Optimized Rolling Grey Model for Electricity Consumption and Power Generation Prediction of China

Miaomiao Wang, Qingwen Luo, Lulu Kuang, Xiaoxi Zhu*

Abstract—**As the largest developing country in the world, China is currently facing the contradiction between power supply shortage and demand growth. Almost three quarters of the electricity supply of China is derived from thermal power (mainly coal combustion). A proper projection of electricity consumption is helpful to deduce China's dependence on coal as a source of energy and thus will be helpful for the health of the environment. Therefore, it is necessary for the government to accurately predict the electricity demand. This paper employs both rolling mechanism and differential evolution algorithm to improve the prediction accuracy of the original grey model. Then, data from the China Federation of Electric Power Industry Development and Environmental Resources Department was adopted as database to test both the efficiency and accuracy of the improved prediction model. Experimental results show that the proposed model clearly outperforms the original grey model with regard to prediction accuracy. In addition, the future electricity consumption and power generation of China have been forecasted until 2025. The results will be useful to guide the electricity supply planning of the power department to promote the balance of power supply and demand.**

Index Terms—**China's electricity consumption; Power generation; Rolling grey prediction model; Optimization; Differential evolution algorithm**

I. INTRODUCTION

In the past twenty years, the electricity demand in China increased by 10% annually, which is a faster growth than that of any other country in the world. Electricity supply is a substantial foundation for both economic construction and social development. In 2010, China has overtaken Japan as the world's second-largest economy. As one of the fastest growing economies in the world, China often suffers from energy shortage, especially with regard to electricity supply. Compared with developed countries, China is still in the stage of high energy (particular electricity) consumption. Thus, it is of prime importance to plan the electricity supply since doing so can help power utilities to make correct scheduling decisions and to maintain a balance between supply and demand.

Electricity demand is affected by various unstable factors including unpredictable weather conditions, sudden social changes, seasonal variations, and dynamic electricity prices. Since electricity demand generally follows an exponential trend, short-term data might offer more advantages to explain the tendency of a country's macro-policy. The commonly used forecasting methods, using exponential smoothing and linear regression, are not suitable. Thus, it is helpful to establish new models using limited samples to forecast the electricity demand. Short-term data prediction using forecasting methods often encounters limited and insufficient data. Therefore, it is of interest to establish an appropriate forecasting model based on such incomplete information and limited samples.

The grey theory is an approach that can be used to construct a model with limited samples to provide better forecasting for short-term problems [1]. The grey prediction model, proposed by Deng [2], is a primary forecasting model in a grey system, which only requires data of the most recent four years [3] for future predictions with reliable and acceptable accuracy. Due to these advantages, GM (1,1) has been successfully applied to many fields, such as energy [4-8], auto industry [9,10], and tertiary industry [11,12].

However, grey prediction models still have potential to improve the prediction accuracy, and several researchers focused on improving the accuracy of the grey prediction model. Zhou and He [1] proposed a novel generalized GM (1,1) model, which they named the GGM (1,1) model to forecast fuel production with the aim to overcome the homogeneous-exponent simulative deviation of the GM (1,1) model, and the unequal conversion between original and white equations in the Discrete GM (1,1) model. Furthermore, Zeng et al. [13] and Wei et al. [14] proposed two different methods to improve the accuracies of the GM (1,N) model and the grey polynomial prediction model, respectively. Li et al. [15] developed an adaptive grey-based approach to forecast the short-term electricity consumption of Asian countries. After that, Zhao and Guo [16], Ding et al. [17], and Wu et al. [18] forecasted the power consumption and power load of different regions in China by using different optimized grey prediction models. For iron and steel, Ma et al. [19] applied the particle swarm optimization (PSO)-based grey model to predict the iron ore import and consumption of China. Furthermore, Li et al. [20] proposed a combination weighting and grey model to forecast the accident early warning system. Both Pao et al. [21] and Ma et al. [12] employed the nonlinear grey Bernoulli model, focusing on predicting CO_2 emissions, energy consumption, and

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economic growth in China, and on the tourist income of China, respectively. Tabaszewski and Cempel [22] used a set of GM (1,1) models to predict values of diagnostic symptoms, and proposed three possible methods that can be used in automated diagnostic systems to counteract the excessive increase of the forecast error. Wang et al. [23] proposed a seasonal grey model (SGM (1,1) model) based on the accumulation operators generated by seasonal factors to forecast the electricity consumption of primary economic sectors.

In this paper, a rolling mechanism is firstly added to the classical GM (1,1,λ) model, and then, a differential evolution (DE) algorithm is employed to optimize the parameter λ of the rolling GM (1,1,λ) model. The electricity consumption and power generation data of China were obtained from the "2010 compilation of statistical data of electric power industry" and the "Summary of the statistical data of the power industry (2010~2017)" and was were adopted to test the efficiency and the accuracy of the improved prediction model. In addition, future projections have also been derived for the electricity consumption and power generation of China for the next eight years.

The remainder of this paper is organized as follows: Section II provides the current energy status of China. Four prediction models and methods are presented in Section III. Section IV presents numerical results and finally, Section V concludes the paper.

II. CURRENT POWER STATUS IN CHINA

Due to the rapid development of the national economy, China's energy demand, especially the demand for electricity, has increased dramatically during the past decade. Figure 1 shows the rapid growth of the electricity consumption in China from 2006 to 2017. To satisfy the increasing demand for electricity, the Chinese government has enhanced its investment in power supply facilities. The total installed capacity of China from 2006-2017 increased sharply with an average annual 10.89% growth as shown in Figure 2. By the end of 2017, the total installed capacity exceeded 1777.03 million kw, indicating a 7.6% increase over the previous year.

