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An optimized grey model for annual power load forecasting

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ABSTRACT

Annual power load forecasting is essential for the planning, operation and maintenance of electric power system, which can also mirror the economic development of a country or region to some extent. Accurate annual power load forecasting can provide valuable reference for electric power system operators and economic managers. With the development of smart grid and renewable energy power, power load forecasting has become a more difficult and challenging task. In this paper, a hybrid optimized grey model (namely Grey Modelling (1, 1) optimized by Ant Lion Optimizer with Rolling mechanism, abbreviated as Rolling-ALO-GM (1, 1)) was proposed. The parameters of Grey Modelling (1, 1) were optimally determined by employing Ant Lion Optimizer, which is a new nature-inspired metaheuristic algorithm. Meanwhile, the rolling mechanism was incorporated to improve the forecasting accuracy. Two cases of annual electricity consumption in China and Shanghai city were selected to verify the effectiveness and feasibility of the proposed Rolling-ALO-GM (1, 1) for annual power load forecasting. The empirical results indicate the proposed Rolling-ALO-GM (1, 1) model shows much better forecasting performance than Grey Modelling (1, 1), Grey Modelling (1, 1) optimized by Particle Swarm Optimization, Grey Modelling (1, 1) optimized by Ant Lion Optimizer, Generalized Regression Neural Network, Grey Modelling (1, 1) with Rolling mechanism, and Grey Modelling (1, 1) optimized by Particle Swarm Optimization with Rolling mechanism. Ant Lion Optimizer, as a new intelligence optimization algorithm, is attractive and promising. The Grey Modelling (1, 1) optimized by Ant Lion Optimizer with Rolling mechanism can significantly improve annual power load forecasting accuracy.

1. Introduction

Power load forecasting is an important component of electricity market [1], which is essential for the planning, operation and maintenance of electric power system [2]. Meanwhile, it is a crucial consideration of economic dispatching of electric power system [3]. The accuracy of power load forecasting is usually influenced by the system operating characteristics [4], economic condition [5], and social situation [6].

As a kind of mid- and long-term power load forecasting, the annual power load forecasting can provide reference for electric power system operators to determine the schedule of power grid [7], and it can also contribute to the formation of generator maintenance scheduling and operation mode [8]. Moreover, the accurate annual power load forecasting can reduce the potential loss due to the mismatching between power supply and demand [9]. The electricity demand is regarded as the barometer of national economy [10], so the accurate annual electric power forecasting can also help the economic managers grasp the future economic development trend of a country or region [11]. Therefore, it is very important to accurately forecast the annual power load [12].

With the deepening of electricity market reform, rapid development of smart grid and the penetration of renewable energy power, power load forecasting is required a higher precision. For the annual power load forecasting, the traditional methods, such as time series analysis [13] and regression method [14] are relatively mature, and their forecasting results usually show good performances. Even so, the forecasting precision still needs to be improved. With the continuous improvement of contemporary science and the gradual deepening of fundamental theory research, the emergence of interdisciplinary theories, such as grey system and artificial intelligence system, provides a solid theoretical basis and mathematical foundation for the effective and practical

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forecasting on annual power load. Kandil et al. [8] applied a knowledge-based expert system for the annual power load forecasting. Hsu and Chen [15] used artificial neural network model to forecast the annual power load of Taiwan. Xia et al. [16] employed the radial basis function neural networks for China's power load forecasting. Farahat [17] combined the neural network technique and fuzzy inference method for annual peak power load forecasting. AlRashidi and El-Naggar [12] used the Kuwaiti and Egyptian networks and particle swarm optimization to forecast the annual peak load. Jia et al. [18] developed the General Simulation (GSIM) theory used for annual power load forecasting. Hong [19] applied support vector regression (SVR) technique to forecast the annual power load in Taiwan. Li et al. [20] developed a hybrid method for annual electricity consumption forecasting, which combined the least squares support vector machine and fruit fly optimization algorithm. Chen [21] proposed a collaborative fuzzy-neural approach based on fuzzy back propagation networks for annual electricity energy consumption prediction in Taiwan. Pai and Hong [22] employed a recurrent support vector machine optimized by genetic algorithm to predict the annual power load. Wang et al. [23] used support vector regression optimized by differential evolution algorithm to forecast the annual electricity consumption. To improve the forecasting accuracy of grey model, Akay and Atak [24] introduced the rolling mechanism for annual electricity demand forecasting in Turkey. Pai and Hong [25] proposed a combined method based on support vector machines and simulated annealing algorithms for annual electricity load forecasting. Zhao et al. [6] proposed a combined forecasting model which employed fruit fly optimization algorithm to determine the weights of logistic curve model and multi-dimensional forecasting model for urban saturated power load analysis.

Grey system theory, proposed by Deng Ju-long in 1980s [26], is a kind of theory for uncertain system, which can solve the uncertain issues with the characteristics of small sample and poor data information [27]. As a kind of often used grey forecasting technique, GM (1, 1) (Grey Modelling (1, 1)) has been employed into many forecasting issues, such as particulate matter concentration forecast [28], wind speed and wind power prediction [29], high technology industrial output forecast [30], per capita annual net income forecast of rural households [31], fuel production forecast [32], and energy consumption prediction [33]. Because the electric power system is a grey system, the GM (1, 1) has been successfully applied to forecast the power load by several researchers, such as Tan et al. [34] as well as Li et al. [35] for annual power load forecast, and Li et al. [36] as well as Bahrami et al. [37] for short-term power load forecast. However, the accuracy of annual power load forecasting is usually affected by political environment, economic development and social condition. In this case, the exponentially growing rule of GM (1, 1) may not show a good forecasting performance in terms of annual power load forecasting. Therefore, to enhance the forecasting performance, the improvement on GM (1, 1) needs to be performed. Recently, several studies have carried on valuable attempts, such as Akay and Atak [24] used GM (1, 1) with rolling mechanism to forecast annual power load, Tan et al. [34] used the chaotic co-evolutionary particle swarm optimization algorithm to determine the parameters of GM (1, 1), and Li et al. [35] proposed an adaptive GM (1, 1) for annual power load prediction. In the past few years, many swarm intelligence algorithms have been proposed and widely employed to solve optimization issues in the real world, such as particle swarm optimization (PSO) [38], genetic algorithm (GA) [39], ant colony optimization (ACO) [40], differential evolution algorithm (DE) [41], and fruit fly optimization algorithm (FOA) [42]. Ant lion optimizer (ALO) is a new nature-inspired metaheuristic algorithm, which was proposed by S. Mirjalili in 2015 [43]. In this paper, the parameters of GM (1, 1) were optimized by employing ALO. Meanwhile, to furtherly improve the forecasting accuracy, the rolling mechanism was also applied for annual power load forecasting. The forecasting performance of this proposed model (namely GM (1, 1) optimized by ALO with Rolling mechanism, abbreviated as Rolling-ALO-GM (1, 1)) was compared with several compared forecasting model and state-of-art forecasting techniques, which include GM (1, 1), PSO-GM (1, 1), ALO-GM (1, 1), Generalized Regression Neural Network (GRNN), Rolling-GM (1, 1), and Rolling-PSO-GM (1, 1).

The main contributions of this paper are as follows:

(1) A new intelligent optimization algorithm, namely ALO is employed to optimally determine the developing coefficient and grey input of GM (1, 1), which can improve the accuracy of annual power load forecasting and show superiority over other method such as least square estimation method and PSO.
(2) Most current studies related to annual power load forecasting by employing grey forecasting technique either combine GM (1, 1) with optimization algorithm or introduce rolling mechanism into GM (1, 1). This paper realizes the combination of grey forecasting model GM (1, 1), intelligent optimization algorithm ALO, and rolling mechanism, which is a new attempt in terms of annual power load forecasting. The forecasting results show this triple combination can significantly enhance the forecasting performance. The proposed method enriches the current annual power load forecasting library.
(3) By using the electricity consumption data from two real-world cases at national level and regional level, namely China and Shanghai city, this study confirms the practicability and effectiveness of the proposed forecasting approach against some state-of-art forecasting techniques in the literature. The empirical results indicate the proposed Rolling-ALO-GM (1, 1) approach can be a promising alternative forecasting technique for annual power load, and ALO is a new nature-inspired metaheuristic algorithm with good development foreground.

