Hindawi
Mathematical Problems in Engineering
Volume 2021, Article ID 5541650, 11 pages
https://doi.org/10.1155/2021/5541650

Research Article

Forecasting Natural Gas Consumption in the US Power Sector by a Randomly Optimized Fractional Grey System Model

Yubin Cai,[1] Xin Ma,[1,2,3] Wenqing Wu,[1] and Yanqiao Deng[1]

[1]*School of Science, Southwest University of Science and Technology, Mianyang 621010, China*
[2]*School of Economics and Management, Southwest University of Science and Technology, Mianyang 621010, China*
[3]*Center for Information Management and Service Studies of Sichuan, Southwest University of Science and Technology, Mianyang 621010, China*

Correspondence should be addressed to Xin Ma; maxin@swust.edu.cn

Received 6 February 2021; Revised 10 September 2021; Accepted 22 October 2021; Published 11 November 2021

Academic Editor: Akif Akgul

Natural gas is one of the main energy resources for electricity generation. Reliable forecasting is vital to make sensible policies. A randomly optimized fractional grey system model is developed in this work to forecast the natural gas consumption in the power sector of the United States. The nonhomogeneous grey model with fractional-order accumulation is introduced along with discussions between other existing grey models. A random search optimization scheme is then introduced to optimize the nonlinear parameter of the grey model. And the complete forecasting scheme is built based on the rolling mechanism. The case study is executed based on the updated data set of natural gas consumption of the power sector in the United States. The comparison of results is analyzed from different step sizes, different grey system models, and benchmark models. They all show that the proposed method has significant advantages over the other existing methods, which indicates the proposed method has high potential in short-term forecasting for natural gas consumption of the power sector in United States.

1. Introduction

Electricity facilitates the development of the national economy and promotes the progress of the industrial society in the present age. Electricity, as high-performance clean energy, has one shortcoming that its sources are too extensive. Among plenty of ways to produce electricity, natural gas is the best choice as a clean fuel, which is better than coal combustion in terms of pollution and more convenient than nuclear energy in resource acquisition [1]. As the world's largest industrial country, among the primary energy sources used by the United States to produce electricity in 2020, natural gas accounted for 38%, coal accounted for 27%, nuclear energy accounted for 20%, and traditional hydropower accounted for 12% [2]. With the closure of many coal plants and nuclear power plants in the United States, natural gas has become the primary electricity production source in the United States [3]. Therefore, it is of great significance to study natural gas consumption in the US power sector. In the early natural gas prediction methods, Hubbert model is one of the earliest established tools [4], and it has been proved to achieve a pleasing effect in the prediction of fossil fuels [5]. Jiang et al. took China’s policies as the driving factor to establish MARKAL, an economic optimization model for predicting natural gas consumption, and applied it to the energy forecast of three major regions in China [6]. Li et al. used the system dynamics model to predictthe natural gas consumption [7]. Szoplik built an artificial neural network to predict natural gas consumption, considering many factors that may influence natural gas consumption, such as calendar and weather, and got effective results [8]. A recent method that combines weather forecasting with artificial intelligence to predict a short-term gas consumption has also been developed [9]. Svoboda et al. established a time series prediction method based on machine learning to study natural gas consumption [10]. In Wang et al.'s work, the multiperiod Hubbert model and the rolling grey model were used to forecast and evaluate the natural gas consumption, respectively [11]. As early as 2012, in the work of Soldo, the Hubbert model and grey forecasting model would become the main tool in forecasting by predicting gas consumption [12]. In the grey model, natural gas consumption prediction as a time series has achieved satisfactory results [13, 14].

Grey prediction technology is an essential branch of grey system theory proposed by Professor Deng [15]. Because it can provide a feasible and effective method to deal with uncertainty, grey forecasting model is often used in the research of energy, environment, industry, economy, and other fields [16–19]. Besides, compared with other prediction models, the grey model is better at conducting small samples experiments. Therefore, the grey model is often used for short-term prediction and provides corresponding decisions to deal with future trends according to the obtained forecasting results. Grey prediction technology is widely used in energy prediction. Qian and Sui designed a discrete grey model that can adapt to any periodic time series and applied it to renewable energy systems [20]. Huang et al. constructed a multivariate interval grey model and further applied it to the prediction of clean energy with the method of fractional connotation prediction [21]. Zhao and Lifeng proposed an adjacent cumulative, discrete grey model to improve the utilization rate of new data, and it demonstrates the effectiveness on nonrenewable energy [22]. The grey prediction model is more mature and feasible in energy application. However, in most studies, there are no applications with large changes in data characteristics.

