018 to 2030, and East Africa has great potential in energy market.

In addition, the results showed that MGM is more accurate than NMGM that may be explained by the linearity of raw data, whilst there are some cusps that means nonlinearity. But after ARIMA correction, the NMGM-ARIMA is more accurate than MGM-ARIMA. The results show that NMGM-ARIMA is an improvement of MGM-ARIMA and MGM when data is nonlinear. And further research is needed on the application and improvement of MGM and NMGM.

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References

1. Madubansi, M.; Shackleton, C. Changing energy profiles and consumption patterns following electrification in five rural villages, South Africa. *Energy Policy* **2006**, *34*, 4081–4092. [CrossRef]
2. Inglesi-Lotz, R. The evolution of price elasticity of electricity demand in South Africa: A Kalman filter application. *Energy Policy* **2011**, *39*, 3690–3696. [CrossRef]
3. Mulugetta, Y. Evaluating the economics of biodiesel in Africa. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1592–1598. [CrossRef]
4. Sokona, Y.; Mulugetta, Y.; Gujba, H. Widening energy access in Africa: Towards energy transition. *Energy Policy* **2012**, *47*, 3–10. [CrossRef]
5. Sanoh, A.; Kocaman, A.S.; Kocal, S.; Sherpa, S.; Modi, V. The economics of clean energy resource development and grid interconnection in Africa. *Renew. Energy* **2014**, *62*, 598–609. [CrossRef]
6. Mentis, D.; Hermann, S.; Howells, M.; Welsch, M.; Siyal, S.H. Assessing the technical wind energy potential in Africa a GIS-based approach. *Renew. Energy* **2015**, *83*, 110–125. [CrossRef]
7. Ouedraogo, N.S. Modeling sustainable long-term electricity supply-demand in Africa. *Appl. Energy* **2017**, *190*, 1047–1067. [CrossRef]
8. Barry, M.L.; Steyn, H.; Brent, A. Selection of renewable energy technologies for Africa: Eight case studies in Rwanda, Tanzania and Malawi. *Renew. Energy* **2011**, *36*, 2845–2852. [CrossRef]
9. Schwerhoff, G.; Sy, M. Financing renewable energy in Africa—Key challenge of the sustainable development goals. *Renew. Sustain. Energy Rev.* **2017**, *75*, 393–401. [CrossRef]
10. Tsikalakis, A.; Tomtsi, T.; Hatziargyriou, N.; Poullikkas, A.; Malamatenios, C.; Giakoumelos, E.; Jaouad, O.C.; Chenak, A.; Fayek, A.; Matar, T.; et al. Review of best practices of solar electricity resources applications in selected Middle East and North Africa (MENA) countries. *Renew. Sustain. Energy Rev.* **2011**, *15*, 2838–2849. [CrossRef]
11. Komendantova, N.; Patt, A.; Barras, L.; Battaglini, A. Perception of risks in renewable energy projects: The case of concentrated solar power in North Africa. *Energy Policy* **2012**, *40*, 103–109. [CrossRef]
12. Lacher, W.; Kumetat, D. The security of energy infrastructure and supply in North Africa: Hydrocarbons and renewable energies in comparative perspective. *Energy Policy* **2011**, *39*, 4466–4478. [CrossRef]
13. Gnansounou, E.; Bayem, H.; Bednyagin, D.; Dong, J. Strategies for regional integration of electricity supply in West Africa. *Energy Policy* **2007**, *35*, 4142–4153. [CrossRef]
14. Lee, N.; Leal, V. A review of energy planning practices of members of the Economic Community of West African States. *Renew. Sustain. Energy Rev.* **2014**, *31*, 202–220. [CrossRef]
15. Ameyaw, B.; Yao, L. Analyzing the Impact of GDP on CO2 Emissions and Forecasting Africa's Total CO2 Emissions with Non-Assumption Driven Bidirectional Long Short-Term Memory. *Sustainability* **2018**, *10*, 3110. [CrossRef]
16. Murphy, J.T. Making the energy transition in rural East Africa: Is leapfrogging an alternative? *Technol. Forecast. Soc. Chang.* **2001**, *68*, 173–193. [CrossRef]
17. Tigabu, A.D.; Berkhout, F.; Van Beukering, P. The diffusion of a renewable energy technology and innovation system functioning: Comparing bio-digestion in Kenya and Rwanda. *Technol. Forecast. Soc. Chang.* **2015**, *90*, 331–345. [CrossRef]
18. Kenfack, J.; Fogue, M.; Hamandjoda, O.; Tatietse, T.T. Promoting renewable energy and energy efficiency in Central Africa. In Proceedings of the World Renewable Energy Congress-Sweden, Linköping, Sweden, 8–13 May 2011; pp. 2602–2609.