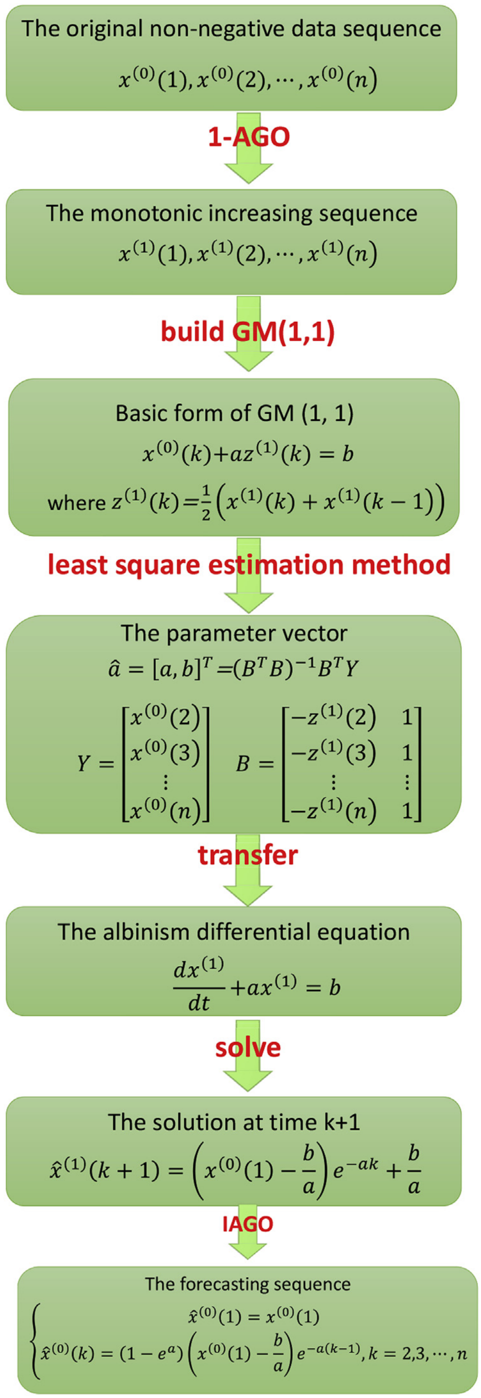
The remainder of this paper is organized as follows: Section 2 introduces the basic theories of GM (1, 1) and ALO, and then the Rolling-ALO-GM (1, 1) proposed in this paper is detailed elaborated; Two case studies at national level and regional level, namely China's annual electricity consumption and annual electricity consumption of Shanghai city are selected to validate the forecasting capacity of Rolling-ALO-GM (1, 1) in Section 3; Section 4 gives the conclusion.

2. Methodology

2.1. GM (1, 1)

Grey system uncovers the inherent regularity of a given data sequence by way of data mining and collating [44]. In grey system theory, the stochastic process is regarded as the grey variable which varies in a certain range and space [45]. GM (1, 1), i.e. first-order one-variable grey model, is an effective forecasting method employed for the issues with uncertain and imperfect information, and the sample data can be as few as four observations when GM (1, 1) is utilized to forecast [27].

Considering many literature have detailed expounded the basic theory of GM (1, 1), such as Pai et al. [28], El-Fouly et al. [29], and Zhao et al. [31], we do not elaborate it again and only give the modelling procedure of GM (1, 1) in intuitive and easily understandable way, which is shown in Fig. 1.



Nomenclature	
GM(1,1)	first-order one-variable grey model
1-AGO	one-time accumulated generating operation
a	developing coefficient
b	grey input
IAGO	inverse accumulated generating operation

Fig. 1. Modelling procedure of GM (1, 1).

2.2. Ant lion optimizer (ALO)

Inspirited by the behavior of ant lions hunting for the ants, S. Mirjalili proposed a new intelligence evolutionary algorithm—Ant lion optimizer (ALO) in 2015 [43]. According to the intelligence behavior of antlions hunting for ants (the detailed elaboration can be found in Mirjalili [43]), the ALO consists of several steps, just as follows.

Step 1: Parameters setting.

The main parameters of ALO include: the number of ants and antlions *Agents_no*; the number of variables *dim*; the maximum iteration number *Max_iteration*; the lower bound $lb = [lb_1, lb_2, \cdots]$ and upper bound $ub = [ub_1, ub_2, \cdots]$ of variables.

Step 2: Position initialization.

The positions of ants and antlions are expressed as Equations (1) and (2), respectively.

$$M_{Ant} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1d} \\ A_{21} & A_{22} & \cdots & A_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nd} \end{bmatrix} \tag{1}$$

$$M_{Antlion} = \begin{bmatrix} AL_{11} & AL_{12} & \cdots & AL_{1d} \\ AL_{21} & AL_{22} & \cdots & AL_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ AL_{n1} & AL_{n2} & \cdots & AL_{nd} \end{bmatrix} \tag{2}$$

where M_{Ant} is the position matrix of each ant; $M_{Antlion}$ is the position matrix of each antlion; A_{ij} represents the *j-th* parameter's value of the *i-th* ant; AL_{ij} represents the *j-th* parameter's value of the *i-th* antlion; $i = 1, 2, \cdots, n j = 1, 2, \cdots, d$.

The entry of M_{Ant} and $M_{Antlion}$ can be calculated by

$$A_{*j} \quad or \quad AL_{*j} = rand*(ub_j - lb_j) + lb_j \tag{3}$$

where A_{*j} and AL_{*j} represent the values of the *j-th* column of matrix; *rand* is the random number generated with uniform distribution in the interval [0, 1]; ub_j and lb_j represent the upper bound and lower bound of the *j-th* variable, respectively.

Step 3: Initial elite selection.

For evaluating each antlion, the fitness function $f[*]$ should be given during optimization, and the matrix M_{OAL} is employed to store the fitness value of antlions.

$$M_{OAL} = \begin{Bmatrix} f[(AL_{11} & AL_{12} & \cdots & AL_{1d})] \\ f[(AL_{21} & AL_{22} & \cdots & AL_{2d})] \\ & & \vdots & \\ f[(AL_{n1} & AL_{n2} & \cdots & AL_{nd})] \end{Bmatrix} \tag{4}$$

where M_{OAL} is the fitness matrix of antlions; $f[*]$ is the fitness function, also called as objective function.

Selecting and saving the elite can maintain the best solution obtained at each step of optimization process for evolutionary algorithm. The elite refers to the best antlion obtained so far in each iteration according to the fitness value, which is also called as the fittest antlion. According to Equation (4), the initial elite and its fitness value can be determined.

Step 4: Iteration start.

For *t-th* iteration, the movement (position) of the *i-th* ant is affected by both the antlion and elite. In this case, ALO assumes that the ant randomly walks around the antlion selected by roulette wheel algorithm and the elite simultaneously. Therefore, the position of the *i-th* ant can be obtained by

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{5}$$

where Ant_i^t is the position of the *i-th* ant at *t-th* iteration; R_A^t is the random walk around the antlion selected by the roulette wheel algorithm at *t-th* iteration; R_E^t is the random walk around the elite at *t-th* iteration.

Random walk is an important adopted approach for modelling the movement of ants and antlions with the stochastic characteristics in ALO. The movement of ants can be described as

$$X(t) = [0, cumsum(2r(t_1) - 1), cumsum(2r(t_2) - 1), \cdots, cumsum(2r(t_n) - 1)] \tag{6}$$

where *cumsum* represents the cumulative sum; t represents the step of random walk; n is the maximum number of iteration; $r(t)$ is a stochastic function, denoted by

$$r(t) = \begin{cases} 1 & if \quad rand > 0.5 \\ 0 & if \quad rand \le 0.5 \end{cases} \tag{7}$$

Then, the ants can update their positions at each step (iteration) of optimization process according to Equations (5)–(7). To ensure the random walks inside the search space, the normalization needs to be done for the position of ants at each iteration, as follows:

$$\tilde{X}_j^t = \frac{\left(X_j^t - a_j\right) \times \left(d_j^t - c_j^t\right)}{\left(b_j - a_j\right)} + c_j^t \tag{8}$$

where $\tilde{X}_j^t$ represents the normalized value of the j-th variable at t-th iteration; a_j is the minimum of random walk of j-th variable; b_j is the maximum of random walk of j-th variable; c_j^t is the minimum of random walk of j-th variable at t-th iteration; d_j^t is the maximum of random walk of j-th variable at t-th iteration.

In ALO, the random walks of ants are applied to all the variables (dimensions), and they are affected by the traps of antlions. To model this consideration, the Equation (9) is given:

$$\begin{cases} c_i^t = Antlion_i^t + c^t \\ d_i^t = Antlion_i^t + d^t \end{cases} \tag{9}$$

where c_i^t represents the minimum of all variables related to the i-th ant at t-th iteration; d_i^t represents the maximum of all variables related to the i-th ant at t-th iteration; $Antlion_i^t$ represents the position of the selected i-th antlion at t-th iteration; c^t is the minimum of all variables at t-th iteration; d^t is the vector including the maximum of all variables at t-th iteration.

In ALO, the antlions are selected by using roulette wheel algorithm according to the fitness value during optimization process. This consideration can make the antlion with fitter performance has higher chance to catch ants.

During the optimization process, the antlions can build the pits proportional to their fitness, and antlions with larger pits (higher fitness) have bigger chance to catch ants. Meanwhile, the antlions throw sands outwards the pit's center when they find ants are in the trap. So, to simulate this behavior of ants sliding towards antlions, the range of random walk is considered to decrease adaptively, described by Equations (10) and (11).

$$c^t = \frac{c^t}{I} \tag{10}$$

$$d^t = \frac{d^t}{I} \tag{11}$$

where I is a ratio, which can be calculated by

$$I = \begin{cases} 10^2 \times \frac{t}{T}, & \frac{t}{T} > 0.1 \\ 10^3 \times \frac{t}{T}, & \frac{t}{T} > 0.5 \\ 10^4 \times \frac{t}{T}, & \frac{t}{T} > 0.75 \\ 10^5 \times \frac{t}{T}, & \frac{t}{T} > 0.9 \\ 10^6 \times \frac{t}{T}, & \frac{t}{T} > 0.95 \end{cases} \tag{12}$$

Step 5: Optimal antlion (final elite) selection.