In the development of the grey model, to solve this problem, Wu et al. proposed a new accumulation method, replacing the first-order accumulation with fractional-order accumulation, which eliminated the randomness of the original data series [23]. A large number of pieces of literature show that the model can obtain better prediction performance when the original data is processed by fractional-order accumulation [24, 25]. With the introduction of new information priority accumulation, the grey model has more choices to process the original data [26]. However, with the introduction of nonlinear parameters, approximating the required parameters of the model has become a new problem.

Many scholars adopt random search algorithm to solve this problem. Bergstra and Bengio et al. applied the random search algorithm to solve the hyperparameter of the model and verified the simplicity and effectiveness of random search in the same field. Compared with other search methods, the application of random search for parameters can quickly and efficiently find equally good or even better models [27]. The random search algorithm has shown some advantages of its algorithm in various fields [28, 29].

According to the literature study, this paper uses the random search to optimize the fractional nonlinear parameters in the nonhomogeneous grey model and designs an application of natural gas consumption in the US power sector which uses the rolling forecast mechanism to forecast the results.

The rest of this paper is organized as follows. Section 2 presents the theory and concept of a nonlinear grey model which needs to be optimized. In Section 3, the concept of the random search algorithm to optimize nonlinear parameters is given. The rolling forecast mechanism and case study of forecasting natural gas consumption in the US power sector are presented in Section 4, and the conclusions are given in Section 5.

2. The Fractional Nonhomogeneous Grey Model and Related Models

This section first presents the construction of fractional nonhomogeneous grey model (FNGM), of which the fractional order is the parameter to be optimized [23]. Then description of other related models is presented briefly, which is used to compare the prediction performance of the models in the case study.

2.1. The Fractional Nonhomogeneous Grey Model. The raw data sequence is $X^{(0)}(k) = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$, and its fractional-order accumulation generation sequence is $X^{(r)}(k) = \{x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n)\}$, r is the fractional parameter, and

$$\begin{aligned} x^{(r)}(k) &= \sum_{i=1}^{k} \begin{bmatrix} r \\ k-i \end{bmatrix} x^{(0)}(i) \\ &= \sum_{i=1}^{k} \frac{r(r+1)\cdots(r+k-i-1)}{(k-i)!} x^{(0)}(i), \quad k = 1, 2, \ldots, n. \end{aligned} \tag{1}$$

The first-order differential equation of the FNGM is

$$\frac{\mathrm{d}x^{(r)}(k)}{\mathrm{d}t} + \alpha x^{(r)}(k) = \beta k, \tag{2}$$

where α is the grey development coefficient and βk is the grey action quantity.

The discrete differential equation of (2) is

$$x^{(r)}(k) - x^{(r)}(k-1) + \alpha z^{(r)}(k) = \beta k, \tag{3}$$

where $z^{(r)}(k) = (x^{(r)}(k) + x^{(r)}(k+1))/2$ is the sequence mean generated of consecutive neighbors of $x^{(r)}(k)$. Set

$$\begin{aligned} \varsigma &= \begin{pmatrix} x^{(r)}(2) - x^{(r)}(1) \\ x^{(r)}(3) - x^{(r)}(2) \\ \vdots \\ x^{(r)}(n) - x^{(r)}(n-1) \end{pmatrix}, \\ \Theta &= \begin{pmatrix} -z^{(r)}(2) & 2 \\ -z^{(r)}(3) & 3 \\ \vdots & \vdots \\ -z^{(r)}(n) & n \end{pmatrix}. \end{aligned} \tag{4}$$

Then the least squares estimation of the FNGM satisfies

$$\begin{pmatrix} \widehat{\alpha} \\ \widehat{\beta} \end{pmatrix} = \left(\Theta^T \Theta\right)^{-1} \Theta^T \varsigma. \tag{5}$$

The solution of the first-order differential equation (2) is

$$\widehat{x}^{(r)}(k)=\left(x^{(0)}(1)-\frac{\widehat{\beta}}{\widehat{\alpha}}+\frac{\widehat{\beta}}{\widehat{\alpha}^{2}}\right)e^{-\widehat{\alpha}(k-1)}+\frac{\widehat{\beta}}{\widehat{\alpha}}k-\frac{\widehat{\beta}}{\widehat{\alpha}^{2}}. \quad (6)$$

The forecasting results of the FNGM were obtained according to the inverse accumulation operation:

$$\begin{aligned}\widehat{x}^{(0)}(k)&=\sum_{i=1}^{k}\begin{bmatrix}-r\\ k-i\end{bmatrix}\widehat{x}^{(r)}(i)\\&=\sum_{i=1}^{k}\frac{-r(-r+1)\cdots(-r+i-1)}{(k-i)!}\widehat{x}^{(r)}(i),\quad k=1,2,\ldots,n.\end{aligned} \quad (7)$$

2.2. Relationship between the Fractional Nonhomogeneous Grey Model and Other Existing Grey Models. Several transformationsof the FNGM are givento compare the model forecasting performance:

When the discrete differential equation (3) of the FNGM is changed to

$$x^{(r)}(k)-x^{(r)}(k-1)+\alpha z^{(r)}(k)=\beta, \quad (8)$$

the FNGM model degenerates to the basic fractional grey model (FGM) [23].