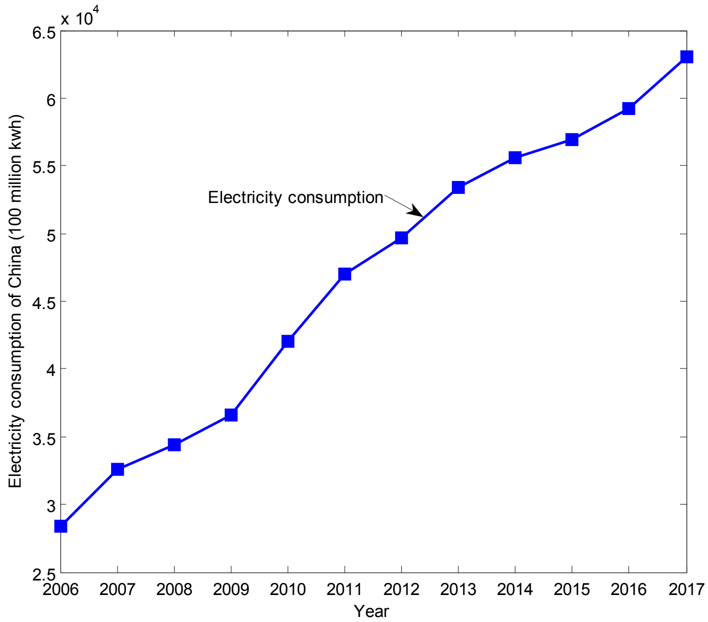

Fig. 1. Electricity consumption curve of China from 2006 to 2017 (100 million kwh)

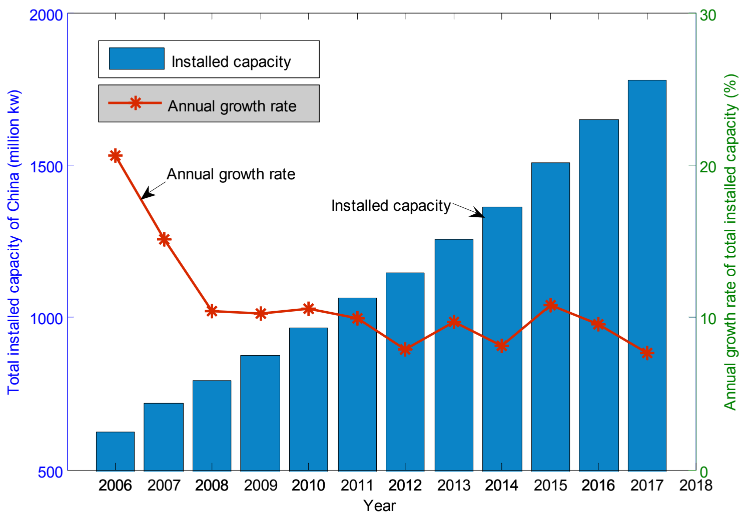

Fig 2. Total installed capacity and its growth rate for China from 2006 to 2017

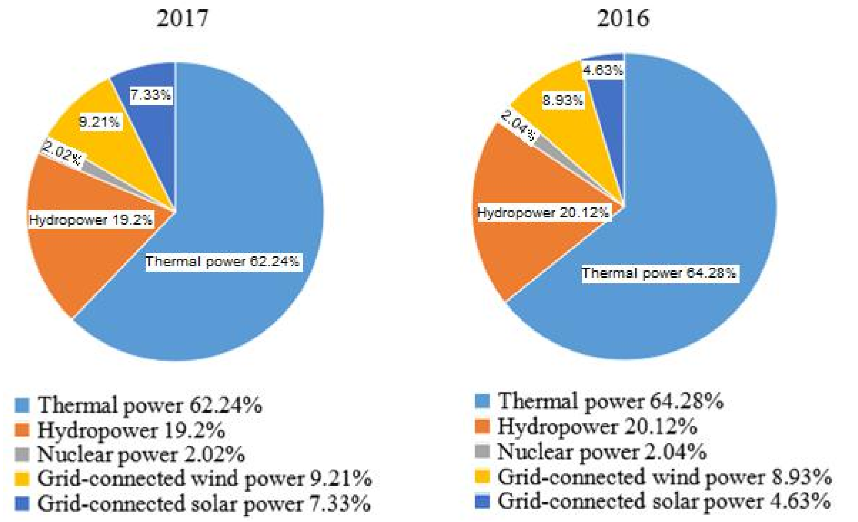

Fig. 3. Percentage of Thermal, Hydro, Nuclear, Grid-connected Wind, and Solar power of the total installed capacity of China from 2016 to 2017

Additionally, thermal power industries in the world account for approximately 24% of the global CO_2 emissions. The Chinese government has focused on environmental problems by encouraging the use of clean energy. In 2017, the percentage of electricity supply in China produced from thermal power facilities has decreased to 62.24% compared with 77.4% in 2007 since "The development of renewable energy planning-the 11th 5-Year Development Program" was released in 2007. As shown in Figure 3, the percentages of new energy power generation (wind and solar power) in 2017 have increased by 2.98% compared with 2016. However, power generation of conventional energy (thermal, hydro, and nuclear power) decreased by 2.98% compared with the previous year. This shows that China has exerted significant efforts to generate electricity from new energy sources. However, due to unreasonable scheduling and distribution of electricity supply, there still exists a shortage in China's electricity supply despite the increasing install capacity. Therefore, it is beneficial and necessary to develop a feasible electricity demand forecasting model for the rational use of electricity and a functioning electricity policy. In this context, a prediction model with higher accuracy and with rolling mechanism optimized by the DE algorithm was developed to forecast electricity demand and power generation of China.

III. MODELS AND METHODS

A. Grey Prediction Models $GM(1,1,\lambda)$

The procedure of the $GM(1,1,\lambda)$ model can be presented as follows:

Step 1: Set the original data sequence:

$$X^{(0)}=\left(x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(m)\right) \tag{1}$$

where, $x^{(0)}(t)$ denotes the value of the behavior series at t, t = 1, 2, …, m.