When the ant reaches the bottom of cone-shaped pit, the antlion will catch it with the jaw. Then, the antlion pulls the ant inside the sand and consumes the prey. Finally, to enhance the chance of catching new ant, the antlion will update its position to that of the latest caught ant and build a new pit. In ALO, the ant is caught only when this ant becomes fitter than the antlion. The position update of antlion is described by

$$Antlion_i^t = Ant_i^t \quad if \; f\left(Ant_i^t\right) > f\left(Antlion_i^t\right) \tag{13}$$

where $Antlion_i^t$ represents the position of selected i-th antlion at t-th iteration, and Ant_i^t represents the position of i-th ant at t-th iteration.

For each iteration, update the position and fitness of antlions according to Equation (13), and then re-determine the elite and update its position if any antlion becomes fitter than the elite determined by the former iteration. When the iteration criteria satisfies, the optimal antlion (final elite) can be obtained.

2.3. The proposed Rolling-ALO-GM (1, 1) model

In this paper, an optimized grey forecasting model is proposed, namely Rolling-ALO-GM (1, 1). In this proposed model, GM (1, 1) is optimized by ALO, and the rolling mechanism is introduced in order to enhance the forecasting performance. The principle of Rolling-ALO-GM (1, 1) is elaborated in the following sub-sections.

2.3.1. Rolling-GM (1, 1)

Rolling mechanism employs the most recent data to forecast future data points [31]. Because the most recent data usually reflect the latest development trend and feature of studied object, the rolling mechanism is able to improve the forecasting accuracy in most cases [46].

There are p data points used for building GM (1, 1), and q data points that need to be forecasted by GM (1, 1) at each rolling operation. The rolling-GM (1, 1) can be described as follows.

Step 1: sequence $\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(p)\}$ is firstly used to build GM (1, 1), and then data points $\{\hat{x}^{(0)}(p+1), \hat{x}^{(0)}(p+2), \cdots, \hat{x}^{(0)}(p+q)\}$ can be forecasted.

Step 2: to embody the most recent data, GM (1, 1) needs to be rebuilt with p new actual data points. To forecast the data points $\{\hat{x}^{(0)}(p+q+1), \hat{x}^{(0)}(p+q+2), \cdots, \hat{x}^{(0)}(p+2q)\}$, the $\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(q)\}$ should be removed from the former sequence, and the latest p data points $\{x^{(0)}(q+1), x^{(0)}(q+2), \cdots, x^{(0)}(q+p)\}$ needs to be employed for rebuilding GM (1, 1).

Step 3: repeat Step 2 till all the data points that need be forecasted are obtained.

The forecasting procedure of rolling-GM (1, 1) is shown in Fig. 2.

2.3.2. ALO-GM (1, 1)

There is no requirement for the statistical distribution of data sample when GM (1, 1) is utilized. The AGO (accumulated generating operation) can reduce the randomness of data points and make the accumulated generation sequence well fit to exponential growth law [47]. Traditionally, two parameters, namely developing parameter a and grey input b are determined by the least square estimation method [44]. However, these two parameters can also be determined by other methods such as intelligent optimization algorithms, which may enhance the forecasting performance of grey model. In this paper, the developing parameter a and grey input b of GM (1, 1) are determined by ALO in order to improve the annual power load forecasting accuracy.

The details of ALO-GM (1, 1) are described as follows.

Step 1: Parameters initialize.

Five parameters need to be set firstly, which are the number of ants and antlions *Agents_no*, number of variables *dim*, maximum iteration number *Max_iteration*, lower bound $lb=[lb_1, lb_2, \cdots]$ and upper bound $ub=[ub_1, ub_2, \cdots]$. In this study, suppose $Agents\_no=100$, $dim=2$, $Max\_iteration=500$, $lb=[-2,0]$, and $ub=[2,100{,}000]$.

Step 2: Evolution starts.

Set $gen=0$, and randomly generate the positions of ants and antlions.

Step 3: Initial optimization.

When utilizing ALO to select the optimal parameters of GM (1, 1), the fitness function $f[*]$ should be established firstly. In this paper, the Mean Absolute Percentage Error (abbreviated as MAPE, shown by Equation (14)) is employed to build the fitness function.

$$MAPE=\frac{1}{n}\sum_{k=1}^{n}\left|\frac{x(k)-\hat{x}(k)}{x(k)}\right|\times 100\% \tag{14}$$

where $x(k)$ is the actual value at time k; $\hat{x}(k)$ is the forecast value at time k.

In ALO-GM (1, 1), the developing parameter a and grey input b of GM (1, 1) are represented by the position of antlion $M_{Antlion}$, namely

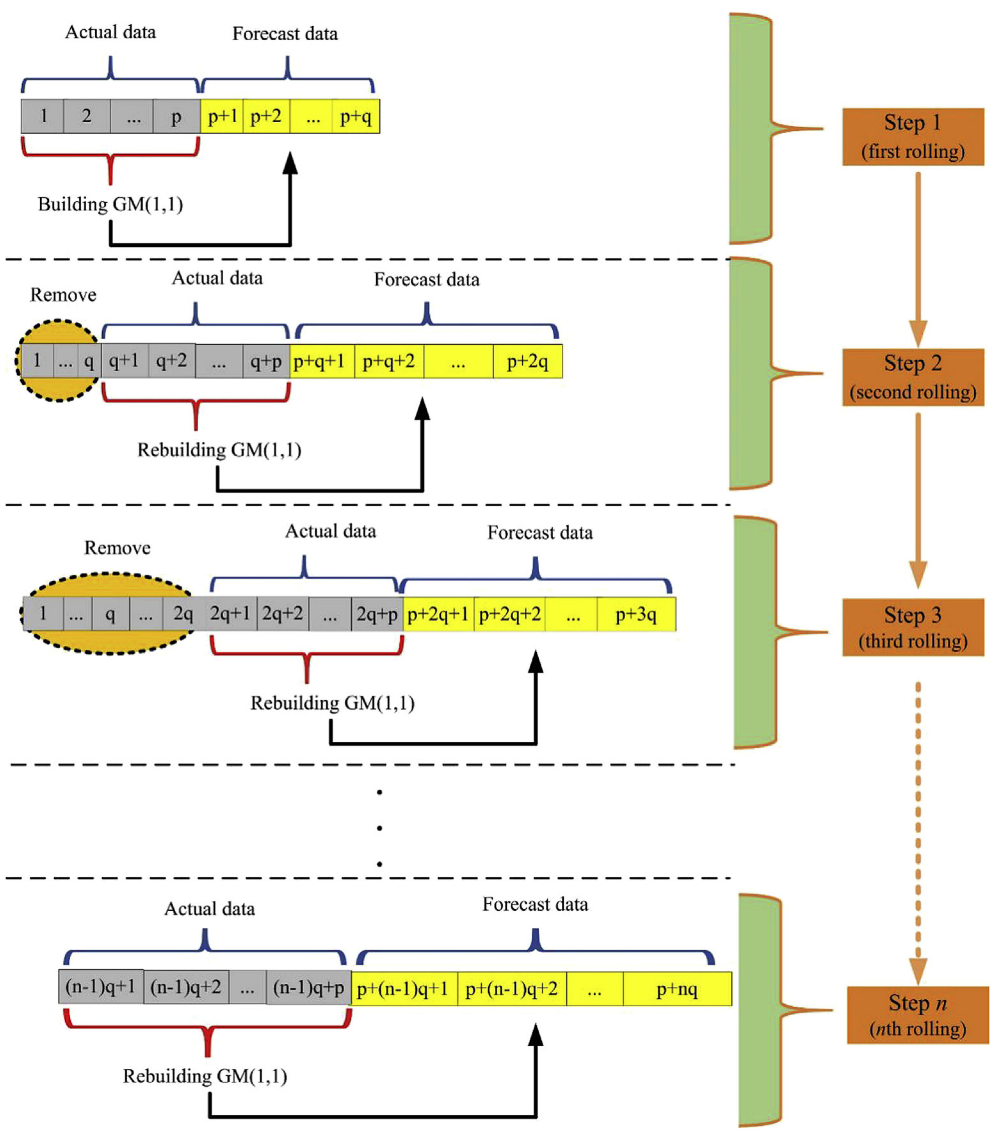


Fig. 2. Forecasting procedure of GM (1, 1) with rolling mechanism.

each column of $M_{Antlion}$. According to the randomly generated antlion position based on Equation (3), GM (1, 1) can be built, and GM (1, 1) forecasting equation can be determined. Suppose the actual data sequence $\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(p)\}$ is used in this step, and then the fitting sequence $\{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(p)\}$ can be obtained according to the built GM (1, 1). Then, the fitness function can be confirmed, which is to minimize the MAPE of fitting data points, defined by

$$f = \min \frac{1}{p} \sum_{k=1}^{p} \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| \times 100\% \tag{15}$$

So far, the elite can be selected at the initial iteration.

Step 4: Offspring evolutions.