By differencing operation, the FGM can be rewritten as

$$x^{(r)}(k+1)=\phi_1 x^{(r)}(k)+\phi_2, \quad (9)$$

which is the fractional discrete grey model (FDGM) [30].

The equation

$$x^{(r)}(k+1)=\phi_1 x^{(r)}(k)+\phi_2 k+\phi_3 \quad (10)$$

is called the fractional nonhomogeneous discrete grey model (FNDGM) [31]. The FNDGM will also be used for comparisons.

When the fractional parameter $r=1$, the fractional-order accumulation is reduced to the first-order accumulation, which is defined by

$$x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i),\quad k=1,2,\ldots,n, \quad (11)$$

and within it, the above four models yeild the grey model (GM), the nonhomogeneous grey model (NGM), the discrete model (DGM), and the nonhomogeneous discrete grey model (NDGM) with the first-order accumulation [23].

When the new information priority accumulation is used to replace the first-order accumulation to process the original sequence, which is

$$x^{(\lambda)}(k)=\sum_{i=1}^{k}\lambda^{k-i}x^{(0)}(i),\quad k=1,2,\ldots,n, \quad (12)$$

then the new information priority accumulation method for the above four models, the new information priority grey model (NIPGM), the new information priority nonhomogeneous grey model (NIPNGM), the new information priority discrete grey model (NIPDGM), and the new information priority nonhomogeneous discrete grey model (NIPNDGM) can be obtained [26].

In the following content, we will compare the performances of the models in the same case study with the same evaluation metrics.

3. Parameter Optimization Based on Random Search

After the fractional-order accumulation operator is selected, how to set the fractional-order parameters of the model becomes vital to make accuracte forecasting. The simplicity and global optimality of random search make it competitive in parameter optimization. The following part of this section introduces the main steps of random search for parameter optimization of grey models.

3.1. Data Set Division. Set the raw data set as $X_{\text{raw}}=\{x(1),x(2),\ldots,x(n)\}$. Firstly, the data set is divided into two parts: modelling subset and prediction subset, denoted as $X_{\text{model}}=\{x(1),\ldots,x(m)\}$ and $X_{\text{test}}=\{x(m+1),\ldots,x(m+t)\}$, $m+t=n$, respectively, where X_{model} is a subset of the established model and X_{test} is a test set to evaluate the final performance of the model and does not participate in establishment of the model. Secondly, the subset of the modelling part $X_{\text{model}}=\{x(1),\ldots,x(m)\}$ is divided into two data sets, training subset $X_{\text{train}}=\{x(1),\ldots,x(\xi)\}$ and validation subset $X_{\text{valid}}=\{x(\xi+1),\ldots,x(\xi+\nu)\}$, $\xi+\nu=m$. The training subset X_{train} is used to estimate model parameters. The validation subset X_{valid} is used to test the out-of-sample accuracy of the model, which aims to improve the generality of the model. The flowchart of this process is shown in Figure 1.

3.2. Optimization Problem Structure. Taking the nonhomogeneous grey model with fractional-order accumulation as an example, the fractional order r in the FNGM is the parameter that needs to be optimized, in which r determines the way to process the original data. The objective is to reach the minimum average absolute error on the validation set $X_{\text{valid}}$with respect to$r$, and within this, the FNGM can obtain excellent prediction performance. Therefore, the optimization problem of fractional order r can be written by the following equation:

$$\min W = \frac{1}{\nu} \sum_{j \in X_{\text{valid}}} \left| x^{(0)}(j) - \hat{x}^{(0)}(j) \right|. \tag{13}$$

3.3. The Randomized Parameter Optimization. For the nonlinear programming problem expressed in (13), traditional mathematical methods are usually difficult to use. Intelligent computing has become the mainstream of the current era, and the method of a random search for optimized parameters can solve this problem with low time consumption.

In the random search algorithm, it takes random sampling in the parameter space as the benchmark, generates evenly distributed random numbers in the interval, calculates the objective function value, and preserves the sampling points with good results by comparing the objective function value. The approximate optimal solution of the optimization problem can be obtained within limited iterations.

