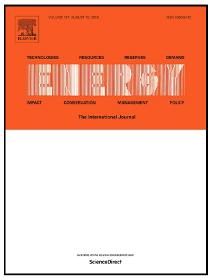

Forecasting Energy Demand in China and India: Using Single-linear, Hybrid-linear, and Non-linear Time Series Forecast Techniques

Qiang Wang, Shuyu Li, Rongrong Li

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Forecasting Energy Demand in China and India: Using Single-linear, Hybrid-linear, and Non-linear Time Series Forecast Techniques

Qiang Wang [1*], Shuyu Li[1], Rongrong Li [1,2]

1. School of Economic and Management, China University of Petroleum (East China), Qingdao, Shandong 266580, P.R. China;
2. School of Management & Economics, Beijing Institute of Technology, Haidian District, Beijing, 100081, R.R. China;

*Corresponding author: qiangwang7@outlook.com, Tel/Fax: 86+532-86983286

Abstract:

Better forecasting energy demand in China and India can help those countries meet future challenges caused by the changes in that demand, as well as inform future global energy needs. In this study, the single-linear, hybrid-linear, and non-linear forecasting techniques based on grey theory are developed to more accurately forecasting energy demand in China and India. These prosed techniques were applied to simulate China's and India's energy consumption of China and India between 1990 and 2016. Three standards (trend map, error measure, and fit method) of analyzing quality of forecast technique are used to quantify the quality of these proposed technique. The results show these proposed techniques have a very high degree of fit, a low error rate, and high fitting precision. For example, the mean absolute percent error of single-linear, hybrid-linear, and non-linear techniques are 1.30-3.08%, 0.80-2.57%, and 2.06-2.19%, respectively. The results of optimality analysis show these proposed models can produce reliable forecasting results in China and India, which might be used to forecasting energy demand in other countries/regions. Our forecasting results show the annual growth rate of India's energy demand from 2017 to 2016 will be 4.49%-5.21% (single-linear), 2.42%-7.04% (hybrid-linear), 0.58%-4.02% (non-linear), respectively. The annual growth rate of China's energy demand from 2017 to 2016 will be 1.48%-1.70% (single-linear), 1.04%-1.49% (hybrid-linear), 1.80%-2.34% (non-linear), respectively. The growth rate of India's energy

consumption is expected to be 2-4 times that of China from 2017 to 2026, indicating India will become even more important in the global energy market.

Keywords: China and India; hybrid linear and nonlinear model; forecasting; energy security.

Nomenclature/ Abbreviations:

GM (1,1)	**grey model with first order and one variable**
ARIMA	Autoregressive Integrated Moving Average
MGM	rolling metabolic grey model
NMGM	non-linear metabolic grey model
ANFIS	Adaptive Network-based Fuzzy Inference System
MSE	mean square error
MAPE	mean absolute percent error
MSPE	mean square percent error
TWh	kilowatt hour
mtoe	Million Tons of Oil Equivalent

1. Introduction

Accurately forecasting energy demand can better predict future changes in energy demand [1], and facilitate the development of countermeasures to meet the challenges caused by the changes [2]. This is particularly true for China and India, which are the largest and second largest developing countries in the world [3]. Energy demand in China and India has increased rapidly. Between 2000 and 2016, energy consumption in China and India increased by 203% and 129%, respectively. In contrast, worldwide energy demand increased by 41% [4]. Energy surpluses and shortages and sharp fluctuations in energy price cannot be avoided without accurately forecasting energy demand. Indeed, energy shortages and sharp increases in energy prices have occurred many times in China and India [5]. These surpluses and shortages significantly impact economic development, individual lives, and social stability . Accurately forecasting future energy demand can help energy policymakers in China and India balance supply and demand, stabilize energy prices, and ensure energy safety. In addition, China and India accounted for half of the growth in global energy demand in 2016 (27.5% from China and 22.7% from India), according to the BP Statistical Review of World Energy 2017[4]. Because these countries are leading contributors to the increased global energy demand, understanding their changes in energy consumption helps reveal trends around the world. To better forecasting energy consumption in China and India, this study developed a hybrid-linear and non-linear prediction model based on grey theory in this work.

The structure of this paper is as follows. The second section reviews the related literature. The third section presents the methods, including two hybrid-linear models and one non-linear model. The fourth section presents the fitting process and optimality analysis. The fifth section presents the prediction results. The sixth section summarizes the paper and offers recommendations.

2. Literature review

Accurate prediction of energy demand is integral to optimizing energy layout. There are many models that can be selected to make targeted prediction according to specific research subjects. However, it is a complex task to correctly apply them to the prediction of different kinds of object combined with their specific characteristic[6]. Recent studies have comprehensively reviewed those forecasting models made by previous generations in the energy field[7]. Among those forecasting methods, related research has showed that the top three most popular models in the field of energy prediction are: Time Series models, Regression-based formulations and Artificial Neural Networks [8]. From these studies, this work summarized that the predictive models can generally be divided into two types according to the mode of operation. First of all, the time series forecasting models are regarded as a traditional prediction method. This analysis method takes into account both the scalability of the sequence development and the randomness caused by chance. The most popular time-series techniques such as regression-based, econometrics, autoregressive integrated moving average (ARIMA) and grey models usually perform well in medium and long-term predictions. Second, the soft computing techniques characterized by deep learning have obvious advantages in high-precision fitting and short-term prediction. Artificial neural networks, fuzzy logic and support vector regression models are the most typical computing techniques and widely used in the forecasting of oil prices, transportation and so on.

For the two broad categories and six specific models mentioned above, this paper has conducted a detailed review, which is summarized in Table 1. From this table, the advantages and disadvantages of several commonly used prediction models can be easily understood. The scope of its application is also introduced. It is worth mentioning that both univariate and multivariate data are suitable for time series forecasting. However, for the unique feature of energy demand data, this work only reviewed and sorted out the prediction models for univariate time series. The six models selected in the following table have all been widely used in the field of energy prediction. However, due to space limitations, there are only 3-4 studies to be displayed behind each model.

Table 1. A summary of several models commonly used for energy prediction

Models	Feature	Advantages	Disadvantages	Applied to
Regression-based	Find out influencing factors; build the regression equation between factors and objectives.	Good at analyzing multi-factor models; provide error checking of model estimation parameters; easy to calculate.	Does not consider the un-testability of certain influence factors; Speculative results cannot reflect periodic wave.	Forecasting the electricity energy consumption in East Saudi Arabia by regression model [9] Forecasting electricity consumption in Italy [10] Forecasting the daily power output of a grid-connected photovoltaic system [11]
ARIMA	Established by regression of the dependent variable only for its lag value and the present value of the random error term.	The mathematical model requires only endogenous variables without resorting to exogenous variables.	Require timing data to be stable; cannot reflect non-linear relationships; the determination of model parameters is complicated.	Forecasting primary energy demand by fuel in Turkey [12] Forecasting energy consumption in Shandong, China [13] Forecasting electricity demand in China by seasonal ARIMA [14]
Grey	Build grey differential model with a small amount of incomplete information; make a vague and long-term description of the development laws of things.	High accuracy; the sample does not need regularity and large numbers; Suitable for medium and long-term prediction.	Ignore the intrinsic mechanism of the system; cannot dynamically reflect system changes.	Forecasting CO_2 emissions, energy consumption and economic growth in China [15] Forecasting electricity demand of Turkey [16] Forecasting annual power load in China [17] Modelling and forecasting CO_2 emissions in the BRICS countries [18]
Fuzzy Logic	Perform fuzzy judgment for systems with unknown models; reasoning solves the regular fuzzy information	High accuracy in reflecting uncertainty qualitative knowledge; good at uncertain situation prediction	Lack of specific prediction formulas; cannot reflect the relationship between predicted values and	Forecasting short-term transmission-loss for the Slovenian power system [19] Forecasting the Taiwan stock exchange capitalization weighted stock index [20]

	problem that is difficult to deal with by conventional methods.	of input variables.	historical data.	Forecasting energy consumption of Iran [21] Forecasting long term electricity consumption in Brazil [22]
Artificial Neural Networks	It abstracts the human brain neural network from the perspective of information processing; usually a logical expression of some kind of algorithm in nature.	Provide self-learning function and high-speed search for optimal solutions; fully approximate any arbitrarily complex nonlinear relationship; can learn and adapt to unknown or uncertain systems.	No ability to explain reasoning process and reasoning basis; cannot work when data is insufficient; turning all reasoning into numerical calculations results in the loss of information.	Forecasting renewable energy consumption in Iran [23] Forecasting long-term energy consumption in Greek [24] Forecasting short-term future load conditions [25] Forecasting natural gas consumption in Szczecin [26]
Support Vector Regression	Find the best compromise between the complexity of the model and the learning ability based on limited sample information.	Can solve machine learning and non-linear problems in the case of small samples; simplify the usual classification and regression issues; can improve generalization performance; less parameters to solve.	Sensitive to missing data; difficult to implement large-scale training samples; difficult to solve multiple classification problem.	Forecasting energy consumption of multi-family residential buildings [27] Forecasting short-term electrical load and calculating the demand response baseline for office buildings [28] Forecasting Turkey's electricity consumption [29]

Table 2. A comparison of the outstanding predictive performance of different models

Models	**Data trend characteristics**		**Forecast period**		**The number of variables**		**Most applied case of energy field**
	Linear	Nonlinear	Long term	Short term	Multivariable	Univariate	
Regression-based	√			√	√		Short-term load forecasting
ARIMA	√		√			√	Electricity price/energy consumption
Grey	√		√			√	Long-term energy consumption
Fuzzy Logic		√		√	√		Short-term electricity consumption
Artificial Neural Networks		√		√	√		Electricity price/energy consumption
Support Vector Regression	√			√		√	Hourly/daily/monthly load demand

Note: The symbol "√" means the relative superiority of predictive performance

By combing the features and advantages of the above six models, this work proves that although these models can all be applied to the forecasting field, there is a gap in forecasting performance of each model. In order to better grasp the outstanding predictive characteristics of each model, a comparison table is drawn from four aspects. Based on Table 2, the predicted performance of each model could be easily understood.