Set gen = gen + 1. The ants update their positions according to the antlions selected by roulette wheel algorithm and the elite (namely the obtained the fittest antlions in Step 3). Then, calculate the fitness value of the ants with new positions. When there exist ants whose fitness values are superior to that of the antlions, these ants will be caught. After that, the antlions update their positions, and then calculate their fitness values again. Finally, re-select the elite and update its position if any antlion becomes fitter than the elite determined by the former iteration. Repeat this step, and stop until the iteration criteria satisfies.

Step 5: Optimization ends.

Different MAPEs of forecasting data during the optimization process will be generated with the changes of parameters values, and the minimum of MAPEs will be found when the optimization ends. Through a number of iterations, the optimal parameters a and b of GM (1, 1) can be found by employing ALO based on Equation (15). Then, the optimal GM (1, 1) can be built, and the future data points can be forecasted.

The procedure of ALO-GM (1, 1) is shown in Fig. 3.

2.3.3. Rolling-ALO-GM (1, 1)

Rolling-ALO-GM (1, 1) refers to the GM (1, 1) optimized by ALO with the introduction of rolling mechanism. The parameters a and b of GM (1, 1) are optimally determined by ALO at each rolling process. So, the forecasting procedure of Rolling-ALO-GM (1, 1) is much more complex than Rolling-GM (1, 1) and ALO-GM (1, 1). The details of Rolling-ALO-GM (1, 1) are described as follows.

Step 1: at the beginning, to forecast the sequence $\{\hat{x}^{(0)}(p+1), \hat{x}^{(0)}(p+2), \cdots, \hat{x}^{(0)}(p+q)\}$, the actual data sequence $\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(p)\}$ is used as the input feeding into ALO-GM (1, 1). Then, the values of parameters a and b are calculated and optimized by ALO based on the fitness function (as shown by Equation (15)), and the forecasting is done.

Step 2: Because the rolling mechanism focuses on the updating data, to forecast the sequence $\{\hat{x}^{(0)}(p+q+1), \hat{x}^{(0)}(p+q+2), \cdots, \hat{x}^{(0)}(p+2q)\}$, the most recent data points $\{x^{(0)}(q+1), x^{(0)}(q+2), \cdots, x^{(0)}(q+p)\}$ are selected as the input feeding into ALO-GM (1, 1). Then, the values of parameters a and b are recalculated and re-optimized by ALO by minimizing the fitness function (as shown by Equation (16)), and the forecasting is performed again.

$$f = \min \frac{1}{p} \sum_{k=1}^{p} \left| \frac{x^{(0)}(q+k) - \hat{x}^{(0)}(q+k)}{x^{(0)}(q+k)} \right| \times 100\% \tag{16}$$

Step 3: Repeat Step 1 and Step 2 until all the data points that need to be forecasted are obtained.

The forecasting procedure of Rolling-ALO-GM (1, 1) is also schematically elaborated in Fig. 4.

3. Case studies

Annual power load forecasting is not only essential for the planning, operation and maintenance of electric power system, but can also mirror the economic development of a country or region. Therefore, two cases are employed in this paper: one is China's annual electricity consumption forecasting (representing the national level forecasting); the other is the annual electricity consumption forecasting of Shanghai city (representing the regional level forecasting).

3.1. Case study one – China's annual electricity consumption forecasting

We firstly present an empirical illustration on China's annual electricity consumption forecasting to examine the effectiveness of our proposed Rolling-ALO-GM (1, 1) model.

3.1.1. Empirical calculation and result

The annual electricity consumption in China is forecasted by employing the proposed Rolling-ALO-GM (1, 1) model. The small sample data between 2001 and 2012 were collected from China Statistical Yearbook (see http://data.stats.gov.cn/english/easyquery.htm?cn=C01), which include 12 data points as shown in Fig. 5.

Selecting the input subset and determining its length are important, which will impact the forecasting performance of GM (1, 1) model [47]. In this paper, we determine the optimal length of input subset by employing the optimal subset method proposed by Wang et al. [47]. By calculating, we found when the length of input subset is set as 7, the forecasting error is the smallest. Therefore, we set $p = 7$ and $q = 1$, which indicates 7 data points are used as the input of Rolling-ALO-GM (1, 1) model and the next one data point is forecasted. The forecasting details of China's electricity consumption are shown in Fig. 6. It can be seen that the parameters a and b of GM (1, 1) will be optimally determined for five times repeatedly. So, we will obtain five optimal parameter a and b.

Fig. 7 shows the iterative MAPE trend of Rolling-ALO-GM (1, 1) searching of optimal parameters for China's electricity consumption forecasting from 2008 to 2012. It can be seen that ALO is an effective and fast algorithm for searching the optimal parameters of GM (1, 1) at each rolling stage.

The optimal values of parameters a and b for forecasting China's electricity consumption from 2008 to 2012 are listed in Table 1. Then, China's electricity consumption from 2008 to 2012 can be forecasted correspondingly, and the forecasting results are also listed in Table 1.

3.1.2. Forecasting performance evaluation

To evaluate the forecasting performance of Rolling-ALO-GM (1, 1) model for China's electricity consumption, two things need to be done: one is the selection of compared forecasting models and the other is to choose the forecasting performance evaluation index.

To compare the forecasting results of different forecasting models, several compared forecasting model and state-of-art forecasting techniques are selected, which are GM (1, 1), PSO-GM (1, 1) [37], ALO-GM (1, 1), GRNN [9], Rolling-GM (1, 1) [24], and Rolling-PSO-GM (1, 1) [48]. Among these six compared models, GM (1, 1), PSO-GM (1, 1) and ALO-GM (1, 1) are a class of forecasting models without rolling mechanism; Rolling-GM (1, 1) and Rolling-PSO-GM (1, 1) are another class of forecasting models with rolling mechanism; GRNN is a kind of radial basis function (RBF) networks, which is a neural-based forecaster.

For GM (1, 1), the electricity consumption sequence from 2001 to 2007 is selected as the input of grey model, and then the values of parameters a and b can be determined, which are listed in

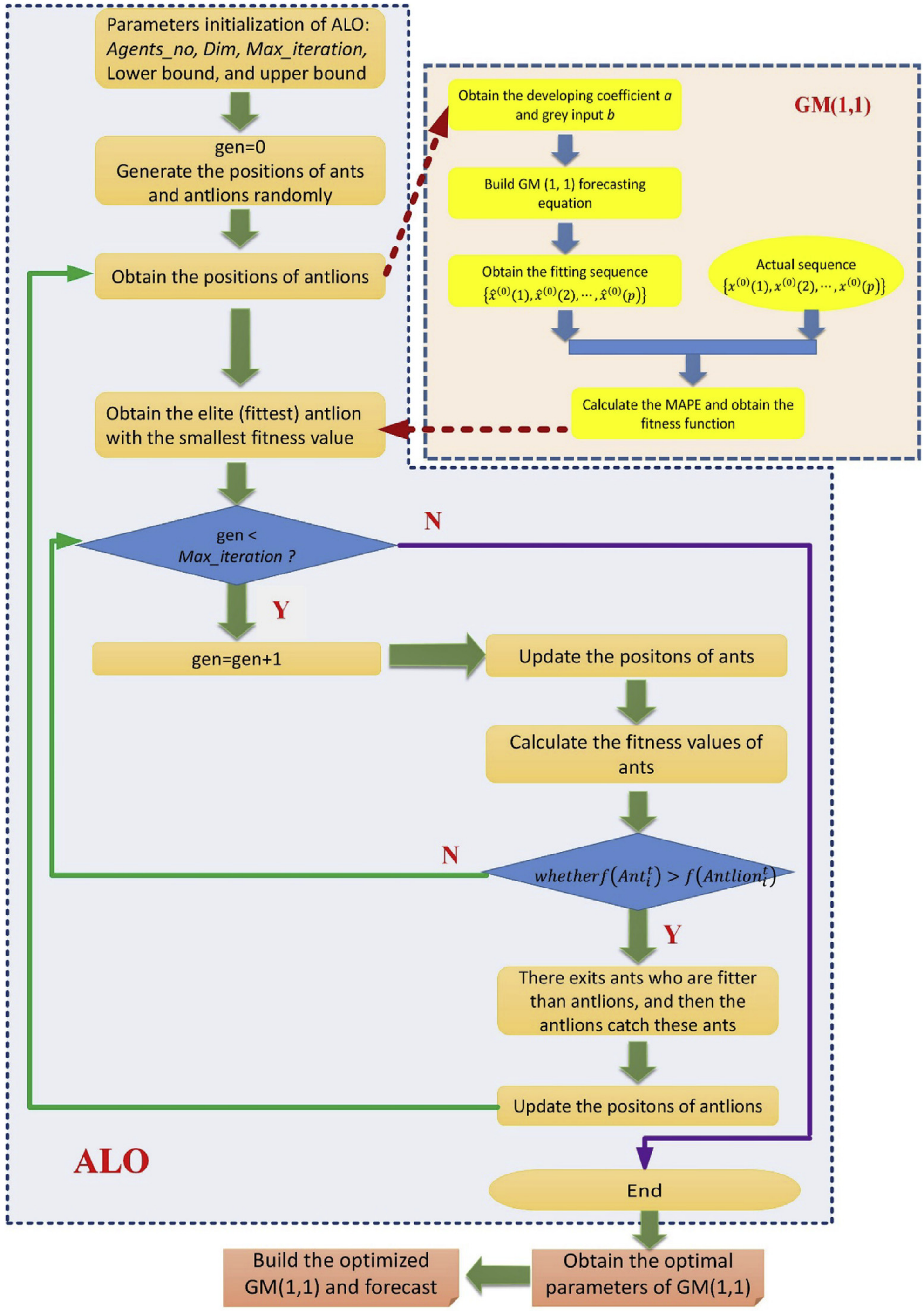


Fig. 3. Flow chart of ALO-GM (1, 1).