Step 2: $X^{(0)}$ is converted into monotonically increasing series by imposing the first order accumulated generating operator:

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

where, $x^{(1)}(t)=\sum_{i=1}^{k}x^{(0)}(i)$.

Step 3: For $X^{(1)}$, a differential equation can be established as:

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=u \tag{3}$$

where a represents the development coefficient and u represents the grey actor.

Step 4: The differential equation (3) can be discrete into a forward and backward difference form as:

$$x^{(1)}(t+1)-x^{(1)}(t)+ax^{(1)}(t)=u \tag{4}$$

$$x^{(1)}(t+1)-x^{(1)}(t)+ax^{(1)}(t+1)=u \tag{5}$$

Then, (4)× λ +(5)× $(1-\lambda)$, and

$$x^{(1)}(t+1)-x^{(1)}(t)=-a\left(\lambda x^{(1)}(t)+(1-\lambda)x^{(1)}(t+1)\right)+u \tag{6}$$

where $\lambda\in[0,1]$, which is a horizontal adjustment coefficient. The value of parameter λ decides the prediction performance. The selecting criterion of λ is to yield the smallest forecasting error rate [24].

Step 5: a and u in equation (3) can be estimated by using Least Squares Estimation:

$$\begin{bmatrix} a \\ u \end{bmatrix}=\left(B^TB\right)^{-1}B^TY \tag{7}$$

where

$$Y=\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(m) \end{bmatrix},$$

$$B=\begin{bmatrix} -\left(\lambda x^{(1)}(1)+(1-\lambda)x^{(1)}(2)\right) & 1 \\ -\left(\lambda x^{(1)}(2)+(1-\lambda)x^{(1)}(3)\right) & 1 \\ \vdots & \vdots \\ -\left(\lambda x^{(1)}(n-1)+(1-\lambda)x^{(1)}(n)\right) & 1 \end{bmatrix}$$

Step 6: Based on the estimated coefficients a and u, the forecasting values of $\hat{x}^{(0)}(t)$ $(t=2,3,\ldots,m)$ can be evaluated according to the following inverse accumulated generating operation (IAGO):

$$\hat{x}^{(1)}(t)=\left(x^{(1)}(1)-\frac{u}{a}\right)e^{-a(t-1)}+\frac{u}{a},\ t=2,3,\ldots,m \tag{8}$$

$$\hat{x}^{(0)}(t)=\hat{x}^{(1)}(t)-\hat{x}^{(1)}(t-1),\ t=2,3,\ldots,m \tag{9}$$

B. Optimization Principle of the Basic DE

The intelligent optimization algorithm has been proved to be efficient and to quickly reach a quasi-optimal solution with little effort in many fields, such as power systems [25,26], supply chain management [27], portfolio optimization [28], and route optimization [29]. As a typical intelligent algorithm, the DE algorithm, proposed by Storn and Price [30], has been successfully applied to solve problems in many scientific and engineering fields due to its many attractive characteristics, such as compact structure, simple use, fast convergence speed, and robustness. The procedure of the classical DE includes five steps: initialization, evaluation, mutation, crossover, and selection. The details are as follows [31]:

Step 1: Input the population size N, the scaling factor $F\in[0,2]$, and the crossover rate $CR\in[0,1]$. Then, individuals in the first generation are generated randomly:

$$x_i(0)=\left(x_{i1}(0),x_{i2}(0),\cdots,x_{iD}(0)\right)$$

Step 2: For each individual $x_i(t)$, evaluate its fitness value $fit(x_i(t))$.

Step 3: The five most frequently used mutation strategies executed in the basic DE include: "DE/rand/1", "DE/best/1", "DE/rand-to-best/1", "DE/best/2", and "DE/rand/2" [32]. In this paper, since the experiments showed that the above five mutation strategies reach the same optimization accuracy on parameter λ of GM (1,1), the first mutation strategy was adopted:

"DE/rand/1": $v_{xid}(t)=x_{r_1d}(t)+F\cdot\left(x_{r_2d}(t)-x_{r_3d}(t)\right)$

where, d = 1, 2, ..., D. The indices $r_1, r_2, r_3\in\{1, 2, \dots, N\}$ are mutually exclusive and randomly generated integers, and $r_1\neq r_2\neq r_3\neq i$.

Step 4: To increase the diversity of the population, crossover operator is designed: first, an integer $d_{rand}\in\{1,2,\ldots,D\}$ is generated randomly; then, the trail vector $u_{xi}(t)=\left(u_{xi1}(t),u_{xi2}(t),\cdots,u_{xiD}(t)\right)$ is obtained by the following equation:

$$u_{xid}(t)=\begin{cases}v_{xid}(t), & \text{if rand}[0,1]\le CR \text{ or } d=d_{rand}\\ x_{id}(t), & \text{otherwise}\end{cases}\qquad(10)$$

$$d=1,2,\cdots,D$$

Step 5: To generate the next generation population, selection operator is implemented by comparing the individuals' fitness value

$$x_i(t+1)=\begin{cases}x_i(t), & \text{if } fit(x_i(t))<fit(u_{xi}(t))\\ u_{xi}(t), & \text{otherwise}\end{cases}\qquad(11)$$

C. DE- $GM(1,1,\lambda)$ model

In the classical GM (1,1) model, the value of parameter λ defines the prediction performance. In this section, the DE algorithm will be employed to optimize the value of parameter λ, ultimately, to improve the forecasting accuracy of the prediction model.

Table I gives the framework of DE-GM (1,1, λ) method. In Table I, the Mean Absolute Percentage Error (MAPE) is a stable accuracy measure which was utilized as criterion to evaluate the forecasting performance of a model [33]. PE denotes the percentage error. After using DE to optimize GM (1,1, λ), a best value of λ was obtained, which can minimize the MAPE value. The criteria of MAPE to evaluate the performance of prediction model are shown in Table II.