The research object of this paper is the energy consumption of China and India. The forecasting work for this set of data includes the following two characteristics: (1) The energy consumption forecasts rely only on historical data, that is to say, this set of data belongs to univariate prediction. (2) The energy consumption of the two countries in the next ten years is the ultimate forecast target, resulting in that the model which has advantages in long-term forecasting needs to be chosen. Through the analysis, conclusion can be drawn that the grey model and its improvement, ARIMA model are suitable for this study.

The overview of the grey model and ARIMA model is as follows. The grey prediction GM (1,1) model was firstly proposed by Deng [30] in 1982 in order to solve the forecasting problem existed in complex, uncertain, and chaotic systems. It requires a limited amount of data to identify the behavior of an unknown system. Whitening differential equations and time response functions are powerful tools for solving grey problems. The ARIMA (Autoregressive Integrated Moving Average) model, which was proposed to solve the problem of predicting the stationary time series, was firstly developed by Box and Jenkins [31]. It expresses the dependent variable as a function of independent variables and prediction errors by constructing linear equations.

For the application studies, those two models and their improved version have all been widely used in energy field with high accuracy. In terms of grey model, Wang and Ye (2016) used a non-linear grey model to predict the future of China's carbon emissions from fossil energy consumption from 2014 to 2020 under low, medium, and high-speed economic growth [32]. Hamzaçebi (2016) used a seasonal grey forecasting SGM (1,1) model to forecast the energy consumption in Turkey [33]. Cheng et al. (2017) used a TSI-GM(1,1) model to predict the monthly energy production of small hydropower plants in China [34]. In terms of ARIMA model, Yuan et al. (2016) applied a GM (1,1) and ARIMA model to forecast primary energy consumption in China. The results showed that the growth rate from 2014 to 2020 would be lower than the growth rate during the first decade of the 21st century [35]. Sutthichaimethee et al. (2017) the ARIMAX model to predict that Thailand’s energy consumption would increase to 49.72% [36]. Janković et al. (2017) predicted energy consumption in Serbia using an ARIMA model. They concluded that demand for oil and renewable energy would increase in the next few years, while demand for natural gas and electricity would decline [37]. Parag Sen et al. (2016) used an ARIMA (1,0,0) × (0,1,1) model to forecast energy consumption and greenhouse gas emissions of from Indian pig iron manufacturing enterprises [38].

Predictive works about energy field done by previous generations mostly focused on a single nation or at a regional level. For example, Tepedino et al. created a forecasting model based on a time series analysis and applied it successfully to study electrical energy consumption in Bulgaria [39]. Xu et al. (2015) predicted energy consumption in Guangdong, China. Using a new GM-ARIMA model, they concluded that the energy consumption structure in Guangdong province will be severe under different economic scenarios [40]. Rébha et al. (2016) used a bottom-up model to forecast the energy consumption of Algeria, concluding that coal consumption may reach 179.78 TWh in 2040 [41]. Barak et al. (2016) applied the ARIMA–ANFIS model to forecast the annual energy consumption in Iran [42]. S Ravichandran et al. (2016) predicted electricity grid energy consumption of Sydney and New South Wales [43]. Suganthi et al. (2016) used an econometric model to study the influence of the socioeconomic variables on energy consumption in India [44]. They forecasted that India's total energy consumption in 2030 would be 22.944 × 1015 kJ. Yong et al. (2017) applied an improved neural network algorithm to predict electricity demand in Queensland and found that improved neural networks have better predictability [45]. MZ Rahman et al. (2017) forecasted the long term energy demand of Bangladesh from 2010 to 2040; results showed that future energy demand will grow rapidly [2]. However, few studies have simultaneously applied a combination of linear and nonlinear methods to predict energy demand in two representative emerging developing countries.

In this paper, the hybrid linear and nonlinear models, which include the rolling metabolic grey model (MGM model), the rolling metabolic grey-autoregressive integrated moving average model (MGM-ARIMA model) and the non-linear metabolic grey model (NMGM model), are used simultaneously to carry out the forecasting work. These three models differ from the traditional grey prediction methods in three ways. First, the MGM model adds rolling metabolic mechanism to system predictions. In each process of continuous sliding, five inputs generate one output. The five inputs can best reflect the system's real-time characteristics. Second, based on the rolling metabolic grey model, the MGM-ARIMA combined model uses the ARIMA model to further improve the predictions of MGM model. Third, the NMGM model adds power coefficients between 0 and 1, which are used to solve linear programming matrices. It makes the final predictive value of non-linear characteristics, greatly expanding the application of the prediction model. The data used in this paper were primary energy consumption figures for China and India from 1990-2016, collected from the BP World Energy Statistical Yearbook [4]. The prediction process, the goodness analysis, and the prediction result are described below.

3. Methods

The grey system was proposed and developed by Professor Deng Ju-long in 1982. It has become an important method in China for prediction, decision-making, assessment, planning control, system analysis, and modeling in many fields, including sociology, economics, and science and technology. The grey system has a unique effect in situations where there are short time series, fewer statistical data, and incomplete information system analysis. Grey prediction is the prediction of the grey system. The grey prediction model is a prediction method that establishes a mathematical model using a small amount of incomplete information. GM (1,1) model is a kind of grey model, which aims at univariate and long-term prediction. It is widely used in different prediction fields and is an effective tool for addressing small sample prediction problems.

Over time, the grey model has been continuously developed and improved. As mentioned in section 2, the traditional grey model has three obvious shortcomings when forecasting process is carried out. In response to this three defects, the improved versions of grey model came into being. First of all, the traditional grey model often uses only a small amount of 5-10 data for modeling during the forecasting process. This leads to the problem that the back of data sequence cannot be fully expressed. To overcome this drawback, rolling metabolic mechanism is proposed. In this mechanism, the five input data will be continuously moved back and replaced, which means that the input data used for each round of forecasting is to remove the oldest data from the previous round and add the latest in the system. This can better reflect the latest feature of system. Second, the traditional GM (1,1) forecasting model is applicable to the case where the growth rate of the original data series is relatively stable. If the original data series is characterized by nonlinear characteristics, the accuracy of the GM (1,1) model prediction results will become not high. The nonlinear grey model has wide adaptability, and can adapt to the non-linear characteristics of the data in real-world problems under the influence of external factors. Finally, the combination model has gradually become the focus of model's improvement. Combined model can overcome the loopholes of single model, and exert both advantages of multiple models simultaneously.

In this paper, both rolling metabolic grey model, nonlinear metabolic grey model and combined MGM-ARIMA model are improved versions of GM (1,1) model, which can greatly improve prediction accuracy and extend the scope of predictive application. In this section, the modeling principles and methodological flows of the proposed three models will be focused on.

3.1. The rolling metabolic grey model

The calculation steps of traditional grey model are as follows:

Step 1: Build first order accumulated generating sequence $x^{(1)}(k)$ based on original series $x^{(0)}(i)$ [46]. Each data in the accumulation sequence follows this accumulation formula: $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$,k = 1,2,⋯,n.

Step 2: Build a differential equation for this accumulated and original sequence: $x^{(0)}(k) + a\left[0.5x^{(1)}(k) + 0.5x^{(1)}(k-1)\right] = \mathrm{b}$. That is to say, the original sequence and 1-AGO sequence satisfy this first order differential equation. This also proves that the prediction process of the grey model is a univariate prediction which is determined by the sequence itself.

Step 3: Prepare parameters for the solution of the differential equation. As the above differential equation shows, unknown constant coefficient parameters 'a' and 'b' are the key of equation solving. Define the matrix: $\hat{r} = [a,b]^T = \left(B^T B\right)^{-1} B^T Y_N$.

Where,

$$Y_N = [x^{(0)}(2),\ x^{(0)}(3),\ldots,x^{(0)}(n)]^T, B = \begin{bmatrix} -(0.5x^{(1)}(2) + 0.5x^{(1)}(1)) & 1 \\ -(0.5x^{(1)}(3) + 0.5x^{(1)}(2)) & 1 \\ \vdots & \vdots \\ -(0.5x^{(1)}(n) + 0.5x^{(1)}(n-1)) & 1 \end{bmatrix}.$$

Step 4: List time response functions and derive predictors. After deriving differential equations on both sides, the following time response function can be obtained: $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$. Based on the prepared parameters, final predictions can be obtained:

$$\hat{x}^{(0)}(k) = \left[x^{(1)}(1) - \frac{\hat{b}}{\hat{a}}\right]\left(1 - e^{\hat{a}}\right)e^{-\hat{a}(k-1)}, k = 2,3,\ldots,n,n+1,\cdots$$

The rolling metabolic grey model is to repeat the above process under the condition of changing the input series: $\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),x^{(0)}(4),x^{(0)}(5)\right\}$.The specific replacement process is: each time the oldest value will be changed by the latest value. This rolling metabolic mechanism will ensure that the input data used for forecasting is the best reflection of system characteristics. Figure 1 shows the specific rolling and calculation process of MGM (1,1) model.