Table 2. Finally, the electricity consumption from 2008 to 2012 can be forecasted, and the results are shown in Table 3.

For PSO-GM (1, 1), the parameters a and b of GM (1, 1) are optimally determined by PSO with the input sample of electricity consumption from 2001 to 2007. Before iterative optimization, the initial parameters of PSO are set as follows: maximum iteration number = 500, swarm size = 100, particle size = 2, the minimum of particle = [−0.137, 13,000], the maximum of particle = [−0.135, 14,000], the minimum of velocity = 0, the maximum of velocity = 1, and learning factors c1 = 1 and c2 = 1. The optimal values of parameters a and b determined by PSO are listed in Table 2, and the forecasting results are shown in Table 3.

For ALO-GM (1, 1), the parameters a and b of GM (1, 1) are optimally determined by ALO with the input sample from 2001 to 2007. The initial parameters' setting are same as that in Section 3.2. Then, the optimal values of parameters a and b are determined by ALO, which are listed in Table 2. The forecasting results are shown in Table 3.

For GRNN, there is only one parameter σ that needs to be determined before forecasting. In this paper, we set σ as default value. Meanwhile, we normalize the sample data and employ the

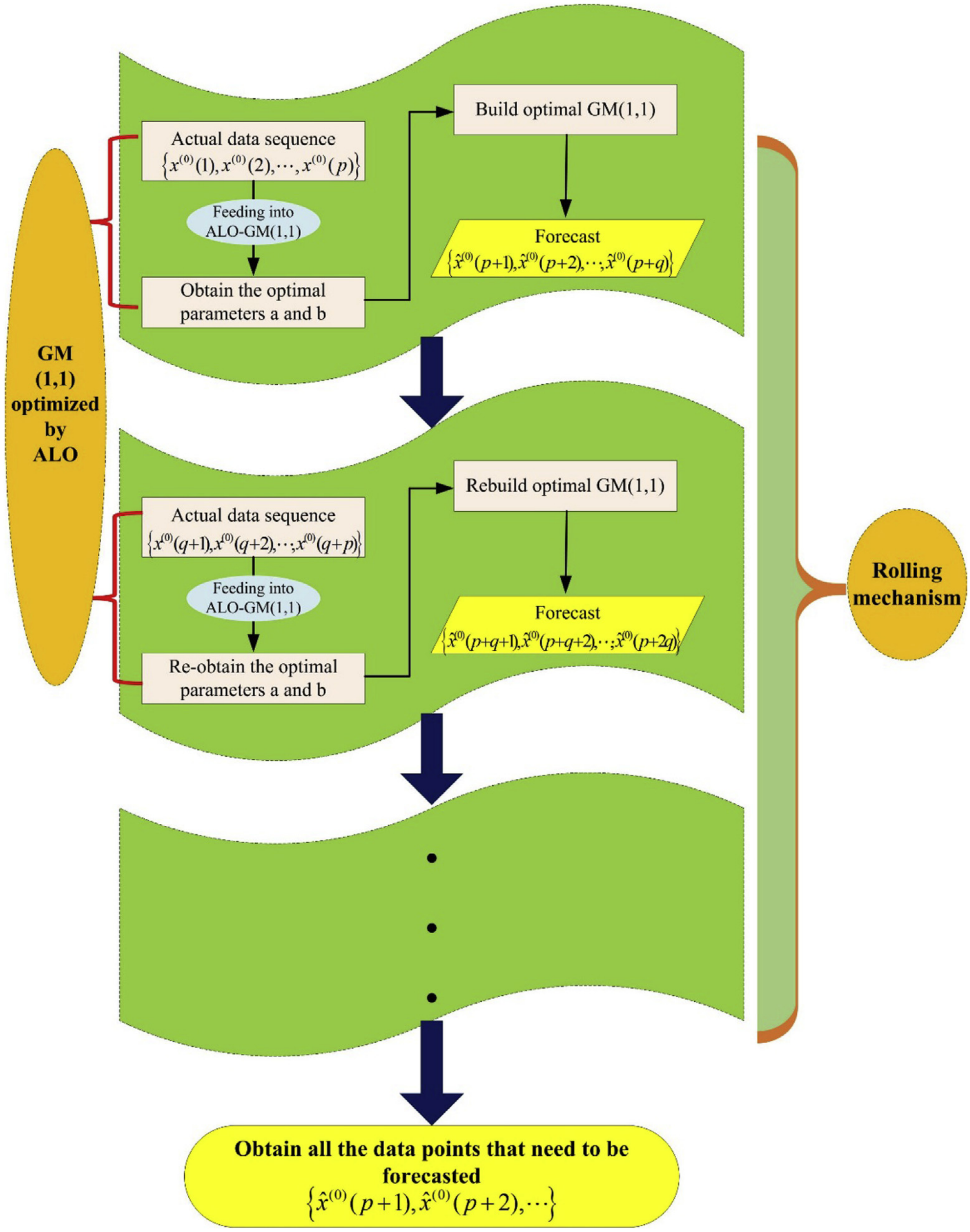


Fig. 4. Flow chart of GM (1, 1) optimized by ALO with rolling mechanism.

last three yearly electricity consumption data as the input variables of GRNN model to perform one-year-ahead forecasting, just as that in Li et al. [9]. This processing method is in accordance with the rolling mechanism, because it always uses the last three new data points to forecast the next data point. Thus, the training sample data is from 2004 to 2007. The forecasting electricity consumption of China from 2008 to 2012 are listed in Table 3.

For Rolling-GM (1, 1), the forecasting principle is shown in Fig. 2. The electricity consumption from 2001 to 2007 are utilized as the input of GM (1, 1), and then the electricity consumption at 2008 is obtained; the data from 2002 to 2008 are inputted into GM (1, 1), and the electricity consumption at 2009 is obtained; and so on. The optimal values of parameters a and b at each rolling stage are listed in Table 2, and the forecasting results are shown in Table 3.

For Rolling-PSO-GM (1, 1), the forecasting principle is the same as Rolling-ALO-GM (1, 1). The different between these two forecasting models is which algorithm is employed to optimally determine the values of parameters a and b of GM (1, 1). The optimal values of parameters a and b of GM (1, 1) determined by PSO at each rolling stage are listed in Table 2, and the forecasting results are given in Table 3.

We further draw Fig. 8 to represent the forecasting results of annual electricity consumption in China from 2008 to 2012 by employing these seven different forecasting models more intuitively and clearly.

From Fig. 8, it can be seen that the forecasting models without rolling mechanism (namely GM (1, 1), PSO-GM (1, 1) and ALO-GM (1, 1)) show poor forecasting performance, because the forecasting results are much larger than actual values. Among these three forecasting models, ALO-GM (1, 1) has higher forecasting

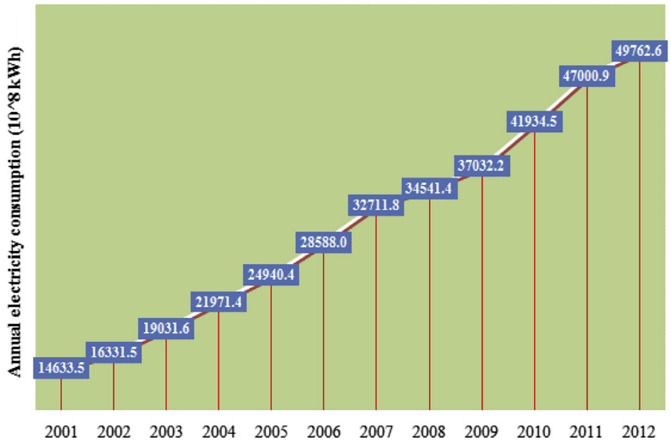


Fig. 5. Annual electricity consumption in China between 2001 and 2012.

accuracy than another two models (namely GM (1, 1) and PSO-GM (1, 1)), but it still has a large gap with the actual value. The forecasting models with rolling mechanism (namely GRNN, Rolling-GM (1, 1), Rolling-PSO-GM (1, 1) and Rolling-ALO-GM (1, 1)) show better forecasting performance than that without rolling mechanism, and the forecasting results are much closer to the actual values. Meanwhile, with the forecasting data point increases, the rolling-based forecasting models have much better forecasting performance than the models without rolling mechanism. The main reason is the rolling-based forecasting models utilize the most recent data to forecast, which can grasp the latest development trend and feature of forecasted object. This finding has also be verified in some other practical issues, such as Gross Domestic Product (GDP) and Interest Rates forecast [49], energy consumption forecast [50], and per capita annual net income forecast of rural households [31].