TABLE I
STEPS OF METHOD 1

Method 1: DE-GM (1,1, λ) method
1. Initialize all parameters of the DE algorithm, and randomly initialize the value of λ within region [0,1].
2. Merge the DE algorithm into the GM (1,1, λ) model: Adopting DE in Section III.B to optimize the key parameter λ of GM(1,1, λ) model, and output the best solution λ^*. Where, the fitness function of DE is calculated as follows: $fit(\lambda)=\text{MAPE}=\frac{1}{m-1}\sum_{t=2}^{m}\lvert\text{PE}(t)\rvert*100\%$; $\text{PE}(t)=\frac{x^{(0)}(t)-\hat{x}^{(0)}(t)}{x^{(0)}(t)}\times100\%,\ t=2,3,\ldots,m$
Bring λ* into the GM (1,1, λ) model for data forecasting, and record the prediction value.

TABLE II
CRITERIA OF MAPE [34]

MAPE (%)	Forecasting power
<10	Highly accurate
10-20	Good
20-50	Reasonable
>50	Inaccurate

D. DE-Rolling $GM(1,1,\lambda)$ model

In the classical GM model, the whole data set is used for prediction. In this paper, a rolling mechanism [3] is added to the DE-GM (1,1, λ) model, which is an efficient technique to improve the accuracy of DE-GM (1,1, λ).

TABLE III
STEPS OF METHOD 2

Method 2: DE-Rolling GM (1,1, λ) method
1. Executing Method 1 on data series $\left(x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(t)\right)$ $(t<m)$ to predicate $x^{(0)}(t+1)$.
2. After $x^{(0)}(t+1)$ is obtained, the new data $x^{(0)}(t+1)$ are added to the data, and the first data $x^{(0)}(1)$ are removed.
3. Then, $x^{(0)}(t+2)$ is predicated by executing DE-GM (1,1,λ) on $\left(x^{(0)}(2),x^{(0)}(3),\ldots,x^{(0)}(t+1)\right)$.
4. This procedure is repeated until the final data $x^{(0)}(m)$ is obtained.

Taking $t=4$ as example, the rolling mechanism described above can be drawn as shown in Fig. 4.

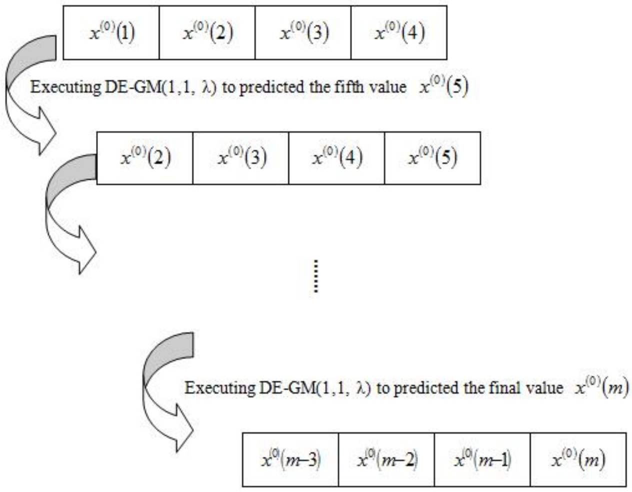

Fig. 4. Rolling mechanism of the DE-GM (1,1, λ) model

Additionally, the fitness function of the DE-Rolling GM (1,1, λ) is evaluated as:

$$fitness\left(\lambda_{\text{Year}}\right)=\min\left(\left|\frac{\text{data}_{\text{Year}}-\hat{\text{data}}_{\text{Year}}}{\text{data}_{\text{Year}}}\right|*100\%\right) \quad (12)$$

where, in this paper, the year ranges from 2009 to 2017.

IV. NUMERICAL EVALUATION

The data (see TABLE IV) was obtained from the China Federation of Electric Power Industry Development and Environmental Resources Department and was used to evaluate and test the forecasting performance of the proposed model and to study the trend of electricity consumption and power generation of China.

For the DE algorithm, selecting the population size will affect the optimization performance of DE. Computational complexity analysis indicates that the larger the population size, the greater the possibility to identify the global optimal solution. However, the quality of the optimal solution does not always improve with increasing population size. Sometimes, increasing the population size will decrease the accuracy of the optimal solution. To improve the search performance of the algorithm, the performance of DE-GM (1,1,λ) under different population sizes is studied in this paper, and the results are shown in Fig. 5.

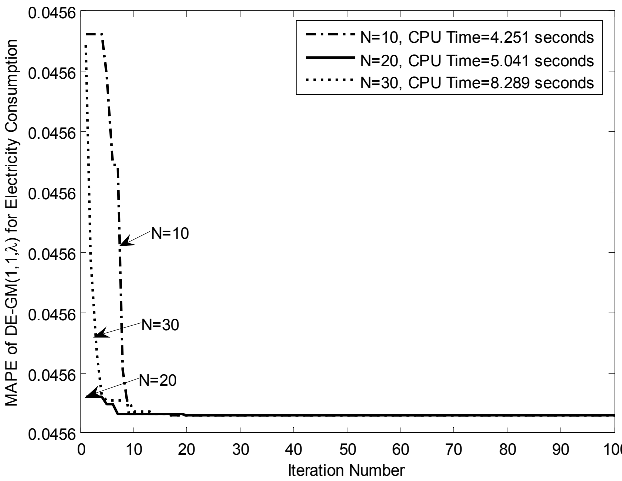

Fig. 5. Performance of DE in Different Population Sizes

Fig. 5 shows that although DE can identify the quasi optimal solution regardless of population size N = 10, 20, or 30, when N = 20, DE has the fastest convergence speed and only requires moderate computing time. To balance the relationship between the search performance and the calculating time, this paper takes N = 20. Other parameters setting of DE algorithm are selected as: maximum iteration number $T_{\max}$ = 100; scaling factor F = 2.0; crossover rate CR = 0.4.