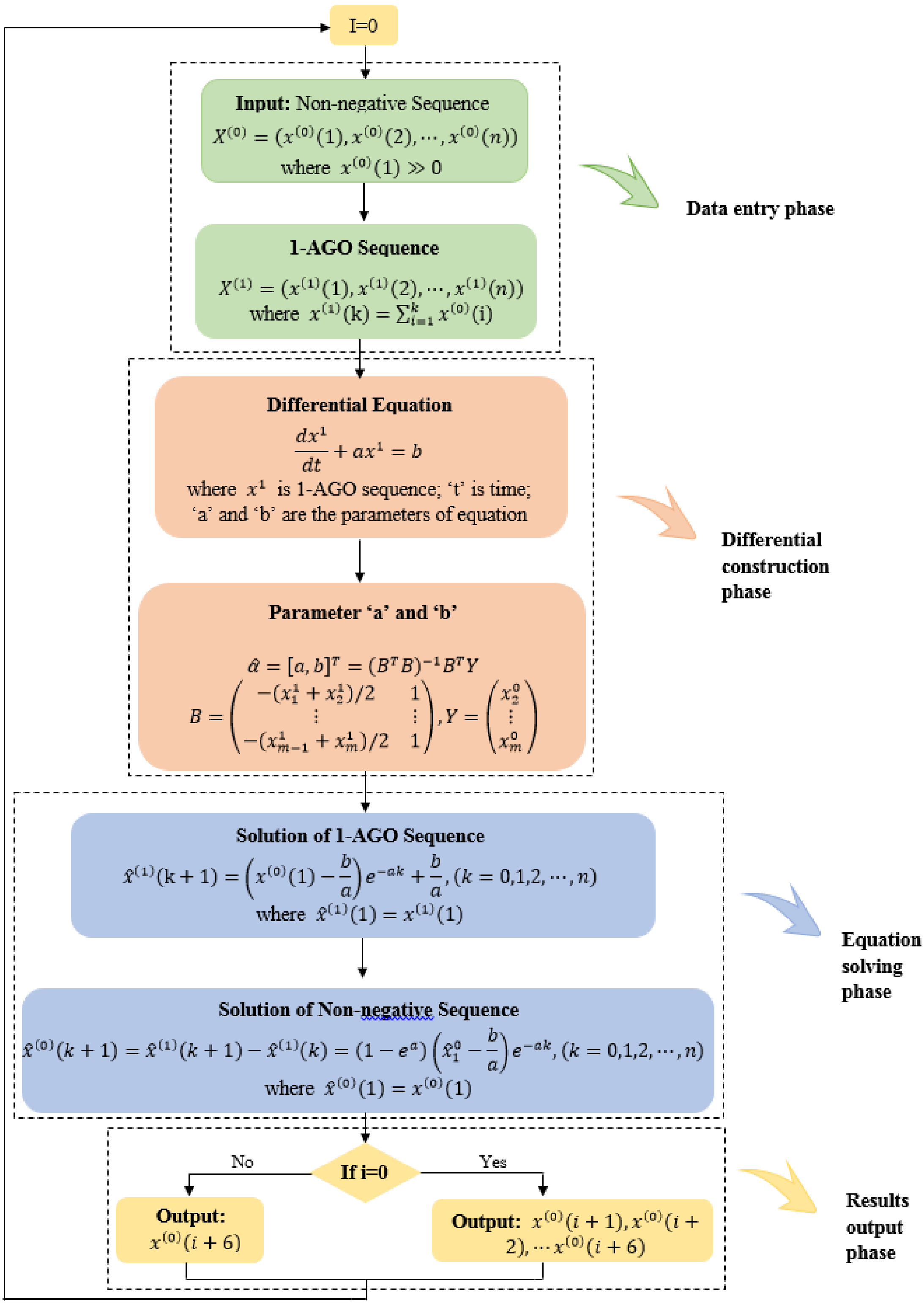


Figure 1. Method flow chart of MGM (1,1) model

3.2. The rolling metabolic grey-autoregressive integrated moving average model

The combined MGM-ARIMA model is an operation method that combines both the MGM and ARIMA models in a progressive form. The basic principle of its prediction can be summarized as using the ARIMA model to modify the prediction results of MGM. To be more specific, there are erratic prediction errors obtained using the rolling metabolic grey model, which often fluctuate widely. Optimizing and revising this series of residuals by ARIMA model can make the error of the predicted value less volatile.

The calculation process of the combined model includes the following three steps:

Step 1: Make the initial prediction by using MGM (1,1) model. This step is consistent with the calculation steps described in Section 3.1. Based on the forecasting results and initial data, the residual series can be got.

Step 2: Re-estimate the residual series. For the residuals calculated in the first step, stationary test and ARIMA forecasting will be carried out until new residual series is obtained.

Step 3: Add the new residual sequence to the original prediction. After calculation, the final predicted values of MGM-ARIMA model can be obtained.

Figure 2 shows the specific calculation process based on the combination model and two levels.

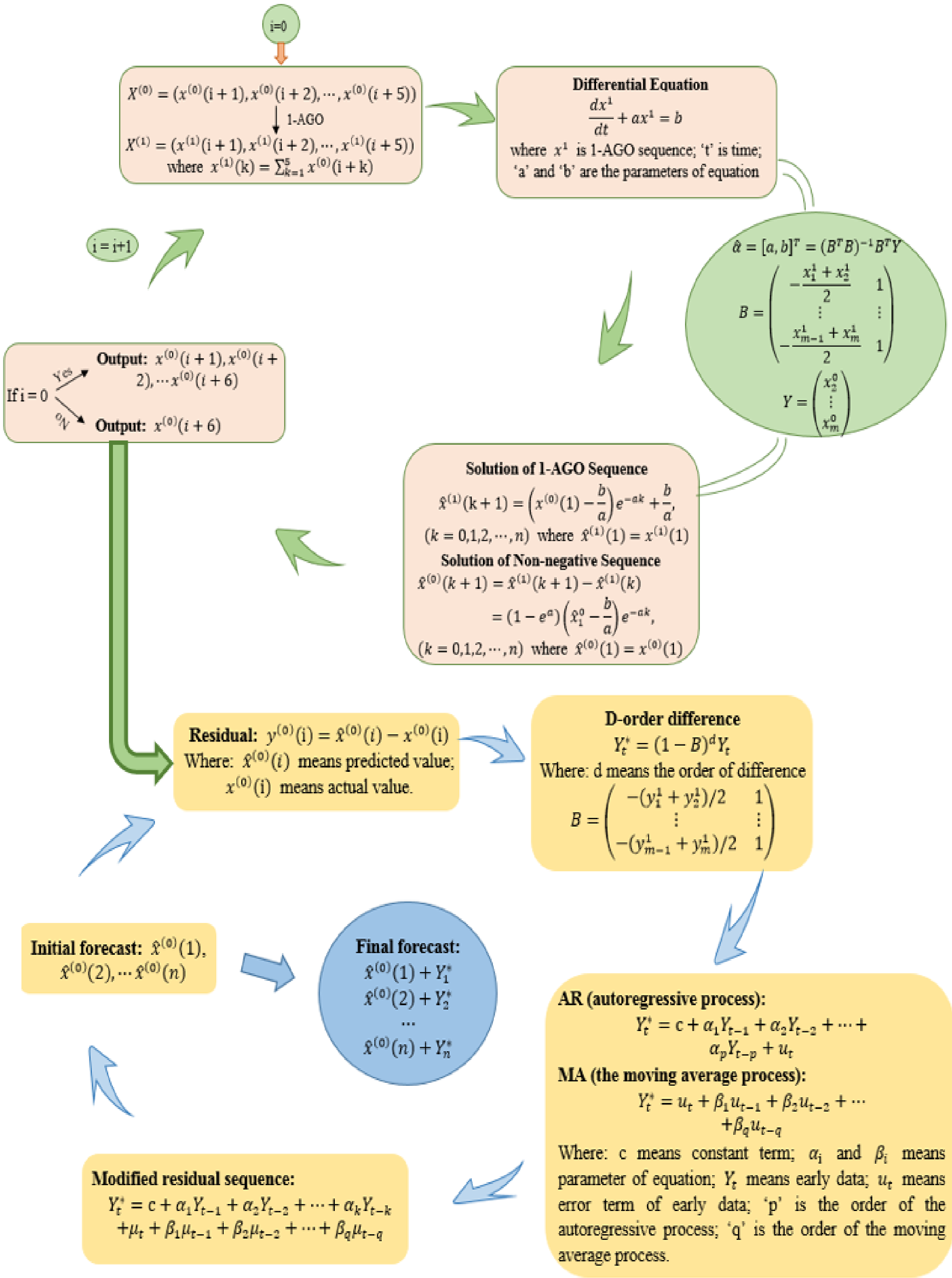


Figure 2. Method flow chart of MGM-ARIMA model

3.3. The non-linear metabolic grey model

The calculation process of nonlinear metabolic grey model is generally same with rolling metabolic grey model. The only difference is that NMGM model adds the power exponent 'α' to the differential equation. New differential equation of nonlinear grey model is: $x^{(0)}(k) + a(0.5x^{(1)}(k) + 0.5x^{(1)}(k-1))^{\alpha} = b$. Among them, 'α' is the power coefficient which determines the degree of nonlinearity. When 'α'=1, the nonlinear metabolic grey equation is the traditional grey equation. Constantly adjusting the value of 'α' results in a constant adjustment of the degree of non-linear reflection [47]. It is well known that a set of numbers cannot always grow linearly or decrease. If only linear grey model is used, short-term fluctuations in the middle part of the year will affect the predictive accuracy. The existence of a power coefficient 'α ' can adapt to the influence of non-linear fluctuations. It can further improve prediction accuracy and can be better applied to solve practical problems. Figure 3 shows the specific formula and calculation process.