19. Conway, D.; Van Garderen, E.A.; Deryng, D.; Dorling, S.; Krueger, T.; Landman, W.; Lankford, B.; Lebek, K.; Osborn, T.; Ringler, C.; et al. Climate and southern Africa's water–energy–food nexus. *Nat. Clim. Chang.* **2015**, *5*, 837. [CrossRef]
20. Conway, D.; Dalin, C.; Landman, W.A.; Osborn, T.J. Hydropower plans in eastern and southern Africa increase risk of concurrent climate-related electricity supply disruption. *Nat. Energy* **2017**, *2*, 946–953. [CrossRef]
21. Rafey, W.; Sovacool, B.K. Competing discourses of energy development: The implications of the Medupi coal-fired power plant in South Africa. *Glob. Environ. Chang.* **2011**, *21*, 1141–1151. [CrossRef]
22. Fant, C.; Schlosser, C.A.; Strzepek, K. The impact of climate change on wind and solar resources in southern Africa. *Appl. Energy* **2016**, *161*, 556–564. [CrossRef]

23. Bazilian, M.; Nussbaumer, P.; Rogner, H.H.; Brew-Hammond, A.; Foster, V.; Pachauri, S.; Williams, E.; Howells, M.; Niyongabo, P.; Musaba, L.; et al. Energy access scenarios to 2030 for the power sector in sub-Saharan Africa. *Util. Policy* **2012**, *20*, 1–16. [CrossRef]
24. Esso, L.J. Threshold cointegration and causality relationship between energy use and growth in seven African countries. *Energy Econ.* **2010**, *32*, 1383–1391. [CrossRef]
25. Al-Mulali, U.; Sab, C.N.B.C. The impact of energy consumption and CO2 emission on the economic growth and financial development in the Sub Saharan African countries. *Energy* **2012**, *39*, 180–186. [CrossRef]
26. Kivyiro, P.; Arminen, H. Carbon dioxide emissions, energy consumption, economic growth, and foreign direct investment: Causality analysis for Sub-Saharan Africa. *Energy* **2014**, *74*, 595–606. [CrossRef]
27. Asumadu-Sarkodie, S.; Owusu, P.A. Forecasting Nigeria's energy use by 2030, an econometric approach. *Energy Sources Part B Econ. Plan. Policy* **2016**, *11*, 990–997. [CrossRef]
28. Emodi, N.V.; Emodi, C.C.; Murthy, G.P.; Emodi, A.S.A. Energy policy for low carbon development in Nigeria: A LEAP model application. *Renew. Sustain. Energy Rev.* **2017**, *68*, 247–261. [CrossRef]
29. Rafindadi, A.A. Does the need for economic growth influence energy consumption and CO2 emissions in Nigeria? Evidence from the innovation accounting test. *Renew. Sustain. Energy Rev.* **2016**, *62*, 1209–1225. [CrossRef]
30. Wu, L.; Liu, S.; Liu, D.; Fang, Z.; Xu, H. Modelling and forecasting CO2 emissions in the BRICS (Brazil, Russia, India, China, and South Africa) countries using a novel multi-variable grey model. *Energy* **2015**, *79*, 489–495. [CrossRef]
31. Lebotsa, M.E.; Sigauke, C.; Bere, A.; Fildes, R.; Boylan, J.E. Short term electricity demand forecasting using partially linear additive quantile regression with an application to the unit commitment problem. *Appl. Energy* **2018**, *222*, 104–118. [CrossRef]
32. Sigauke, C.; Chikobvu, D. Daily peak electricity load forecasting in South Africa using a multivariate non-parametric regression approach. *ORiON* **2010**, *26*. [CrossRef]
33. Ziramba, E. Price and income elasticities of crude oil import demand in South Africa: A cointegration analysis. *Energy Policy* **2010**, *38*, 7844–7849. [CrossRef]
34. Odhiambo, N.M. Electricity consumption and economic growth in South Africa: A trivariate causality test. *Energy Econ.* **2009**, *31*, 635–640. [CrossRef]