Table IV provides the actual values of electricity consumption and power generation of China (2005-2017). The values in Table IV are from the China Federation of Electric Power Industry Development and Environmental Resources Department.Tables V and VI show the predicted results and the percentage errors of electricity consumption and power generation using four models. Figures 6-9 are drawn based on the data presented in Tables V and VI. Figures 6 and 7 more intuitively and clearly show the gaps between the four prediction models and the actual value. Figures 8 and 9 show percentage errors of the four prediction models for electricity consumption and power generation of China, respectively.

In Table V, the best identified value of λ in the DE-GM (1,1,λ) model is λ^* = 0.42419538345853; and the best found values of λ in DE-Rolling GM (1,1,λ) model are $\lambda^*_{\{2009\text{-}2017\}}$ = {0.15509982605890, 1, 0.65542212937978, 0.08700530662786, 0.34055201367078, 0.23744728766230, 0, 0.63416346198740, 1}. In Table VI, the best identified value of λ in the DE-GM (1,1,λ) model is λ^* = 0.40160352224665; and the best identified values of λ in the DE-Rolling GM (1,1,λ) model are $\lambda^*_{\{2009\text{-}2017\}}$ = {0.17785393240218, 1, 0.63695789444329, 0.07532105753939, 0.36121529419271, 0.26699033398297, 0, 0.68773028849322, 1}.

The prediction accuracy is directly related to the prediction performance of the model. Therefore, to further compare the prediction performance of all four prediction models, besides MAPE, the other two precision measurement methods (named mean squared error (MSE) and mean absolute deviation (MAD)) were also used for the accuracy comparison of the four models. MAD and MSE are defined as follows:

$$\text{MSE}=\frac{1}{m}\sum_{t=1}^{m}\left(\hat{x}^{(0)}(t)-x^{(0)}(t)\right)^2 \quad (13)$$

$$\text{MAD}=\frac{1}{m}\sum_{t=1}^{m}\left|\hat{x}^{(0)}(t)-x^{(0)}(t)\right| \quad (14)$$

Based on the data in Tables V and VI, the MAPE, MSE, and MAD of the four models are given in Table VII.

TABLE IV
ACTUAL ELECTRICITY CONSUMPTION AND POWER GENERATION OF CHINA (2005-2017) (100 MILLION KWH)

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Electricity Consumption	24781	28368	32565	34380	36598	41999	47026	49657	53423	55637	56933	59198	63000
Power Generation	24975	28499	32644	34510	36812	42278	47306	49865	53721	56045	57399	59897	64200

Data sources: “2010 compilation of statistical data of electric power industry” and “Summary of the statistical data of the power industry (2010-2017)” from the China Federation of Electric Power Industry Development and Environmental Resources Department.

TABLE V
FORECASTED VALUES AND ERRORS OF ELECTRICITY CONSUMPTION USING THE FOUR MODELS

Year	Actual Electricity Consumption (100 million kwh)	Predicted Value							
		GM (1,1)		DE-GM (1,1,λ)		Rolling GM (1,1)		DE-Rolling GM (1,1,λ)	
		Forecasted value	PE (%)	Forecasted value	PE (%)	Forecasted value	PE (%)	Forecasted value	PE (%)
2005	24781	-	-	-	-	-	-	-	-
2006	28368	31529.7859	-11.1456	31362.7956	-10.5569	-	-	-	
2007	32565	33700.1744	-3.4858	33510.9633	-2.9048	-	-	-	
2008	34380	36019.9641	-4.7701	35806.2679	-4.1485	-	-	-	
2009	36598	38499.4391	-5.1954	38258.7874	-4.5379	38155.0801	-4.2545	36597.9999	3.181e-013
2010	41999	41149.5916	2.0224	40879.2901	2.6660	38743.5014	7.7513	40158.5720	4.3820
2011	47026	43982.1704	6.4726	43679.2819	7.1167	46015.1825	2.1494	47026.0000000001	1.238e-013
2012	49657	47009.7329	5.3311	46671.0568	6.0131	53324.1529	-7.3849	49657.0000	0
2013	53423	50245.7011	5.9474	49867.7507	6.6549	54319.7595	-1.6786	53423.0000	0
2014	55637	53704.4208	3.4735	53283.3993	4.2302	56784.4440	-2.0623	55637.0000	0
2015	56933	57401.2254	-0.8224	56932.9999	5.000e-012	59123.8268	-3.8480	57201.1350	-0.4709
2016	59198	61352.5038	-3.6394	60832.5768	-2.7612	58919.4142	0.4705	59198.0000	0
2017	63000	65575.7729	-4.0885	64999.2518	-3.1734	60915.4460	3.3088	61985.6526	1.6100

TABLE VI
FORECASTING VALUES AND ERRORS OF POWER GENERATION USING THE FOUR MODELS

Year	Actual Power Generation (100 million kwh)	Predicted Value							
		GM (1,1)		DE-GM (1,1,λ)		Rolling GM (1,1)		DE-Rolling GM (1,1,λ)	
		Forecasted value	PE (%)	Forecasted value	PE (%)	Forecasted value	PE (%)	Forecasted value	PE (%)
2005	24975	-	-	-	-	-	-	-	-
2006	28499	31549.6229	-0.7043	31329.6817	-9.9325	-	-	-	-
2007	32644	33759.6482	-3.4176	33509.8486	-2.6523	-	-	-	-
2008	34510	36124.4840	-4.6783	35841.7287	-3.8589	-	-	-	-
2009	36812	38654.9746	-5.0064	38335.8795	-4.1396	38269.4874	-3.9592	36812.0000000001	-3.1624e-013
2010	42278	41362.7240	2.1648	41003.5929	3.0143	39032.4698	7.6766	40509.1240	4.1839
2011	47306	44260.1491	6.4386	43856.9470	7.2909	46393.8241	1.9282	47306.0000000002	-3.691e-013
2012	49865	47360.5364	5.0224	46908.8600	5.9282	53651.5644	-7.5936	49865.0000	0
2013	53721	50678.1033	5.6642	50173.1492	6.6042	54491.2938	-1.4338	53721.0000	0
2014	56045	54228.0630	3.2419	53664.5934	4.2473	57068.2291	-1.8257	56045.0000	0
2015	57399	58026.6946	-1.0935	57399.0000037609	-6.5520e-09	59644.7015	-3.9124	57644.3065	-0.4273
2016	59897	62091.4172	-3.6636	61393.2760	-2.4980	59485.0697	0.6877	59896.9999	3.887e-013
2017	64200	66440.8702	-3.4904	65665.5054	-2.2827	61747.6525	3.8198	62920.4381	1.9930