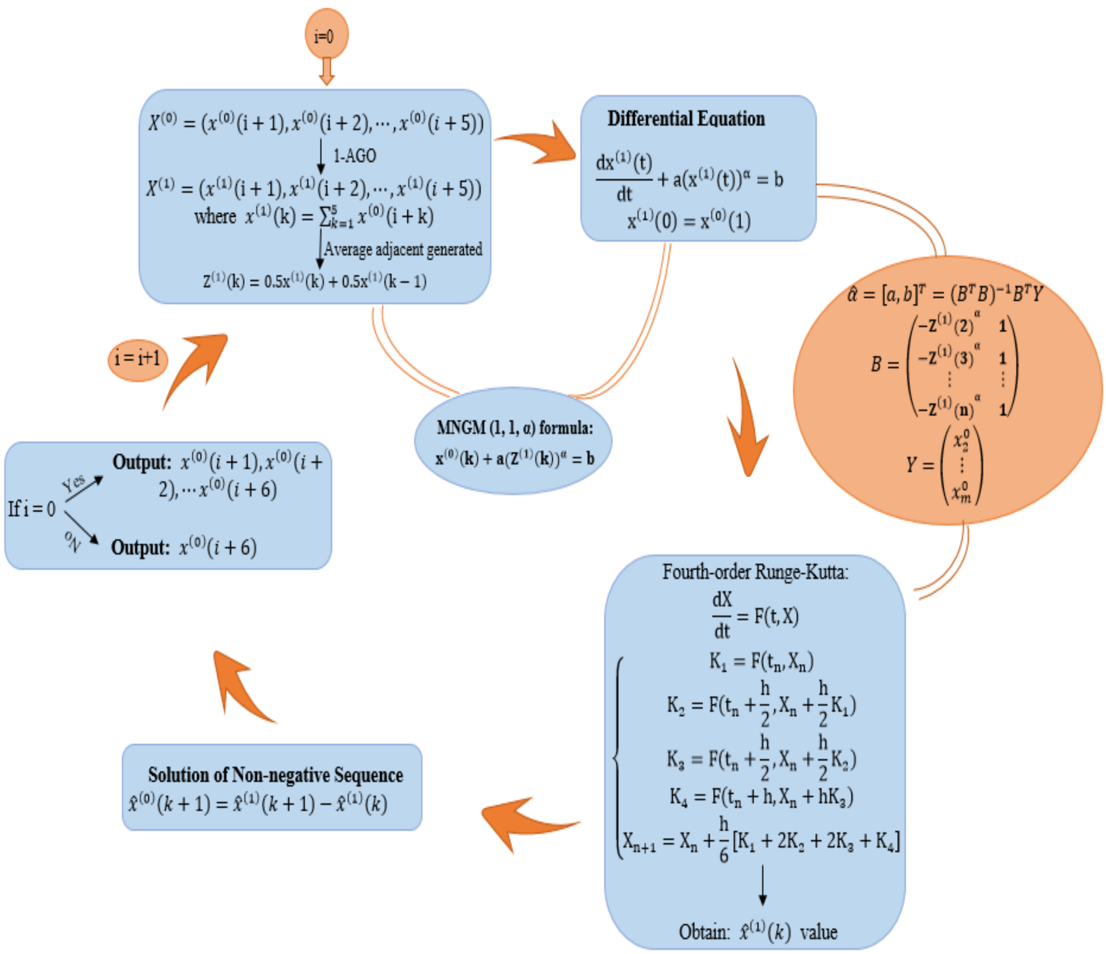


Figure 3. Method flow chart of NMGM (1,1) model

4. Empirical results

This research is concerned with the calculation process and the predictive goodness of the three prediction models. The complete prediction process consists of two parts. The first part is making predictions based on existing data; the second part is making predictions about unknown future data. This study refers to the prediction of existing data as the fitting process and the prediction of unknown data as the prediction process. The goodness of fit is judged by comparing the existing data and the predicted data. Using this approach, the fit of the three models will be measured. Then, the prediction accuracy of the three models can be displayed.

All data used for this study were derived from the BP World Energy Statistical Yearbook. Figure 4 provides a histogram of energy consumption in China and India; the line chart shows the growth rate of energy consumption. Energy consumption in China and India experienced an upward trend from 1990 to 2016. The growth rate of China's energy consumption continuously slowed after 2011, with a steady 2% growth rate in the final three years. By comparison, the growth rate of energy consumption in India, fluctuated cyclically by approximately 5%. After 2013, the growth rate of India's energy consumption began to exceed China's growth rate. India's level of energy consumption has become the fastest in the world.

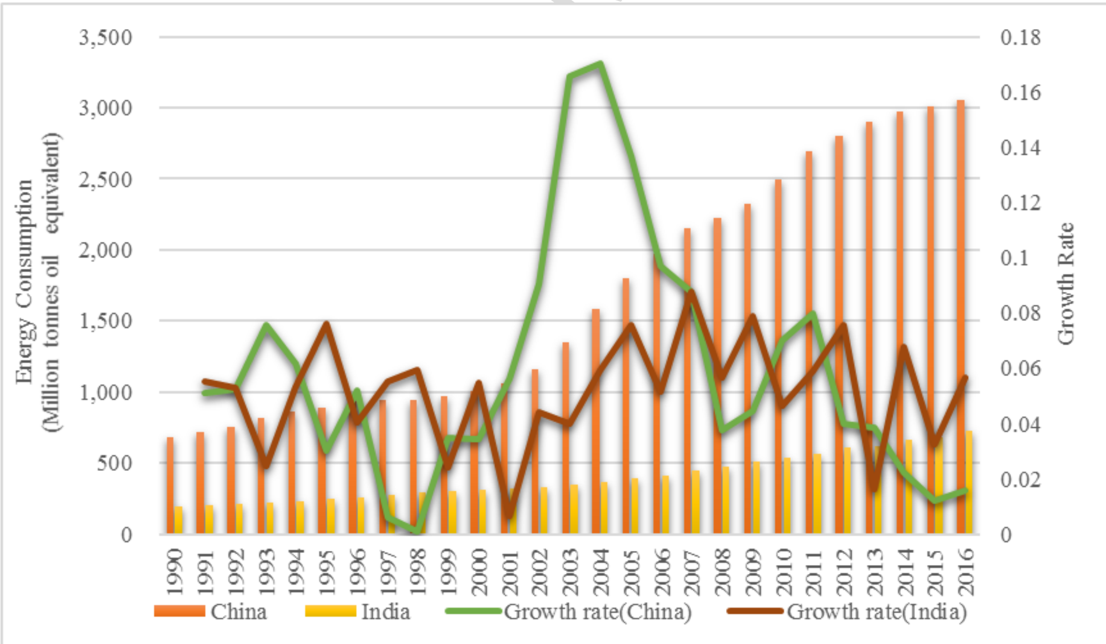


Figure 4. The energy consumption and growth rate of China and India: 1990 to 2016

Source: BP statistical review of world energy 2017 [4]

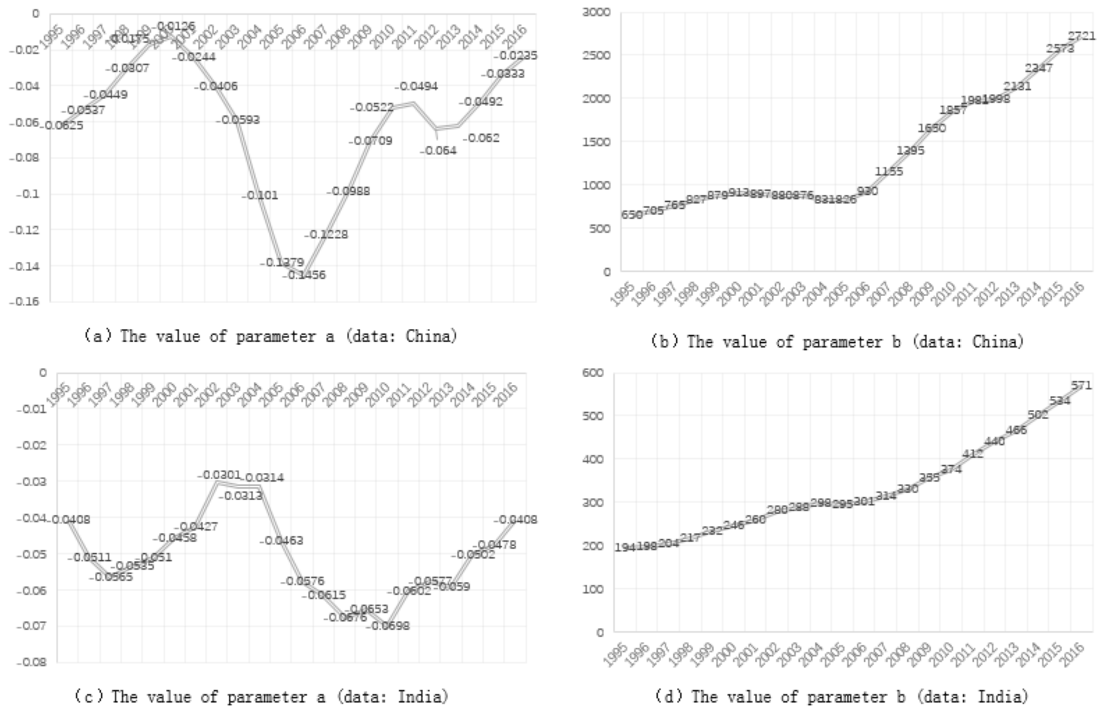
4.1. Fitting process

This process involves the fitting of the data sequence itself. In general, this process uses the prediction model to predict the data for 1990-2016. Because data are already available for this timeframe, the known data can be compared with the predicted data, measuring the model's prediction accuracy. To a certain extent, the prediction accuracy represents the model's prediction ability. This provides an important reference value for measuring the degree of reference for the next step.

4.1.1. Metabolic Grey (1,1) model

The difference between the rolling metabolic grey model and the traditional grey model is the increasing number of iterations. Each iteration is a calculation process of a traditional grey model. The core of the grey model is the differential equation. The key to solving the differential equation lies in the acquisition of parameters 'a' and 'b'. This paper selected five-dimensional data to determine the model. Initially, the model used 1990-1994 data as the basis for the forecast, generating a set of parameters and obtaining a forecast for 1995. Then, based on the principle of innovation, the data for years 1991-1995 became the new basis for the construction equation, leading to a forecast value for 1996. The process continued in circulatory way to generate all the predicted data.

Figure 5 shows the series of parameter values. Combined with the calculation process in Figure 1 and the results in Figure 5, Table 3 shows the specific fitting values.



(a) The value of parameter a (data: China)

(b) The value of parameter b (data: China)

(c) The value of parameter a (data: India)

(d) The value of parameter b (data: India)

Figure 5. The parameter values produced by the MGM (1,1) model

Table 3. Predictions for 1990 to 2016 using the Rolling Metabolism Grey Model

Year	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**
China	683.209	714.699	760.794	809.861	862.092	917.692	947.142	977.380	978.419
India	194.988	206.227	214.815	223.760	233.079	242.785	261.966	278.398	291.839
Year	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
China	967.688	978.193	1026.31	1102.39	1216.89	1464.84	1796.08	2090.13	2257.09
India	306.700	316.358	329.003	330.267	341.877	354.391	381.545	413.914	441.668
Year	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
China	2385.83	2424.98	2467.54	2596.39	2848.45	3000.12	3071.45	3085.21	3094.88
India	479.062	508.667	549.763	572.761	603.587	644.725	661.628	693.519	713.871

4.1.2. Metabolic Grey Model-Auto Regressive Integrated Moving Average Model

The MGM-ARIMA model is based on the residual sequence obtained by comparing the predicted values in Table 3 with the actual values. The core of ARIMA model predictions is that the sequence should be nonstationary[13]. The prediction residual (shown in Figure 6) reveals a random trend of volatility and is not stable. Therefore, the residual sequence could be processed using the ARIMA model.