35. Deng, J. *Grey System Fundamental Method*; Huazhong University of Science and Technology: Wuhan, China, 1982.
36. Xie, N.M.; Yuan, C.Q.; Yang, Y.J. Forecasting China's energy demand and self-sufficiency rate by grey forecasting model and Markov model. *Int. J. Electr. Power Energy Syst.* **2015**, *66*, 1–8. [CrossRef]
37. Kang, J.; Zhao, H. Application of Improved Grey Model in Long-term Load Forecasting of Power Engineering. *Syst. Eng. Procedia* **2012**, *3*, 85–91. [CrossRef]
38. Jouini, R.; Lemlouma, T.; Maalaoui, K. Employing Grey Model forecasting GM (1, 1) to historical medical sensor data towards system preventive in smart home e-health for elderly person. In Proceedings of the 12th International Wireless Communications & Mobile Computing Conference, Paphos, Cyprus, 5–9 September 2016; pp. 1086–1091.
39. Jiang, Y.; Yao, Y.; Deng, S.S.; Ma, Z. Applying grey forecasting to predicting the operating energy performance of air cooled water chillers. *Int. J. Refrig.* **2004**, *27*, 385–392. [CrossRef]
40. Wang, Q.; Li, S.; Li, R. Will Trump's coal revival plan work?-Comparison of results based on the optimal combined forecasting technique and an extended IPAT forecasting technique. *Energy* **2019**, *169*, 762–775. [CrossRef]
41. Truong, D.; Ahn, K.K. Wave prediction based on a modified grey model MGM(1,1) for real-time control of wave energy converters in irregular waves. *Renew. Energy* **2012**, *43*, 242–255. [CrossRef]
42. Tang, N.; Zhang, D.J. Application of a Load Forecasting Model Based on Improved Grey Neural Network in the Smart Grid. *Energy Procedia* **2011**, *12*, 180–184. [CrossRef]
43. Lee, C.C.; Wan, T.J.; Kuo, C.Y.; Chung, C.Y. Modified Grey Model for Estimating Traffic Tunnel Air Quality. *Environ. Monit. Assess.* **2007**, *132*, 351–364. [CrossRef]
44. Wang, Q.; Li, S.; Li, R. Forecasting energy demand in China and India: Using single-linear, hybrid-linear, and non-linear time series forecast techniques. *Energy* **2018**, *161*, 821–831. [CrossRef]
45. Akay, D.; Atak, M. Grey prediction with rolling mechanism for electricity demand forecasting of Turkey. *Energy* **2007**, *32*, 1670–1675. [CrossRef]

46. Kumar, U.; Jain, V. Time series models (Grey-Markov, Grey Model with rolling mechanism and singular spectrum analysis) to forecast energy consumption in India. *Energy* **2010**, *35*, 1709–1716. [CrossRef]
47. Wang, Q.; Song, X.; Li, R. A novel hybridization of nonlinear grey model and linear ARIMA residual correction for forecasting U.S. shale oil production. *Energy* **2018**, *165*, 1320–1331. [CrossRef]
48. Wang, Q.; Song, X. Forecasting China's oil consumption: A comparison of novel nonlinear-dynamic grey model (GM), linear GM, nonlinear GM and metabolism GM. *Energy* **2019**, *183*, 160–171. [CrossRef]