TABLE VII
COMPARATIVE ANALYSIS OF FORECASTING ERRORS

Models	MAPE (%)	MSE	MAD
Actual Electricity Consumption			
GM (1,1)	4.6995	4.9926e+006	2.0573e+003
DE-GM (1,1,λ)	4.5636	5.0729e+006	2.0019e+003
Rolling GM (1,1)	3.6565	4.3151e+006	1.7876e+003
DE-Rolling GM (1,1,λ)	0.7181	4.9866e+005	346.9901
Power Generation			
GM (1,1)	4.5488	4.6444e+006	2.0010e+003
DE-GM (1,1,λ)	4.3707	4.8131e+006	1.9268e+003
Rolling GM (1,1)	3.6486	4.5217e+006	1.8117e+003
DE-Rolling GM (1,1,λ)	0.7338	5.3626e+005	365.9716

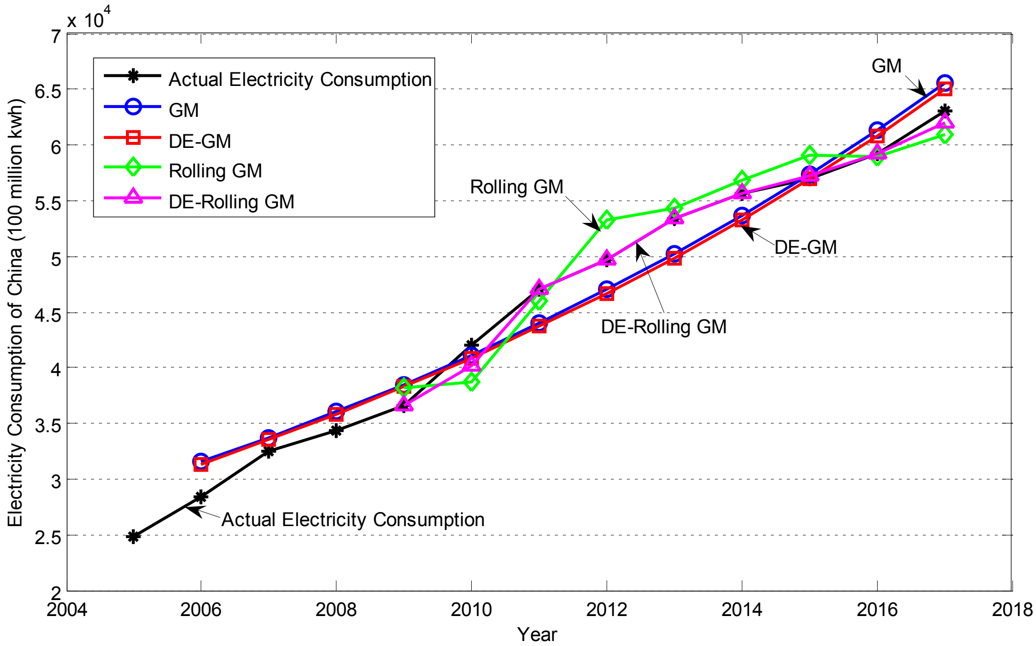

Fig. 6. Comparison of the actual and forecasting electricity consumption curves

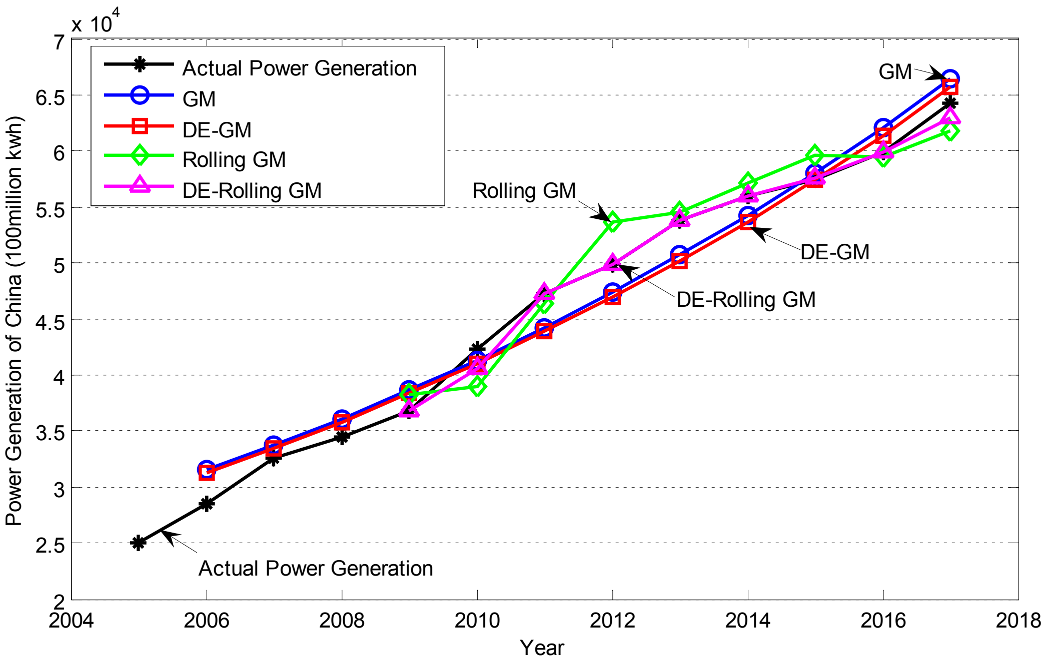

Fig.7. Comparison of the actual and forecasting power generation curves

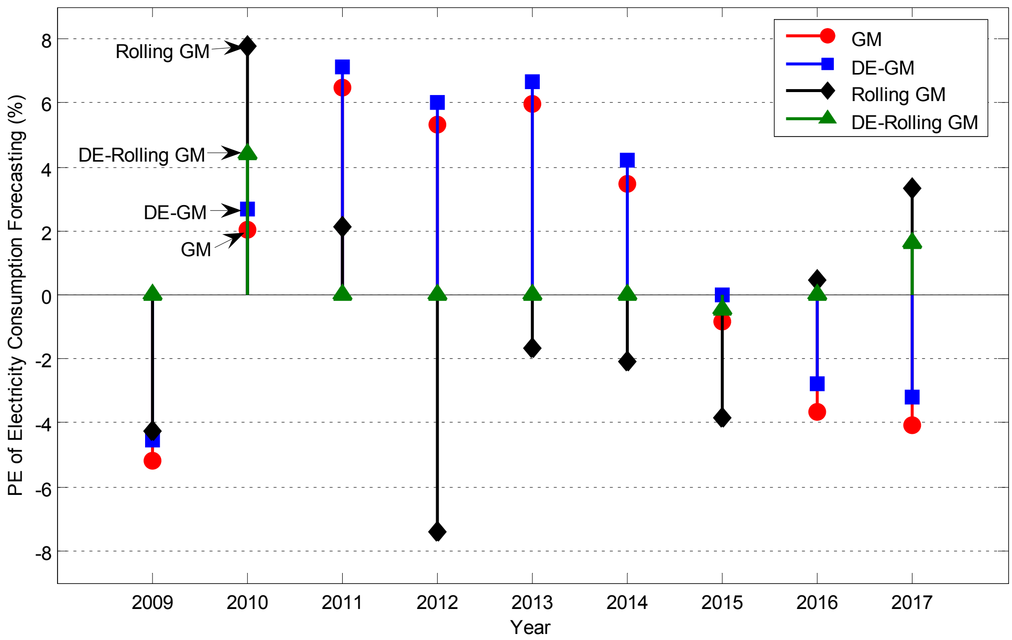

Fig. 8. Percentage error graph of electricity consumption forecasting using four models (2009-2017)

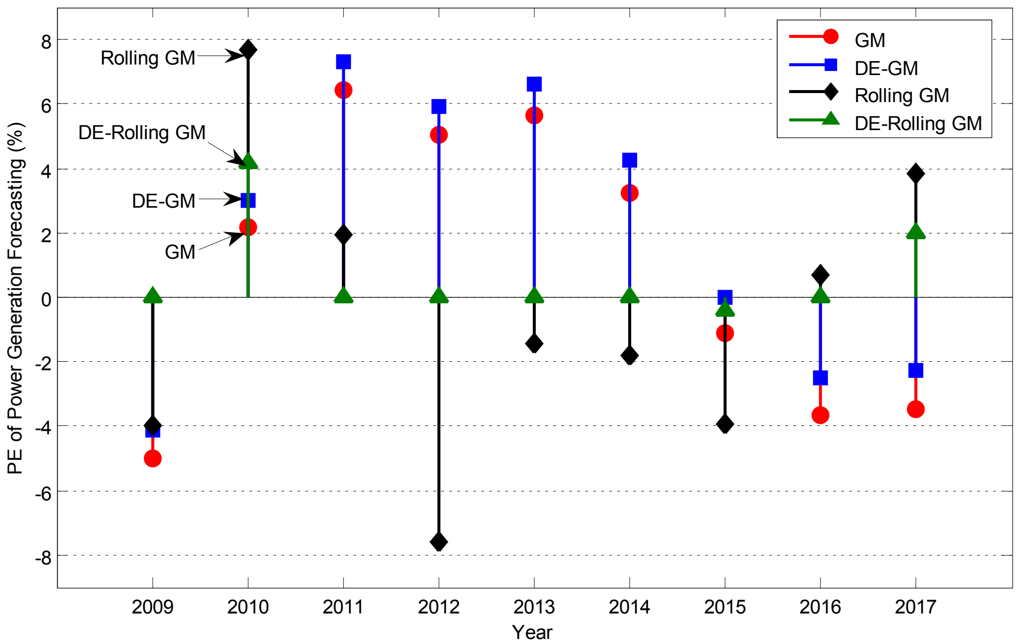

Fig. 9. Percentage error graph of power generation forecasting using four models (2009-2017)

Table VII shows that the accuracy of the DE-Rolling GM (1,1,λ) model is outperforms those of the other three models, since the MAPE, MSE, and MAD of DE-Rolling GM (1,1,λ) are the smallest of the four models. Table VII also shows that the accuracy of the DE-GM (1,1,λ) model is higher than that of the classical GM (1,1) model, and the accuracy of DE-Rolling GM (1,1,λ) model is higher than that of the Rolling GM (1,1) model. Therefore, these results indicate that the optimized parameter λ can improve the prediction accuracy. Figures 6 and 7 show that the fitting degree of DE-Rolling GM (1,1,λ) to the actual data is the highest among the four models. Moreover, Figures 8 and 9 indicate more intuitively that the percentage error of the DE-Rolling GM (1,1,λ) is almost the lowest of the four models.

Since the DE-Rolling GM (1,1,λ) model has the highest accuracy among all four models, the DE-Rolling GM (1,1,λ) model was adopted to predict the electricity consumption and power generation of China for the next eight years (2018-2025), and the forecasting results are presented in TABLE VIII.