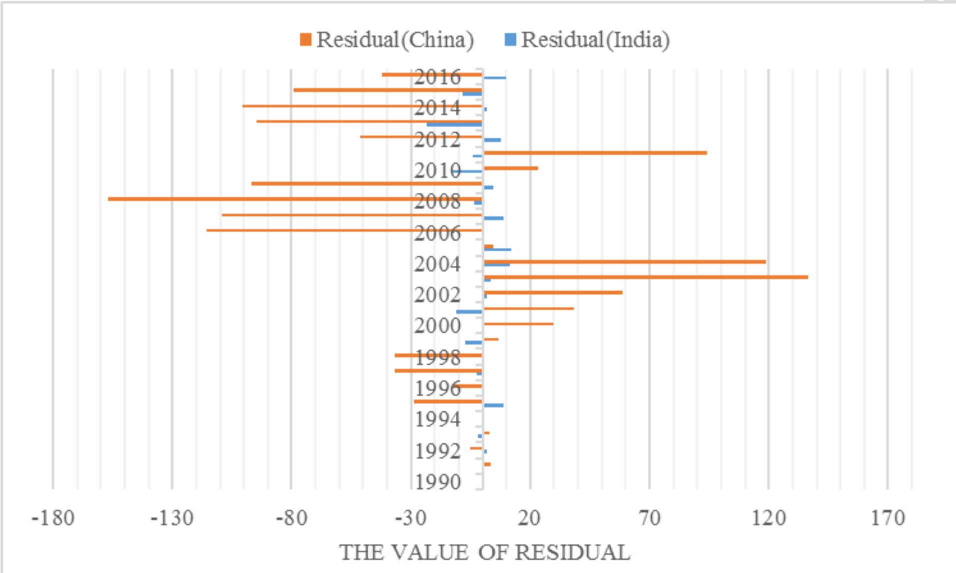


Figure 6. The residual produced by MGM (1,1) model

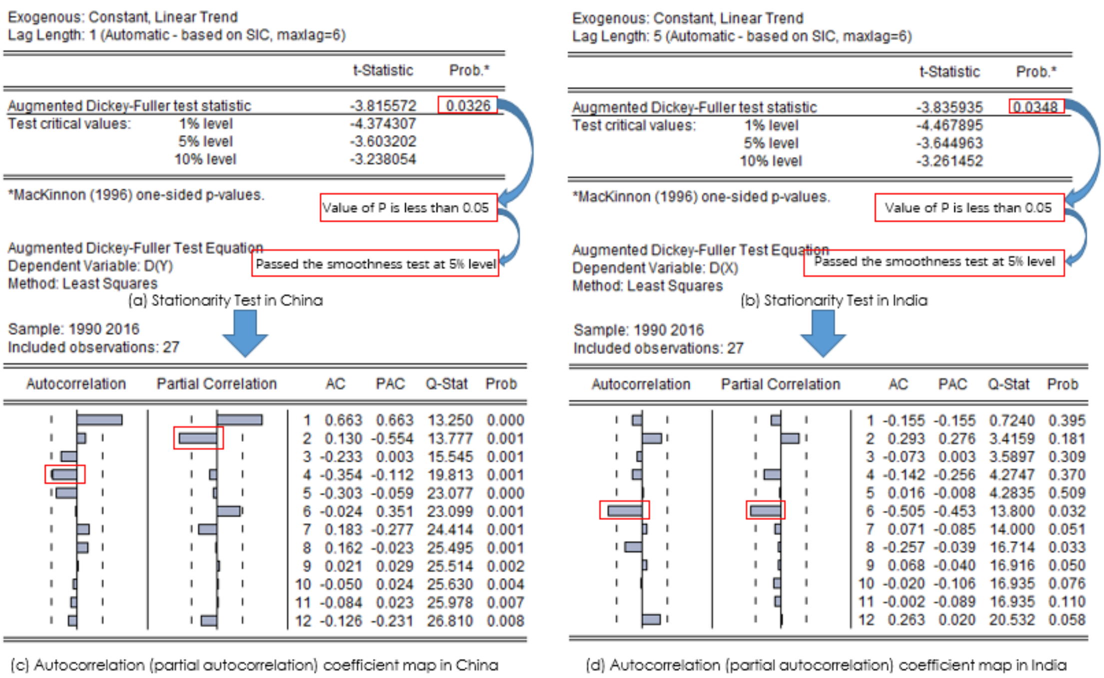


Figure 7. Stationary test results and autocorrelation (partial autocorrelation) coefficient map developed using Eviews 7.2

The first step to predict the non-stationary sequence was to use the differences to make it smooth. Figures 7(a) and (b) show that after the zero-order difference, the p values were all less than 0.05. This means the sequence passed the stationary test[48]. Then, the autocorrelation and partial autocorrelation coefficients are plotted for stationary sequences. Figure 7(c) shows that the autocorrelation coefficient fell within 2 times the standard deviation after the third order, and the partial autocorrelation graph fell within 2 times the standard deviation within the second order. Figure 7(d) shows that the autocorrelation coefficient fell within the range of the 6th order, and the partial autocorrelation figure fell within the range of the 5th order. Based on software simulations and experiments, the ARIMA (2,0,3) and ARIMA (5,0,6) models were applied to predict the residual sequence.

Finally, the parameter results can be obtained after operation. The simulation effect diagram (shown in Figure 8) shows that the two R-squared values both exceeded 0.75, indicating the model had a high degree of excellence.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
T	-4.281018	10.80152	-0.396335	0.6965
C	14.90358	112.2842	0.132731	0.8959
AR(1)	0.753659	0.367009	2.053516	0.0548
AR(2)	0.090491	0.358014	0.252758	0.8033
MA(1)	-0.372345	0.579308	-0.642740	0.5285
MA(2)	-1.498010	0.787392	-1.902497	0.0732
MA(3)	-1.345519	0.527821	-2.549195	0.0201

R-squared	0.861031	Mean dependent var	-18.07647
Adjusted R-squared	0.814708	S.D. dependent var	74.33418
S.E. of regression	31.99753	Akaike info criterion	10.00069
Sum squared resid	18429.16	Schwarz criterion	10.34198
Log likelihood	-118.0086	Hannan-Quinn criter.	10.09535
F-statistic	18.58759	Durbin-Watson stat	2.277659
Prob(F-statistic)	0.000001		

(a) ARIMA (2,0,3) model in residual sequence of China

Both values of R are greater than 0.75

Variable	Coefficient	Std. Error	t-Statistic	Prob.
T	-0.204180	0.283452	-0.720336	0.4896
C	2.606185	2.955910	0.881686	0.4009
AR(1)	-0.561438	0.733404	-0.765523	0.4636
AR(2)	-0.814038	0.691623	-1.176997	0.2694
AR(3)	0.262396	0.914728	0.286856	0.7807
AR(4)	-0.178797	1.149543	-0.155537	0.8798
AR(5)	-0.512476	1.470666	-0.348465	0.7355
MA(1)	-0.059507	3.294899	-0.018060	0.9860
MA(2)	0.688351	4.778439	0.144053	0.8886
MA(3)	-5.283927	3.365300	-1.570121	0.1508
MA(4)	-1.694808	4.128241	-0.410540	0.6910
MA(5)	-1.092927	6.184064	-0.176733	0.8636
MA(6)	-5.183033	4.284773	-1.209640	0.2572

R-squared	0.956458	Mean dependent var	-0.056082
Adjusted R-squared	0.898401	S.D. dependent var	8.753520
S.E. of regression	2.790143	Akaike info criterion	5.178063
Sum squared resid	70.06408	Schwarz criterion	5.822770
Log likelihood	-43.95869	Hannan-Quinn criter.	5.329937
F-statistic	16.47465	Durbin-Watson stat	2.247999
Prob(F-statistic)	0.000113		

(b) ARIMA (2,0,3) model in residual sequence of India

Figure 8. Calculated results from the ARIMA model produced by Eviews 7.2

The parameters above were integrated; Table 4 shows the final forecasted energy consumption in China and India based on the MGM-ARIMA model.

Table 4. Predictions for 1990 to 2016 using the MGM-ARIMA Model

Year	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**
China	657.498	710.691	739.241	807.394	844.489	877.058	949.410	921.808	955.348
India	193.447	203.885	215.249	221.351	231.354	250.933	261.060	272.515	291.616
Year	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
China	972.932	965.931	1030.19	1132.39	1317.08	1503.33	1792.94	2068.73	2289.79
India	298.178	314.872	319.709	327.805	344.765	361.522	387.891	413.419	442.472
Year	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
China	2308.38	2449.39	2521.49	2639.48	2754.93	3021.51	3047.56	3072.44	3102.99
India	481.600	513.275	546.272	575.402	615.043	630.472	659.819	691.558	716.819

4.1.3. Nonlinear Metabolic Grey Model

Two approaches were introduced to improve and innovate the nonlinear metabolic grey model[49]. First, adding power coefficients changed the model's application range from linear to nonlinear. As the power coefficient value approached 1, the predicted values reflected more linear features and fewer non-linear features. Conversely, as the power coefficient approached 0, the predictive value reflected more nonlinear features and fewer linear features[50]. Second, combining the non-linearity with the metabolic principle continuously changed the value of the power factor through a rolling mechanism. This study selected five elements to predict the next element. Figure 9 details the rolling mechanism and forecasting process. By adding the new element and eliminating the old element, each round will generate one prediction. Therefore, in the fitting process of the complete nonlinear model, there are a total of 23 exponentiation values, shown in Figure 10.