49. Wang, Q.; Li, S.; Li, R. China's dependency on foreign oil will exceed 80% by 2030: Developing a novel NMGM-ARIMA to forecast China's foreign oil dependence from two dimensions. *Energy* **2018**, *163*, 151–167. [CrossRef]
50. Lee, Y.S.; Tong, L.I. Forecasting energy consumption using a grey model improved by incorporating genetic programming. *Energy Convers. Manag.* **2011**, *52*, 147–152. [CrossRef]
51. Bahrami, S.; Hooshmand, R.A.; Parastegari, M. Short term electric load forecasting by wavelet transform and grey model improved by PSO (particle swarm optimization) algorithm. *Energy* **2014**, *72*, 434–442. [CrossRef]
52. Ding, S.; Hipel, K.W.; Dang, Y.-g. Forecasting China's electricity consumption using a new grey prediction model. *Energy* **2018**, *149*, 314–328. [CrossRef]
53. Chen, C.I. Application of the novel nonlinear grey Bernoulli model for forecasting unemployment rate. *Chaos Solitons Fractals* **2008**, *37*, 278–287. [CrossRef]
54. Xu, N.; Ding, S.; Gong, Y.D.; Bai, J. Forecasting Chinese greenhouse gas emissions from energy consumption using a novel grey rolling model. *Energy* **2019**, *175*, 218–227. [CrossRef]
55. Zeng, X.; Shu, L.; Yan, S.; Shi, Y.; He, F. A novel multivariate grey model for forecasting the sequence of ternary interval numbers. *Appl. Math. Model.* **2019**, *69*, 273–286. [CrossRef]
56. Li, S.; Wang, Q. India's dependence on foreign oil will exceed 90% around 2025-The forecasting results based on two hybridized NMGM-ARIMA and NMGM-BP models. *J. Clean. Prod.* **2019**, *232*, 137–153. [CrossRef]
57. Naylor, T.H.; Seaks, T.G.; Wichern, D.W. Box-Jenkins Methods: An Alternative to Econometric Models. *Int. Stat. Rev.* **1972**, *40*, 123–137. [CrossRef]
58. Kumar, U.; Jain, V. ARIMA forecasting of ambient air pollutants (O 3, NO, NO 2 and CO). *Stoch. Environ. Res. Risk Assess.* **2010**, *24*, 751–760. [CrossRef]
59. Nieto, P.G.; Lasheras, F.S.; García-Gonzalo, E.; de Cos Juez, F.J. PM10 concentration forecasting in the metropolitan area of Oviedo (Northern Spain) using models based on SVM, MLP, VARMA and ARIMA: A case study. *Sci. Total Environ.* **2018**, *621*, 753–761. [CrossRef]
60. Singh, S.; Mohapatra, A. Repeated wavelet transform based ARIMA model for very short-term wind speed forecasting. *Renew. Energy* **2019**, *136*, 758–768.
61. Swain, S.; Nandi, S.; Patel, P. Development of an ARIMA Model for Monthly Rainfall Forecasting over Khordha District, Odisha, India. In *Recent Findings in Intelligent Computing Techniques*; Springer: Singapore, 2018; pp. 325–331.
62. Nyangarika, A.M.; Tang, B.J. Oil Price Factors: Forecasting on the Base of Modified ARIMA Model. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2018.
63. Prasad, S.; Choubey, M. Forecasting India's Total Exports: An Application of Univariate Arima Model. *J. Int. Econ.* **2018**, *9*, 60–68.