Among the rolling-based forecasting models, Rolling-ALO-GM (1, 1) obtains the highest forecasting accuracy at every forecasting points. This indicates the ALO can determine much more optimal parameters' values for GM (1, 1) than least square estimation method and PSO in terms of annual power load forecasting.

To furtherly evaluate the forecasting performance of different models, three frequently used indictors are selected, namely Percentage Error (PE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The PE and RMSE can be calculated by Equations (17) and (18), respectively.

$$PE = \frac{x(k) - \hat{x}(k)}{x(k)} \times 100\% \tag{17}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(x(k) - \hat{x}(k)\right)^2} \tag{18}$$

where $x(k)$ is the actual value at time k, and $\hat{x}(k)$ is the forecast value at time k.

The PEs of seven forecasting models are listed in Table 4. It can be seen that Rolling-ALO-GM (1, 1) model has higher forecasting accuracy than another six models at every forecasting year.

The calculation results of MAPE and RMSE are listed in Table 5. It is verified again that the forecasting models with rolling mechanism show better forecasting performance than the models without rolling mechanism. According to the criterion of MAPE listed in Table 6, the forecasting models with rolling mechanism have excellent forecasting power because their obtained MAPEs are less than 10%, and Rolling-ALO-GM (1, 1) is the best due to the smallest MAPE. However, the models without rolling mechanism only obtain good forecasting performance, and the forecasting errors are much bigger. The RMSE calculation results of seven forecasting models also indicate the same findings as that of MAPE. One interesting finding is that the GRNN model has better forecasting performance than the compared models without rolling mechanism (namely GM (1, 1), PSO-GM (1, 1), and ALO-GM (1, 1)), because the rolling mechanism is included when then GRNN is employed to forecast, which can embody the latest data information. However, the GRNN shows worse forecasting capacity compared with the rolling-GM (1, 1), rolling-PSO-GM (1, 1), and rolling-ALO-GM (1, 1), mainly due to its required large training sample which cannot be meet in this case study.

In conclusion, the PE at every forecasting point, MAPE and RMSE of Rolling-ALO-GM (1, 1) are the smallest among these seven different forecasting models. Therefore, it can be safely concluded that the proposed Rolling-ALO-GM (1, 1) model which the parameters of GM (1, 1) are optimally determined by the new evolutionary algorithm ALO with rolling mechanism for annual power load forecasting is effective and practical. The ALO-GM (1, 1) model shows better forecasting performance than GM (1, 1) and PSO-GM (1, 1) no matter with rolling mechanism or not, which indicates the newly proposed intelligent evolutionary algorithm ALO is an attractive and effective optimization tool for annual power load forecasting. Because the rolling mechanism utilizes the most recent data as the input of forecasting model which can consider the latest development trend and characteristics of forecasted object, the grey model with rolling mechanism shows better forecasting performance than that without rolling mechanism. Meanwhile, it can be also concluded that GM (1, 1) which the parameters are determined by intelligent optimization algorithm can obtain better forecasting results than that are determined by least square estimation method.

3.2. Case study two — annual electricity consumption forecasting for Shanghai city

In order to further check the robustness and effectiveness of proposed Rolling-ALO-GM (1, 1) model, we present another case study based on the annual electricity consumption forecasting for Shanghai city at the regional level.

3.2.1. Empirical calculation and result

The small sample data for annual electricity consumption of Shanghai city between 2001 and 2012 were collected from Shanghai Statistical Yearbook 2013 (see http://www.stats-sh.gov.cn/data/toTjnj.xhtml?y=2013e), which are shown in Fig. 9.

By calculation, we set $p = 7$ and $q = 1$, which indicates 7 data points are also used as the input of Rolling-ALO-GM (1, 1) model in this case study, and the next one data point is forecasted. The forecasting details of Shanghai's electricity consumption are the same as that of China case.

The optimal values of parameters a and b for forecasting Shanghai's electricity consumption from 2008 to 2012 are listed in Table 7. Then, Shanghai's electricity consumption from 2008 to 2012 can be forecasted correspondingly, which are also listed in Table 7.

3.2.2. Forecasting performance evaluation

The compared forecasting models and forecasting performance evaluation index are the same as that in China case. The forecasting results of different forecasting models for Shanghai's electricity consumption are shown in Table 8 and Fig. 10.

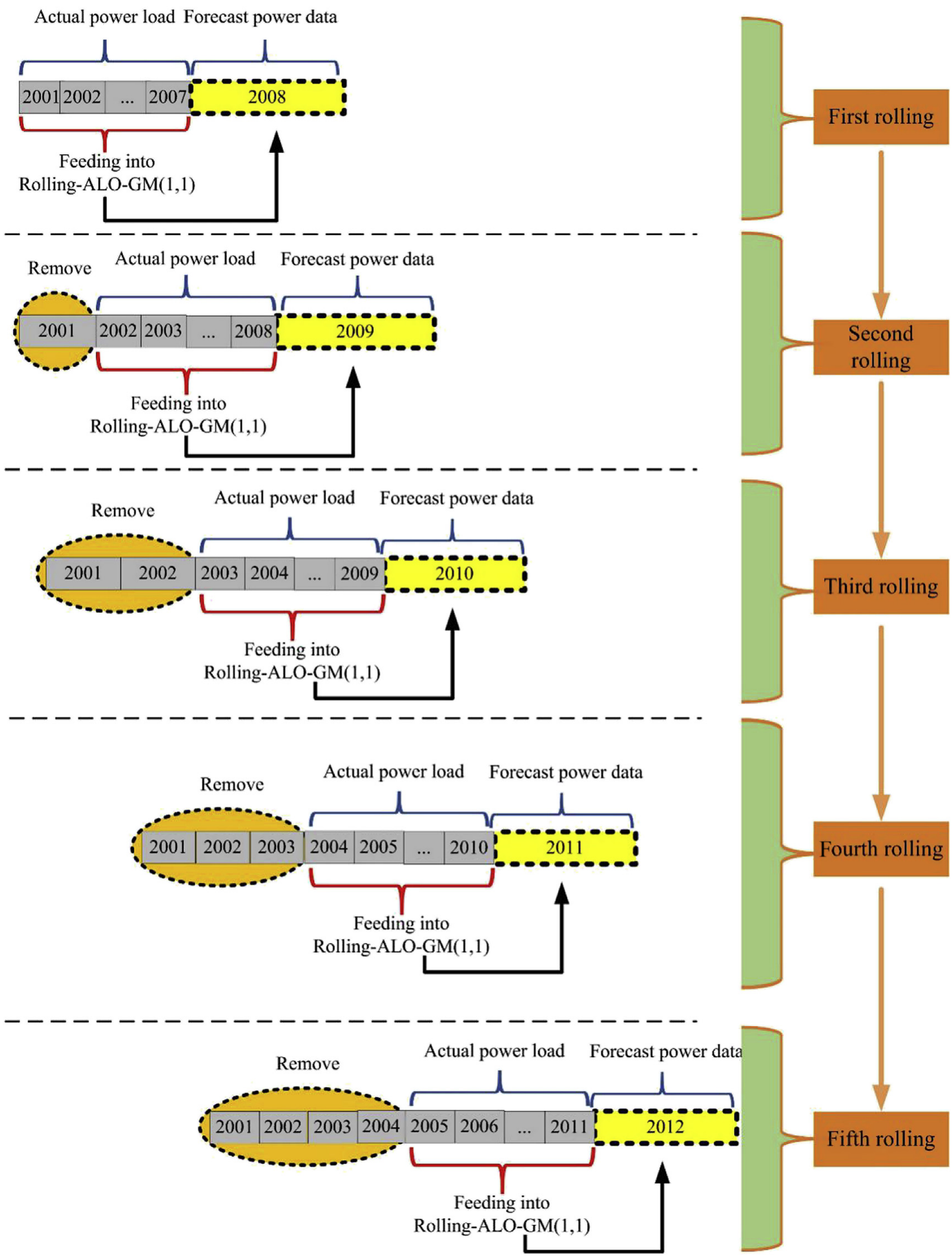
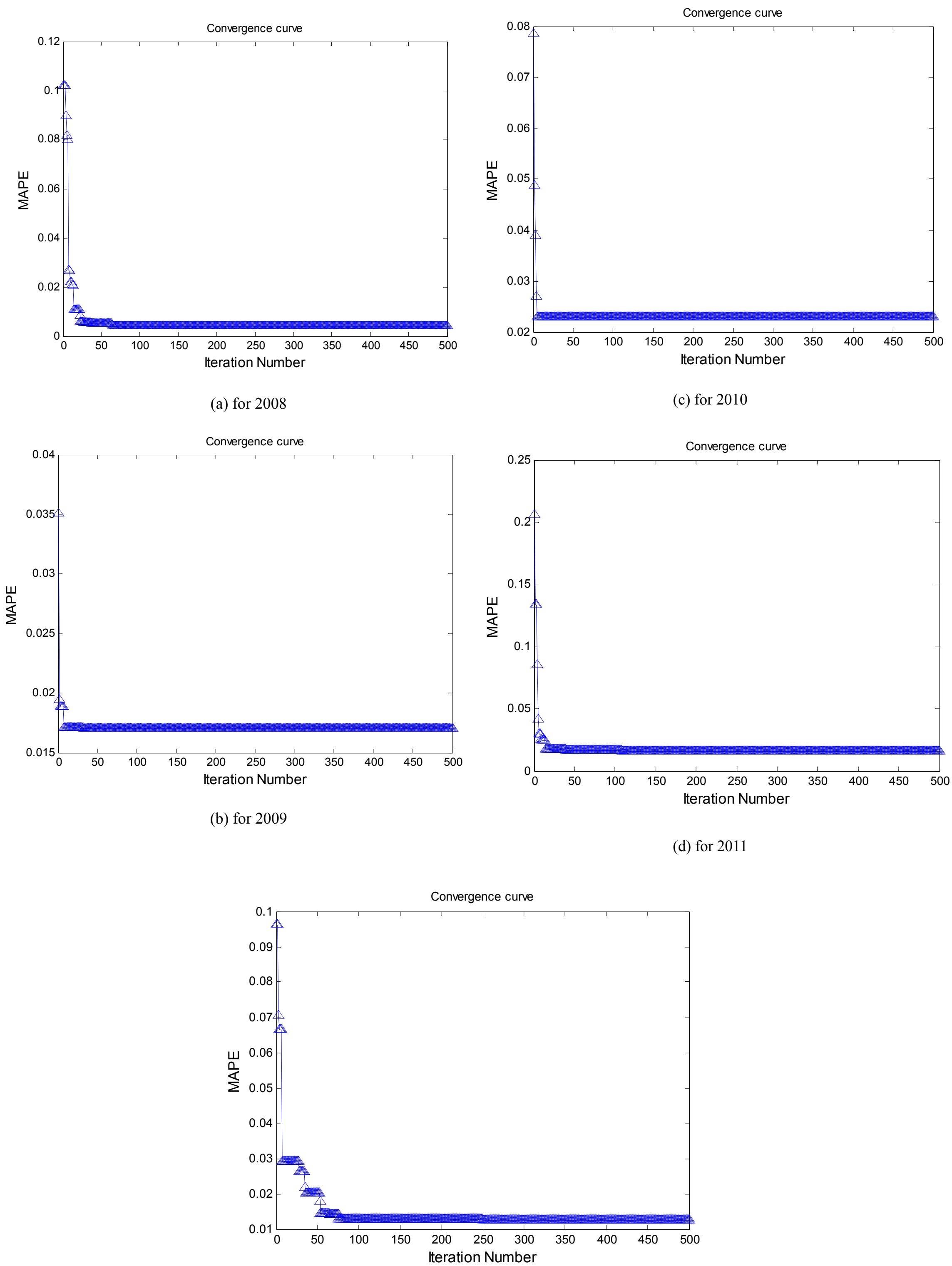