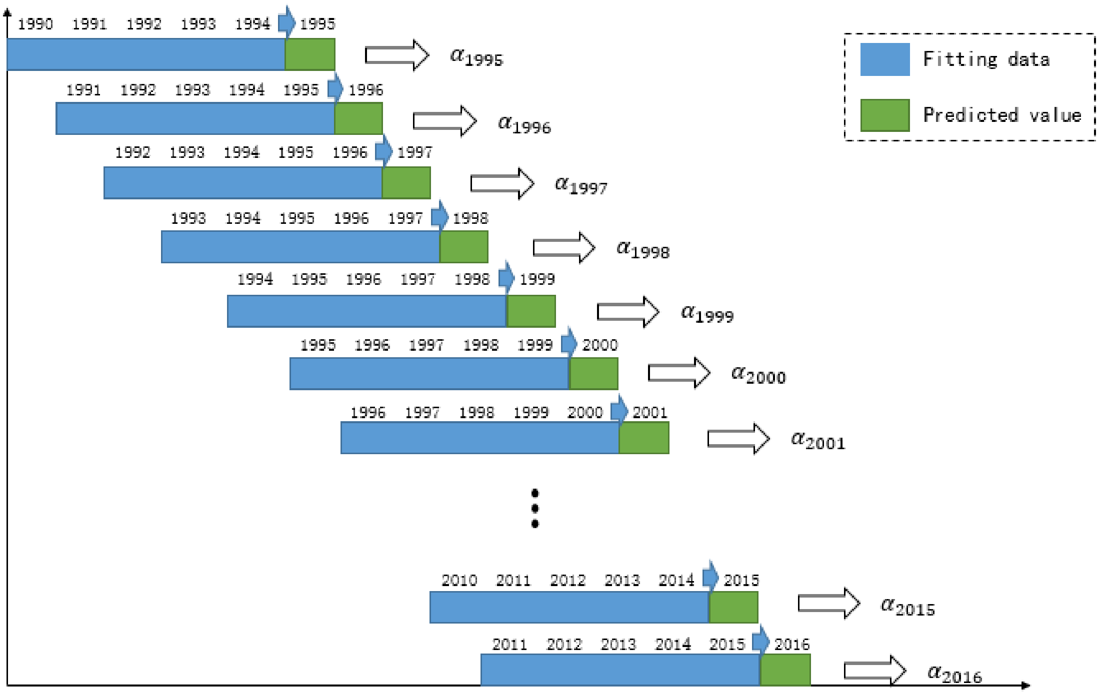


Figure 9. Rolling-generation of model coefficients

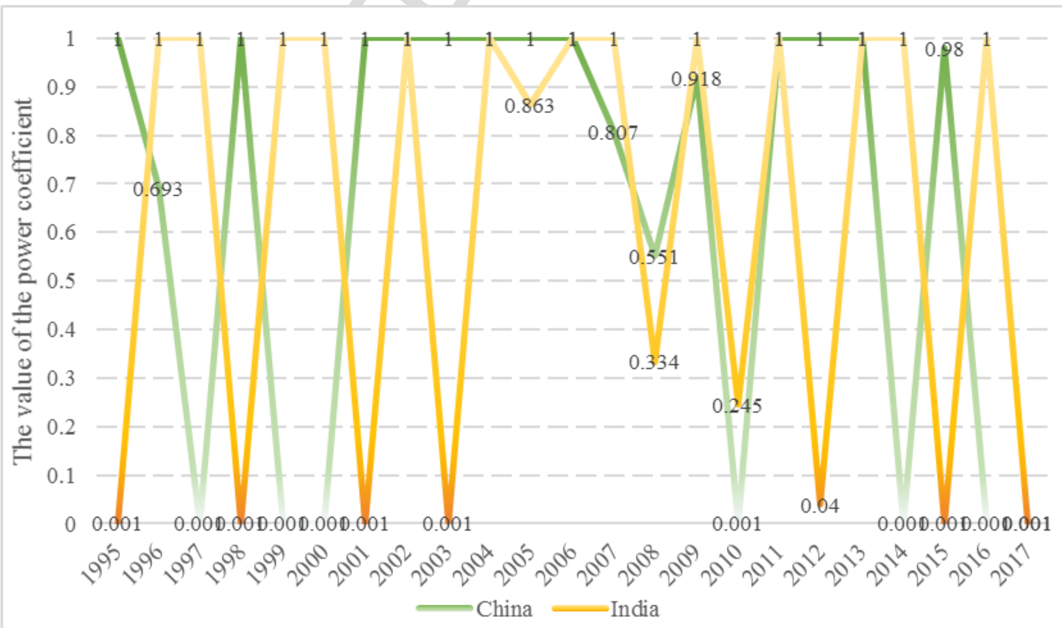


Figure 10. The value of the power coefficient

Next, the power coefficient in Figure 10 will be introduced into the model equation. After that, the final fitting results are obtained and presented in Table 3.

Table 5. Predictions from 1990 to 2016 of Nonlinear Metabolic Grey Model

Year	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**
China	683.209	714.843	760.842	809.801	861.911	912.466	913.293	970.503	962.513
India	194.988	205.569	215.654	222.295	227.262	241.927	267.008	270.593	288.725
Year	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
China	944.200	986.457	1042.70	1109.55	1240.56	1514.30	1843.62	2041.58	2148.42
India	309.080	307.593	326.962	325.768	338.488	358.887	383.004	419.214	432.039
Year	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
China	2335.81	2313.68	2421.32	2624.41	2887.23	2896.03	3017.84	3023.78	3037.69
India	479.331	497.929	546.291	556.481	597.543	651.119	641.994	686.374	706.024

4.2. Optimality analysis

Assessing model accuracy helps determine the predictive effects of the selected models, and provides a standard for the reference values of the predicted results. Studies have highlighted many methods for judging prediction accuracy[51]. Three typical standards were selected for this research.

The first judgement method is a trend map. By plotting the forecast curve and the actual curve, the trend graph can reflect the model's predictive effect. Figure 11 presents the fitted trend map for this study. The original data for China are expressed in grey lines. The top of the map is the trend effect map for the Chinese data. The original data for India are expressed in blue lines. The lower one in the map is the trend effect map for the India data. The distance between the eight curves shows that the fitted values of the three models were close to the actual values, indicating that the predictions generated by the three models worked well.

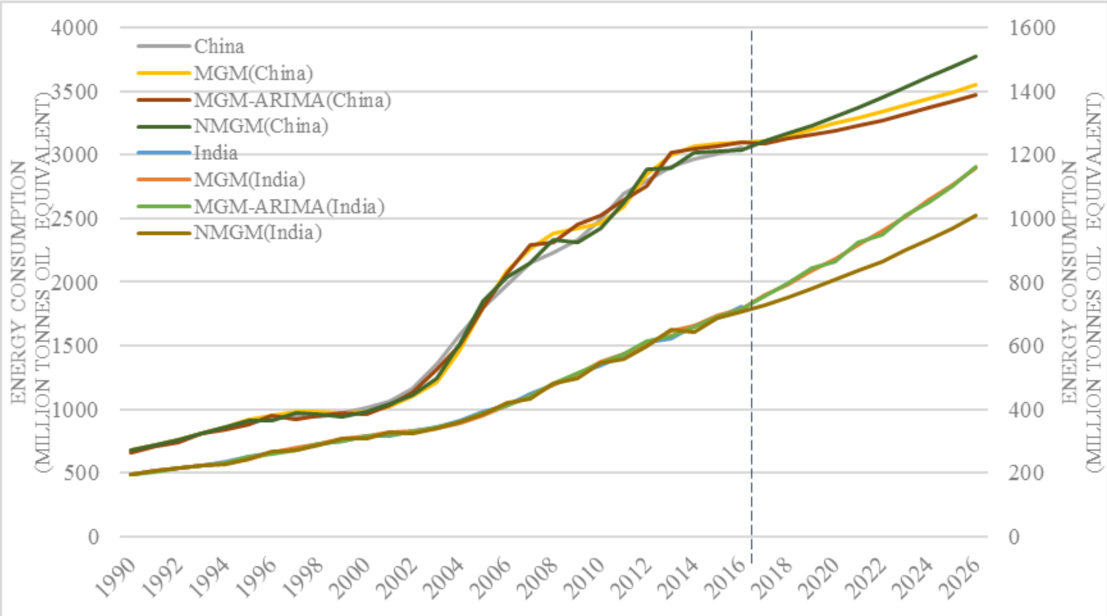


Figure 11. Fitted trend charts for the two data sets

However, using a trend map does not quantify prediction accuracy with a specific number. Two methods help mitigate this loophole.

The second judgement method uses the error measure. Mean square error (MSE), mean absolute percent error (MAPE), and mean square percent error (MSPE) are commonly used tools to measure prediction errors. The specific formulas are shown below.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \qquad (1)$$

$$\mathrm{MAPE} = \sum_{i-1}^{n}\left|\frac{y_i - x_i}{x_i}\right| \times \frac{100}{n} \qquad (2)$$

$$\mathrm{MSPE} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left[\frac{y_i - x_i}{x_i}\right]^2} \qquad (3)$$

The y_i value in the formula represents the predicted value, and the x_i represents the actual value. The formula can be used to calculate three kinds of error values for each model. Table 6 shows the specific calculation results. In terms of MAPE, the error range of each model is clearly defined. Among them, the error of MGM model is between 1.2% and 3.1%, while that of MGM-ARIMA model and NMGM model are 0.8%-2.6% and 2%-2.2%, respectively. Although three models have different error fluctuation range, all less than 5% proves that the models used in this study is valid and reliable. In addition, these outcomes of MSPE and MSE also show that the model was highly accurate for making predictions.

Table 6. The MAPE, MSPE, and MSE values for the three models

		MGM Model	**MGM-ARIMA Model**	**NMGM Model**
MAPE	China	3.078%	2.571%	2.189%
	India	1.298%	0.804%	2.061%
MSPE	China	0.007624032	0.005807776	0.005531738
	India	0.003368737	0.001821212	0.004620884
MSE	China	5214.584275	3537.045378	2317.862973
	India	59.8645875	19.57259121	125.968069

The third judgement method is the goodness of fit method. This study used MAPE to represent the goodness of fit. Because the goodness of the three models differed in different years, the minimum value of goodness in each year can judge the overall effect of each model. A spider web diagram shows that the minimum values of goodness all exceeded 90% for both China and India data. This level significantly exceeds the lowest standard of goodness, which is 75%. This further confirmed that the fitting effect of each model was very good.