64. Hossain, M.Z.; Ali, M.Z.; Samad, Q.A. ARIMA model and forecasting with three types of pulse prices in Bangladesh: A case study. *Int. J. Soc. Econ.* **2006**, *33*, 344–353. [CrossRef]
65. Zhang, G. Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing* **2003**, *50*, 159–175. [CrossRef]
66. Al-Musaylh, M.S.; Deo, R.C.; Adamowski, J.F.; Li, Y. Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia. *Adv. Eng. Inform.* **2018**, *35*, 1–16. [CrossRef]
67. Jiang, S.; Yang, C.; Guo, J.; Ding, Z. ARIMA forecasting of China's coal consumption, price and investment by 2030. *Energy Sources Part B Econ. Plan. Policy* **2018**, *13*, 190–195. [CrossRef]
68. Mehedintu, A.; Sterpu, M.; Soava, G. Estimation and Forecasts for the Share of Renewable Energy Consumption in Final Energy Consumption by 2020 in the European Union. *Sustainability* **2018**, *10*, 1515. [CrossRef]
69. Wang, Q.; Li, S.; Li, R.; Ma, M.; Forecasting, U.S. shale gas monthly production using a hybrid ARIMA and metabolic nonlinear grey model. *Energy* **2018**, *160*, 378–387. [CrossRef]

70. Ludlow, J.; Enders, W. Estimating non-linear ARMA models using Fourier coefficients. *Int. J. Forecast.* **2000**, *16*, 333–347. [CrossRef]
71. Chen, S.; Jeong, K.; Härdle, W.K. Recurrent support vector regression for a non-linear ARMA model with applications to forecasting financial returns. *Comput. Stat.* **2015**, *30*, 821–843. [CrossRef]
72. Zhang, G.; Ma, M.; Zhang, M.; Wu, J.; Pan, B.; Li, J.; Wang, J. Improving daily occupancy forecasting accuracy for hotels based on EEMD-ARIMA model. *Tour. Econ.* **2017**, *23*, 1496–1514. [CrossRef]
73. Ordóñez, C.; Lasheras, F.S.; Roca-Pardiñas, J.; de Cos Juez, F.J. A hybrid ARIMA–SVM model for the study of the remaining useful life of aircraft engines. *J. Comput. Appl. Math.* **2019**, *346*, 184–191. [CrossRef]
74. Lee, Y.S.; Tong, L.I. Forecasting time series using a methodology based on autoregressive integrated moving average and genetic programming. *Knowl. Based Syst.* **2011**, *24*, 66–72. [CrossRef]
75. Barak, S.; Sadegh, S.S. Forecasting energy consumption using ensemble ARIMA–ANFIS hybrid algorithm. *Int. J. Electr. Power Energy Syst.* **2016**, *82*, 92–104. [CrossRef]
76. Dindarloo, S. Reliability forecasting of a Load-Haul-Dump machine: A comparative study of ARIMA and Neural Networks. *Qual. Reliab. Eng. Int.* **2016**, *32*, 1545–1552. [CrossRef]
77. Díaz-Robles, L.A.; Ortega, J.C.; Fu, J.S.; Reed, G.D.; Chow, J.C.; Watson, J.G.; Moncada-Herrera, J.A. A hybrid ARIMA and artificial neural networks model to forecast particulate matter in urban areas: The case of Temuco, Chile. *Atmos. Environ.* **2008**, *42*, 8331–8340. [CrossRef]
78. Wang, Q.; Jiang, F. Integrating linear and nonlinear forecasting techniques based on grey theory and artificial intelligence to forecast shale gas monthly production in Pennsylvania and Texas of the United States. *Energy* **2019**, *178*, 781–803. [CrossRef]
79. Zhang, X.; Tuo, W.; Song, C. Application of MEEMD-ARIMA combining model for annual runoff prediction in the Lower Yellow River. *J. Water Clim. Chang.* **2019**. [CrossRef]
80. Matyjaszek, M.; Fernández, P.R.; Krzemień, A.; Wodarski, K.; Valverde, G.F. Forecasting coking coal prices by means of ARIMA models and neural networks, considering the transgenic time series theory. *Resour. Policy* **2019**, *61*, 283–292. [CrossRef]