Fig. 6. Forecasting procedure of China's electricity consumption by employing Rolling-ALO-GM (1, 1) model.

Form Fig. 10, it can be seen that the forecasting models with rolling mechanism show better forecasting performance than that without rolling mechanism except in the year of 2008. With the forecasting data point increases, the gap between the actual electricity consumption and forecasted electricity consumption by rolling-free models becomes larger and larger.

The PEs of seven forecasting models in Shanghai case are listed in Table 9. It is very interesting to find that the Rolling-ALO-GM (1, 1) model obtains the smallest gap between the actual value and forecasted value only in 2009, and the PSO-GM (1, 1), Rolling-PSO-GM (1, 1), Rolling-GM (1, 1), and GRNN model obtain the smallest gap in 2008, 2010, 2011, and 2012, respectively. This finding is quite different from that in China case. However, the Rolling-ALO-GM (1, 1) model obtains the second smallest gap in 2010, 2011, and 2012. Meanwhile, it can also be seen that the largest absolute value of PE is 5.07% in 2008 for Rolling-ALO-GM (1, 1) model, but that are



(a) for 2008

(c) for 2010

(b) for 2009

(d) for 2011

(e) for 2012

Fig. 7. The iterative MAPE evolution of Rolling-ALO-GM (1, 1) searching of optimal parameters.

30.47%, 31.33%, 28.90%, 6.46%, 8.84%, and 6.41% for GM (1, 1), PSO-GM (1, 1), ALO-GM (1, 1), GRNN, Rolling-GM (1, 1), Rolling-PSO-GM (1, 1), respectively.

The calculation results of MAPE and RMSE for Shanghai case are listed in Table 10. It indicates the Rolling-ALO-GM (1, 1) model has the best forecasting performance due to its obtained the smallest MAPE and RMSE. It also verifies again that the forecasting models with rolling mechanism show better forecasting performance than that without rolling mechanism. This Shanghai case also shows the ALO-GM (1, 1) model shows better forecasting performance than

Table 1
Optimal parameters' values and forecasting results for 2008–2012.

Year	Parameters		Forecasting result
	a	b	
2008	−0.13,541	13,539.96	37,455.17
2009	−0.11,950	16,403.29	39,934.54
2010	−0.10,135	19,800.00	42,007.32
2011	−0.09,698	22,459.68	46,204.80
2012	−0.09,578	24,851.93	50,788.50

GM (1, 1) and PSO-GM (1, 1) no matter with rolling mechanism or not, which proves again the newly proposed intelligent evolutionary algorithm ALO is an attractive and effective optimization tool for annual power load forecasting. In terms of MAPE, the GRNN has the worst forecasting performance among the forecasting models with rolling mechanism. However, in term of RMSE, the GRNN obtains better forecasting result than the rolling GM (1, 1), but worse than Rolling-PSO-GM (1, 1) and Rolling-ALO-GM (1, 1). Meanwhile, we also calculated the mean absolute deviation (MAD) for comparing the GRNN and rolling GM (1, 1), and found the rolling

Table 2
The parameters' values determined by different compared forecasting models.

Year	GM (1, 1)		PSO-GM (1, 1)		ALO-GM (1, 1)		Rolling-GM (1, 1)		Rolling-PSO-GM (1, 1)	
	a	b	a	b	a	b	a	b	a	b
2008	−0.13,641	13,431.41	−0.13,575	13,516.93	−0.13,541	13,539.95	−0.13,641	13,431.41	−0.13,575	13,516.93
2009							−0.11,903	16,516.68	−0.1198	16,398.93
2010							−0.10,134	19,839.95	−0.1014	19,704.35
2011							−0.09,579	22,515.02	−0.0964	22,538.37
2012							−0.09,572	24,940.13	−0.09,609	24,827.26

Table 3
Forecasting results of different compared models [Unit: 10^8 kWh].

Year	GM (1, 1)	PSO-GM (1, 1)	ALO-GM (1, 1)	GRNN	Rolling-GM (1, 1)	Rolling-PSO-GM (1, 1)
2008	37,470.97	37,494.65	37,455.18	38,527.34	37,470.97	37,494.65
2009	42,947.25	42,946.18	42,886.36	39,951.8	40,041.43	40,015.25
2010	49,223.87	49,190.32	49,105.09	41,451.95	42,081.06	41,837.07
2011	56,417.8	56,342.33	56,225.56	43,117.64	45,904.09	46,154.7
2012	64,663.11	64,534.21	64,378.54	45,226.78	50,929.62	50,859.54

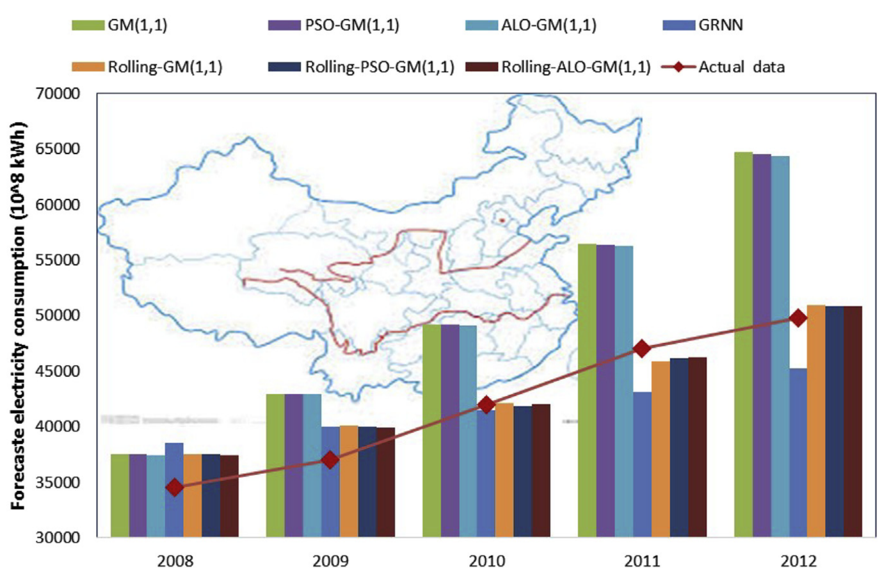


Fig. 8. Forecasting results of China's electricity consumption from 2008 to 2012 by different models.

Table 4
PE comparison of different forecasting models [Unit: %].