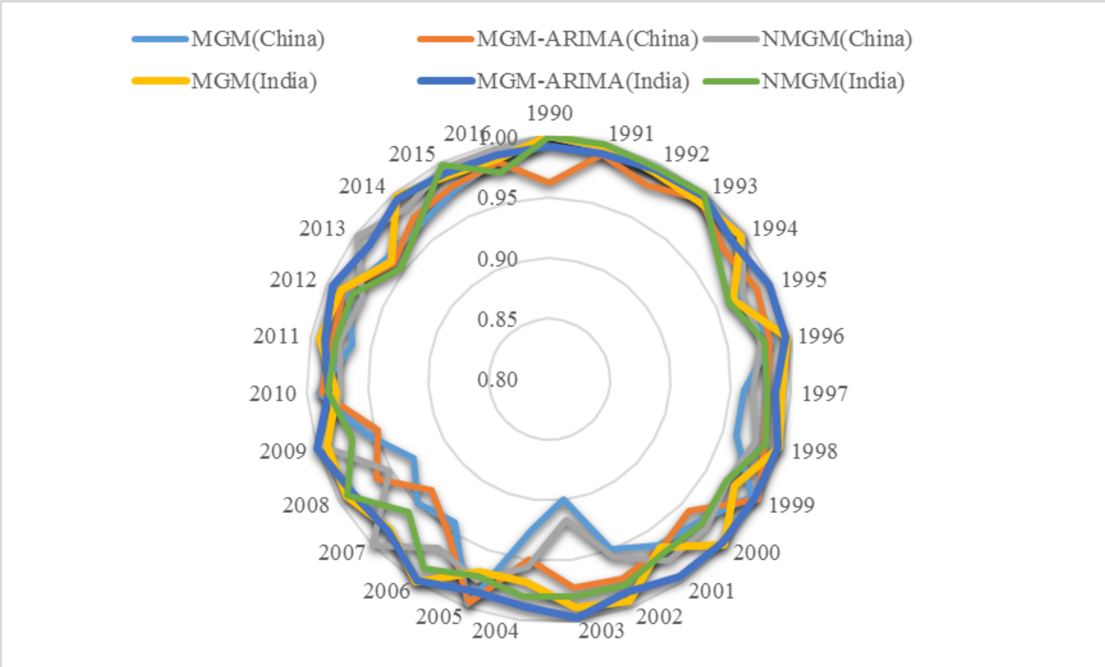


Figure 12. The mean absolute percent error of the three models

In summary, the three criteria all show that the model passes the goodness of fit test. The MGM (1, 1) model, MGM-ARIMA model, and NMGM model have a very high degree of fit, an extremely low error rate, and high fitting precision. Therefore, they could all be used to support the next stage's prediction process, with persuasive forecasting ability and strong usability as a reference value.

5. Forecasting results and discussions

The simulation exercises and analysis above provided a clear operational understanding of the three models. The calculation steps to apply the models for predictions are consistent with the calculation steps to assess fit. As such, this work do not repeat the forecasting process description here. Instead, the prediction results are directly presented [52].

The three models were used separately to predict China and India data. As such, the final predictions consisted of two sets of data, each with three values. Figure 13 presents the predicted result graph. Figure 14-15 presents the incremental trend graph. Figure 16-17 presents the growth rate graph.

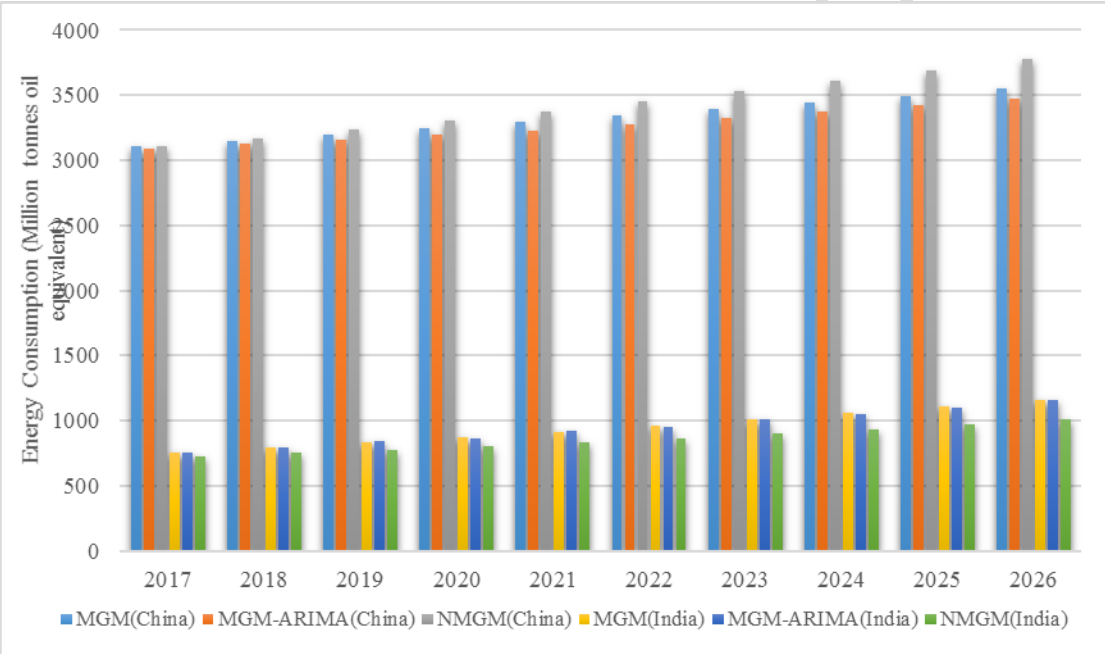


Figure 13. The final predictive data of China and India period 2017 to 2026

In Figure 13, different color bars represent the final predictions for different models. The top three bars represent China; the short three bars represent India. There are deviations in the predicted values of the different models; however, the three predicted results show a common upward trend. In terms of energy consumption, the combined energy consumption of China and India are projected to account for more than 30% of the world's total energy consumption in ten years; the total energy consumption of developing and developing economies are projected to account for more than 60% of the world total. Therefore, in the next ten years, China and India are predicted to remain driving forces in global energy consumption.