To further explore the electricity utilization, the ratio of electricity consumption to electricity generation was calculated from 2005 to 2025, and the results are shown in Table IX. Based on the data in Tables VIII and IX, the ratio curves of electricity consumption and power generation (2005-2025) and the growth trend of China's electricity consumption and power generation for the next eight years are presented in Figure 10.

TABLE VIII
FORECASTING RESULTS (2018-2025) BASED ON DE-ROLLING GM (1,1,λ)

Year	Electricity consumption: Best found value of parameter λ	Electricity consumption: Forecasting results (100 million kwh)	Power generation: Best found value of parameter λ	Power generation: Forecasting results (100 million kwh)
2018	0.56471315806054	66308.0951	0.56617111016713	67944.0455
2019	0.47911037980164	70156.8678	0.47947685788859	72337.7556
2020	0.51729787243814	74044.3628	0.51782123675458	76798.2998
2021	0.49866820649168	78239.6720	0.49919547247237	81642.6474
2022	0.50739111871292	82626.3249	0.50786461010381	86737.9715
2023	0.50322521945293	87282.1533	0.50374617285558	92178.6666
2024	0.50519632130281	92188.6815	0.50568403352268	97946.9016
2025	0.50425954334697	97376.8658	0.50476805316580	104082.9798

TABLE IX
RATIO OF ELECTRICITY CONSUMPTION TO POWER GENERATION

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Ratio Value	0.9922	0.9954	0.9976	0.9962	0.9942	0.9934	0.9941	0.9958	0.9945	0.9927	0.9919	0.9883	0.9813
Year	2018	2019	2020	2021	2022	2023	2024	2025					
Ratio Value	0.9759	0.9699	0.9641	0.9583	0.9526	0.9469	0.9412	0.9356					

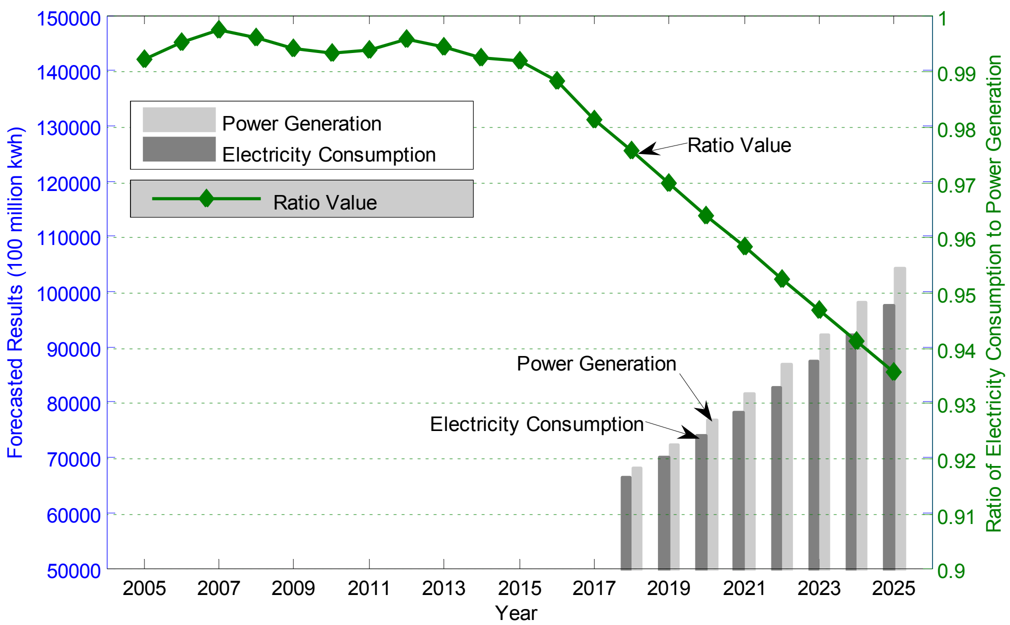

Fig. 10. Forecasting curves of electricity consumption and power generation of China (2018-2025) based on DE-Rolling GM (1,1,λ) and ratio of electricity consumption to power generation (2005-2025)

Table VIII shows that the electricity consumption and power generation of China are increasing, showing a steady growth over the next eight years; however, the growth rate of electricity consumption is not as fast as that of power generation after 2012. As intuitively visible from Figure 10, the ratio of electricity consumption to power generation fluctuated from 2005 to 2012, but has been in decline since 2012. Based on the prediction data using DE-Rolling GM (1,1,λ) model, the ratio may decrease to 0.9356 in 2025.

V. Conclusion

Affected by many unstable and unpredictable factors in economy and social development, guaranteeing a realistic electricity supply is a great challenge for the power utilities of China and of other countries. Hence, forecasting the electricity consumption is important for every government. Along with the high-speed growth of industrialization and urbanization in China, the electricity consumption and power generation in China maintains a rapid growth.

This paper constructs a prediction model by using the GM (1,1,λ) model based on rolling mechanism and DE algorithm. This experimental study has demonstrated that the proposed DE-Rolling GM (1,1,λ) model achieves a higher accuracy than three other assessed models, which suggests that adopting this approach for the modeling of China's electricity consumption and power generation is both reliable and efficient. Based on the DE-Rolling GM (1,1,λ) prediction model, considering trends of historical data, the electricity consumption and power generation of China will reach 9737.687 billion kWh and 10408.298 billion kWh, respectively, in 2025. In addition, the results show that the ratio of electricity consumption to power generation has decreased since 2012, and this deceleration is accelerating, which indicates that China's power utilization rate is gradually declining. If effective measures will not be taken in the future, China's ratio of electricity consumption to power generation is likely to decrease from 0.9813 in 2017 to 0.9356 by 2025. Therefore, the power sector should pay attention to this trend and initiate corresponding measures (such as slowing down the growth of power generation) to avoid a further decline of the power utilization rate, to save resources. The proposed prediction model provides a basis for electricity supply planning for power departments to ensure the balance of power supply and demand and to improve the utilization rate of electricity.

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