Year	GM (1, 1)	PSO-GM (1, 1)	ALO-GM (1, 1)	GRNN	Rolling-GM (1, 1)	Rolling-PSO-GM (1, 1)	Rolling-ALO-GM (1, 1)
2008	−8.48	−8.55	−8.44	−11.54	−8.48	−8.55	**−8.44**
2009	−15.97	−15.97	−15.81	−7.88	−8.13	−8.06	**−7.84**
2010	−17.38	−17.30	−17.10	1.15	−0.35	0.23	**−0.17**
2011	−20.04	−19.88	−19.63	8.26	2.33	1.80	**1.69**
2012	−29.94	−29.68	−29.37	9.11	−2.35	−2.20	**−2.06**

Note: The smallest gap between the actual value and forecasted value at each year is in bold.

Table 5
Results of MAPE and RMSE.

Index	GM (1, 1)	PSO-GM (1, 1)	ALO-GM (1, 1)	GRNN	Rolling-GM (1, 1)	Rolling-PSO-GM (1, 1)	Rolling-ALO-GM (1, 1)
MAPE (%)	18.36	18.28	18.07	7.59	4.33	4.17	**4.04**
RMSE (10^8 kWh)	9026.71	8964.44	8864.51	3472.7	2011.17	1977.32	**1928.99**

Note: The entry with the smallest value is in bold.

Table 6
Criteria of MAPE [33].

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

GM (1, 1) is superior to GRNN because the MADs of GRNN and rolling GM (1, 1) are 61.27 and 56.04, respectively. Therefore, it can be concluded that the grey forecasting model may outperform the neural-based forecasting technique under the condition of sample size.

4. Conclusion

In this paper, a hybrid optimized grey model is proposed for improving the forecasting accuracy of annual power load, which Grey Modelling (1, 1) is optimized by Ant Lion Optimizer with Rolling mechanism. The empirical results of two real-world case studies at national level and regional level show this proposed Rolling-ALO-GM (1, 1) model outperforms GM (1, 1), PSO-GM (1, 1), ALO-GM (1, 1), GRNN, Rolling-GM (1, 1), and Rolling-PSO-GM (1, 1). Employing the Ant Lion Optimizer to optimally determine the parameters of GM (1, 1) is effective and workable. Especially after introducing the rolling mechanism, the forecasting accuracy of annual power load can be significantly improved.

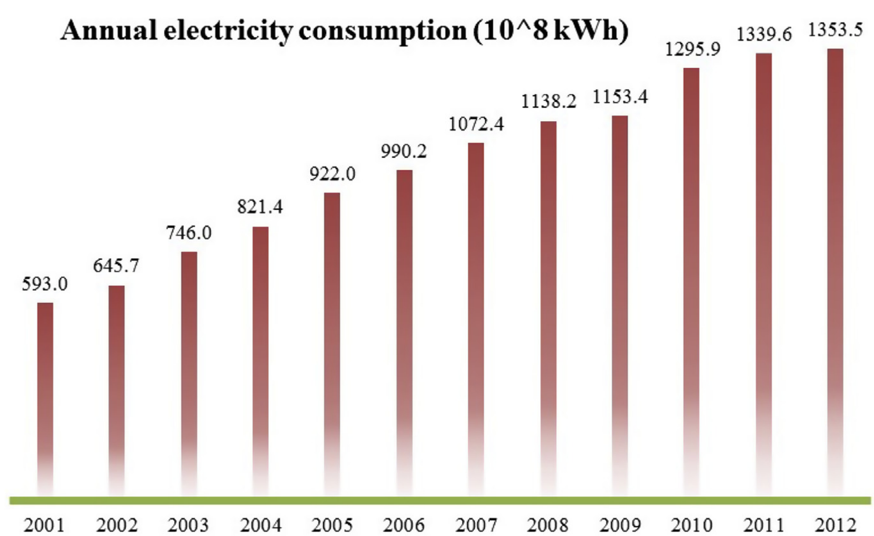


Fig. 9. Annual electricity consumption in Shanghai city between 2001 and 2012.

Table 7
Optimal parameters' values and forecasting results for Shanghai case.

Year	Parameters		Forecasting result
	a	b	
2008	−0.0944	591.27	1195.96
2009	−0.0850	595.50	1130.44
2010	−0.0700	777.68	1308.34
2011	−0.0673	839.69	1386.04
2012	−0.0556	935.12	1416.25

This proposed model with higher annual power load forecasting accuracy can contribute to the better formation of power grid as well as generator maintenance scheduling for electric power system operators, and it can also help the economic managers grasp the future economic development trend.

The advantages of Rolling-ALO-GM (1, 1) proposed in this paper includes: (1) it also has great forecasting performance when the sample size is small, but the neural-based forecasting technique may fail to work well; (2) it is of easy operation, because the program codes of GM (1, 1) and ALO is short and easily understandable,

Table 8
Forecasting results of different compared models [Unit: 10^8 kWh].

Year	GM (1, 1)	PSO-GM (1, 1)	ALO-GM (1, 1)	GRNN	Rolling-GM (1, 1)	Rolling-PSO-GM (1, 1)	Rolling-ALO-GM (1, 1)
2008	1198.74	1176.54	1195.96	1204.09	1198.74	1177.77	1195.96
2009	1320.64	1304.39	1314.35	1227.86	1255.28	1090.67	1130.44
2010	1454.92	1446.14	1444.47	1248.70	1271.94	1303.32	1308.34
2011	1602.86	1603.29	1587.48	1277.56	1358.79	1400.75	1386.04
2012	1765.84	1777.51	1744.64	1296.66	1428.11	1440.21	1416.25

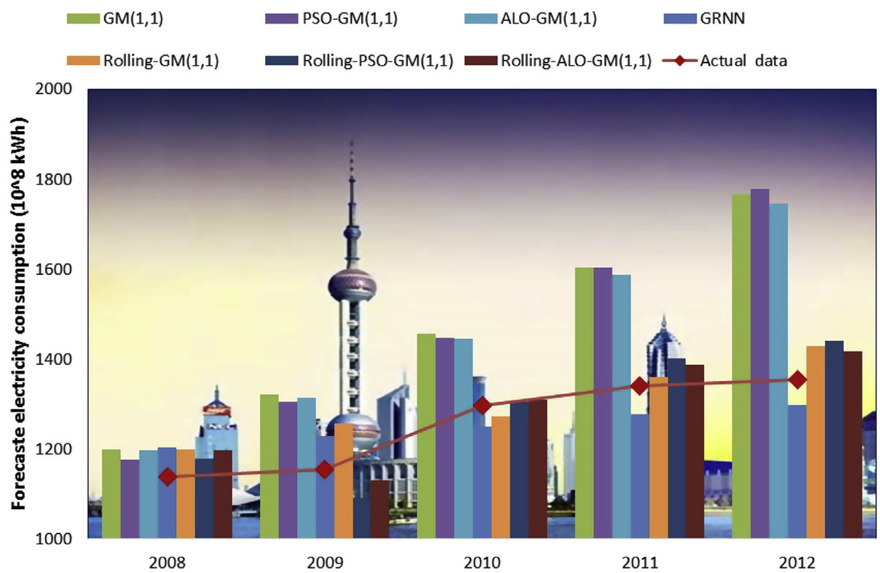


Fig. 10. Forecasting results of Shanghai's electricity consumption.

Table 9
PE comparison of different forecasting models [Unit: %].

Year	GM (1, 1)	PSO-GM (1, 1)	ALO-GM (1, 1)	GRNN	Rolling-GM (1, 1)	Rolling-PSO-GM (1, 1)	Rolling-ALO-GM (1, 1)
2008	−5.32	**−3.37**	−5.07	−5.79	−5.32	−3.47*	−5.07
2009	−14.50	−13.09	−13.96	−6.46	−8.84	5.44*	**1.99**
2010	−12.27	−11.60	−11.47	3.64	1.85	**−0.57**	−0.96*
2011	−19.65	−19.68	−18.50	4.63	**−1.43**	−4.56	−3.47*
2012	−30.47	−31.33	−28.90	**4.20**	−5.52	−6.41	−4.64*

Note: The smallest gap between the actual value and forecasted value at each year is in bold, and the second smallest gap is labeled with an asterisk (*).

Table 10
MAPE and RMSE in Shanghai case.

Index	GM (1, 1)	PSO-GM (1, 1)	ALO-GM (1, 1)	GRNN	Rolling-GM (1, 1)	Rolling-PSO-GM (1, 1)	Rolling-ALO-GM (1, 1)
MAPE (%)	16.44	15.81	15.58	4.94	4.59	4.09	**3.23**
RMSE (108 kWh)	243.43	243.39	230.56	61.95	64.13	57.99	**44.98**

Note: The entry with the smallest value is in bold.

which makes it be easily extended to other practical issues and areas; (3) the inclusion of rolling mechanism can grasp the latest data information, which contributes to improve the forecasting accuracy; and (4) the developing coefficient and grey input of GM (1, 1) are automatically and optimally determined by ALO, which can enhance the forecasting capacity of grey forecasting model. However, this proposed Rolling-ALO-GM (1, 1) also has certain drawbacks, for example, it cannot take the economic and social factors into consideration. This drawback can be avoided by using GM (1, n) model, which is also a valuable research direction. In the future research, ALO can be employed to optimize the support vector machine and neural network for other forecasting issues, such as short-term power load forecasting, electricity price forecasting, and wind speed forecasting.

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