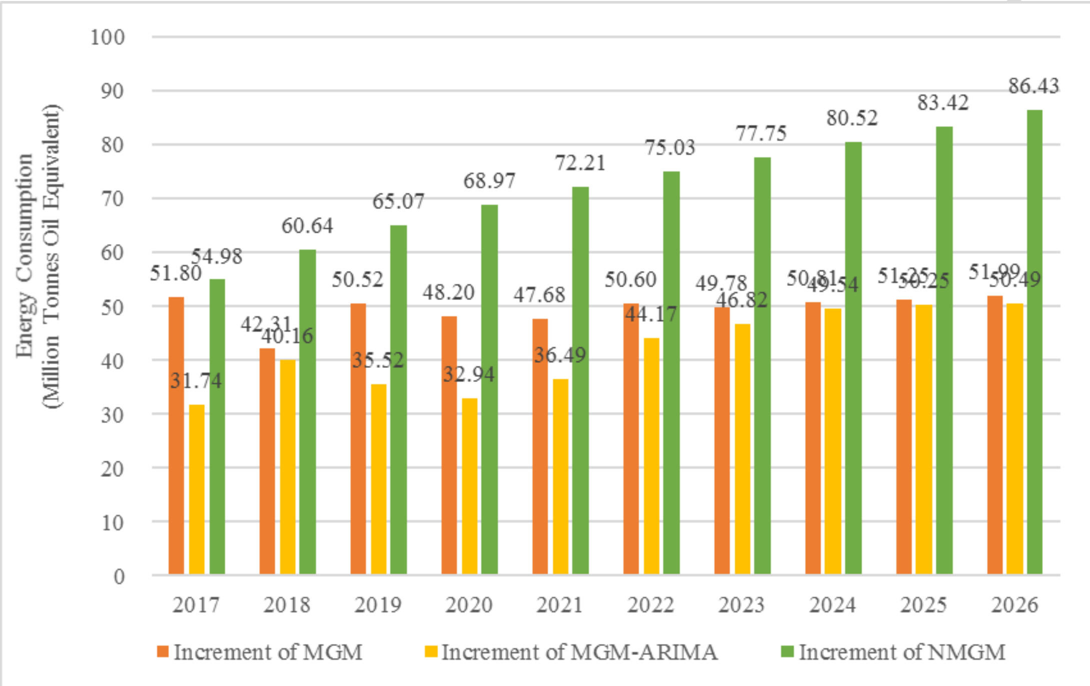


Figure 14. Net increase in energy consumption in China

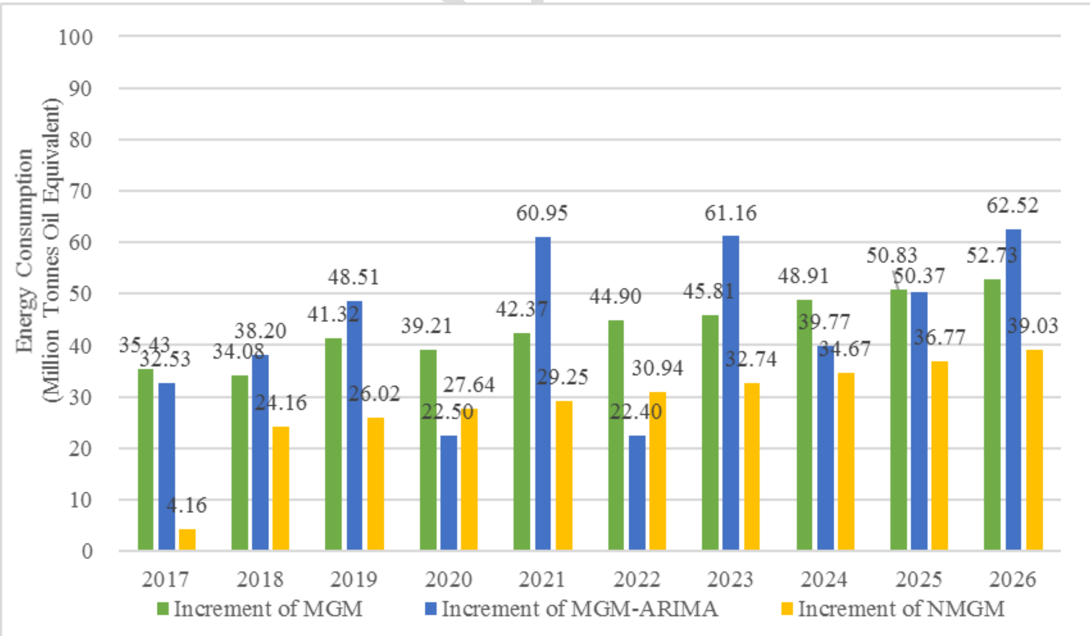


Figure 15. Net increase in energy consumption in India

Measured in terms of net increase, Figure 14 represents China's annual net energy growth, and Figure 15 represents annual net energy growth of India. Since three models give three prediction results, each group of energy increments also consists of three structures. For China, the annual net growth in the next decade will remain between 30 mtoe-87 mtoe. In contrast, India’s energy increase will fluctuate from 20 mote to 60 mote. Results show that the annual incremental increase in energy consumption by the two countries is projected to increase more than before. On a worldwide scale, based on current global energy consumption growth trends, China and India will likely experience additional increases in net energy consumption over the next ten years.

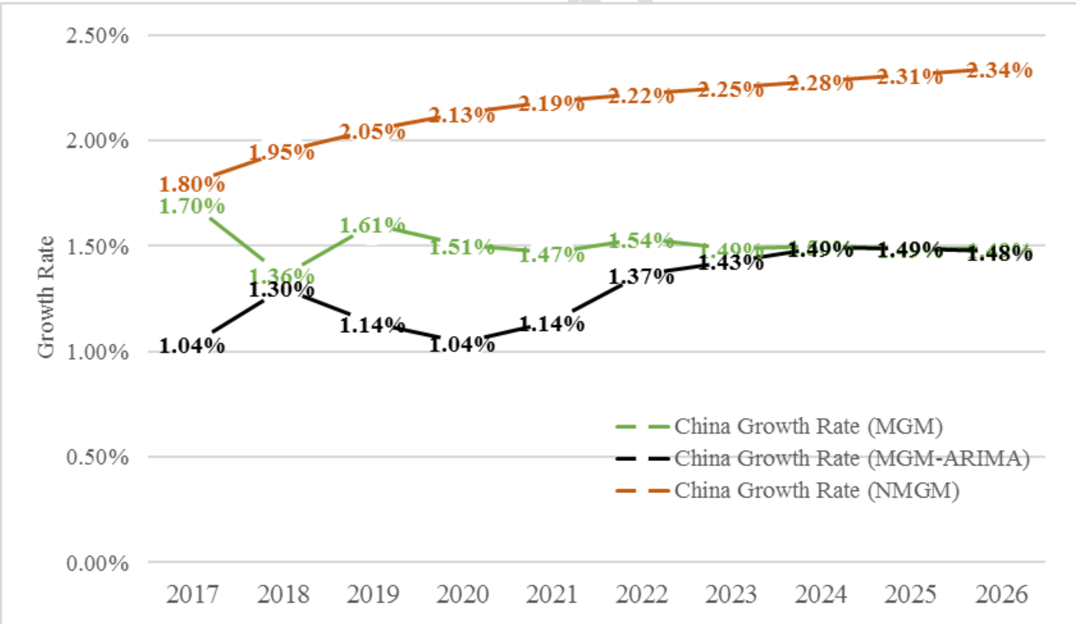


Figure 16. The rate of increase in China’s energy consumption

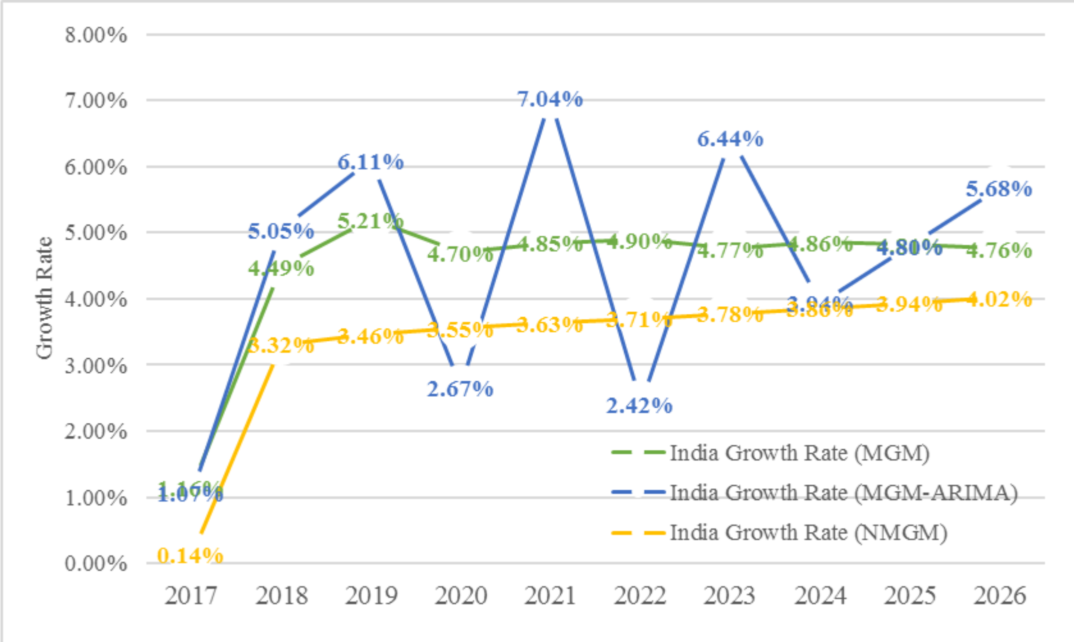


Figure 17. The rate of increase in India's energy consumption

Figure 16 and Figure 17 represent the average annual growth rates of China and India, respectively. Separately, China's annual growth rate during next ten years is predicted to be relatively stable with little fluctuation and remains around 1.5%. In contrast, India's annual growth rate is predicted to significantly fluctuates from 2% to 7% with a few more years at around 4.5%. After comparing those two groups of data, the growth rate of energy consumption in China is far less than the growth rate in India. As a result, China's future energy consumption is projected to increase slightly, while India is expected to experience a more significant increase. China's net energy growth of China is predicted to rise steadily; India's is projected to fluctuate each year.

6. Conclusion

This study is aimed to develop linear, hybrid-linear, and non-linear time-series forecast techniques based on the grey model to more accurately forecasting energy demand in China and India.

Rolling metabolic grey model (MGM) is proposed as single-linear time series forecast technique to overcome the drawback of traditional grey model. The traditional grey model often uses only a small amount of 5-10 data for modeling during the forecasting process. This leads to the problem that the back of data sequence cannot be fully expressed. With MGM, the five input data will be continuously moved back and replaced, which means that the input data used for each round of forecasting is to remove the oldest data from the previous round and add the latest in the system. This can better reflect the latest feature of system.

The combined MGM-ARIMA is proposed as hybrid-linear time series forecast technique. There are erratic prediction errors obtained using the rolling metabolic grey model, which often fluctuate widely. Optimizing and revising this series of residuals by ARIMA model can make the error of the predicted value less volatile. Using the ARIMA model to modify the prediction results of MGM, the proposed hybrid-single time series forecast technique can overcome the loopholes of single model, and exert both advantages of multiple models simultaneously.

The non-linear metabolic grey model (NMGM) is developed as non-linear time series forecast technique. The NMGM is generally same with rolling metabolic grey model. New differential equation of nonlinear grey model is:

$x^{(0)}(k) + a\left[0.5x^{(1)}(k) + 0.5x^{(1)}(k-1)\right]^{\alpha} = b$. Among them, 'α' is the power coefficient which determines the degree of nonlinearity. The existence of a power coefficient 'α' can adapt to the influence of non-linear fluctuations. It can further improve prediction accuracy and can be better applied to the non-linear characteristics of the data in real-world problems under the influence of external factors.

Trend map, error measure, and fit method – three standards of quantify the quality of forecast techniques – are selected to analyze the quality of these proposed time-series forecast techniques. The results show these proposed techniques have a very high degree of fit, a low error rate, and high fitting precision. For example, the mean absolute percent error of MGM, MGM-ARIMA, and NMGM forecast techniques are 1.30-3.08%, 0.80-2.57%, and 2.06-2.19%, respectively. Based on the results of optimality analysis, this work thinks that these proposed forecast techniques can produce reliable forecasting results in China and India. Meanwhile, this study also recommends that these proposed forecast techniques might be used to forecasting energy demand in other countries/regions.

Our forecasting results show energy demand in China and Indian will continue to growth. In addition, the growth rate of future energy demand in India will be higher than that of China. To be more specific, the annual growth rate of India's energy demand from 2017 to 2016 will be 4.49%-5.21% for MGM technique, 2.42%-7.04% for MGM-ARIMA, 0.58%-4.02% for NMGM, respectively. And the annual growth rate of China's energy demand from 2017 to 2016 will be 1.48%-1.70% MGM,

1.04%-1.49% MGM-ARIMA, 1.80%-2.34% NMGM, respectively. Generally, the growth rate of India's energy consumption is expected to be 2-4 times that of China from 2017 to 2026. Thus, India will become even more important in the global energy market from the perspective of growth rate.

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Highlights:

- Single-, Hybrid-linear, nonlinear forecasting techniques are used.
- Error of single-, hybrid-linear, nonlinear forecasting techniques are <3.08%.
- Annual growth of India's energy demand varies from 0.58%-7.04% for 2017-26.
- Annual growth of China's energy demand varies from 1.04% to 2.34% for 2017-26.
- India will play more important role in the future global energy market.