This paper uses a random search algorithm to search the optimal fractional order r of the FNGM. The algorithm is summarized in Algorithm 1.

3.4. Complexity Analysis. The number of training set samples, validation set samples, and algorithm iteration times are defined as n_{train}, n_{valid}, and n_{iter}. And the process of obtaining the optimal model is divided into five parts in the following paragraph.

3.4.1. Fractional-Order Accumulation. The time complexity of accumulation operation is mainly about the binomial coefficient in (1), and time complexity for one calculation of the binomial coefficient $\left[\begin{matrix} r \\ k-i \end{matrix}\right]$ is$2k - 2i + 1$, and thus the total is

$$\sum_{k=1}^{n_{\text{train}}} \sum_{i=1}^{k} 2(k-i+1) = \sum_{k=1}^{n_{\text{train}}} k(k+1) = \frac{1}{3} n_{\text{train}} (n_{\text{train}}+1)(n_{\text{train}}+2). \tag{14}$$

For particular cases, if $r = 1$, there are no binomial coefficients in the accumulation. So, the time complexity $T_1(n)$ of fractional-order accumulation is

$$T_1(n) = \begin{cases} O\left(n_{\text{train}}^3\right), & r \neq 1 \\ O(1), & r = 1 \end{cases}. \tag{15}$$

3.4.2. Least Squares. For (5), the operation of $\Theta^T\Theta$involves a matrix with shape 2×2; it needs $4(n_{\text{train}} - 1)$ multiplications. The inverse$(\Theta^T\Theta)^{-1}$ requires 4^3 multiplications, and this value is independent of n_{train}; the operation $\Theta^T\varsigma$ means multiplying one matrix by another in which their shapes are $2 \times n_{\text{train}}$ and $n_{\text{train}} \times 1$, respectively; the multiplications are $2(n_{\text{train}} - 1)$; similarly, the multiplications of matrixes $(\Theta^T\Theta)^{-1}$ and $\Theta^T\varsigma$ need 4 multiplications. So, the complexity of the least squares is the sum of the total number of multiplications, $6n_{\text{train}} - 63$. And the time complexity is

$$T_2(n) = O(n_{\text{train}}). \tag{16}$$

3.4.3. Time Response Function. Consider the number of multiplications in (6); the time complexity $T_3(n)$ for time response function is

$$T_3(n) = O(1). \tag{17}$$

3.4.4. Fractional-Order Inverse Accumulation. The time complexity $T_4(n)$ of inverse accumulation operation is similar to the fractional-order accumulation, and it can be expressed as

$$T_4(n) = \begin{cases} O\left(\left(n_{\text{train}} + n_{\text{valid}}\right)^3\right), & r \neq 1 \\ O(1), & r = 1 \end{cases}. \tag{18}$$

3.4.5. Random Search Algorithm. Every iteration includes one construction of the model, and the algorithm actually excutes a cyclic process. So, the total time complexity $T(n)$ of the optimal model is

$$\begin{aligned} T(n) &= n_{\text{iter}} \cdot \left(T_1(n) + T_2(n) + T_3(n) + T_4(n)\right) \\ &= \begin{cases} O\left(n_{\text{iter}} \cdot \left(n_{\text{train}}^3 + n_{\text{train}} + \left(n_{\text{train}} + n_{\text{valid}}\right)^3 + 1\right)\right), & r \neq 1 \\ O\left(n_{\text{iter}} \cdot \left(n_{\text{train}} + 3\right)\right), & r = 1 \end{cases}. \end{aligned} \tag{19}$$

According to (19), it indicates that the total time complexity of obtaining the optimal model is related to n_{train}, n_{valid}, and n_{iter}, but in our small sample time series forecasting work, the number of n_{train} and n_{valid} is much smaller than n_{iter}, so the time complexity of the entire work is mainly determined by n_{iter}.

4. Case Study

In this section, we use the data set of natural gas consumption in the US power sector to verify the FNGM optimized by the random search algorithm. In this case, we will compare the results obtained by the models mentioned in Section 2 and the prediction method given in Section 4.2. In the first subsection of this part, several indicators for evaluating model performance are given to facilitate the measurement of prediction accuracy between models. The forecasting results are discussed in the last section.

4.1. Model Evaluation Metrics. For the original data set $X = \{x(1), x(2), \ldots, x(n)\}$, the prediction resultsare denoted as $\hat{X} = \{\hat{x}(1), \hat{x}(2), \ldots, \hat{x}(n)\}$. We use three commonly used metrics to evaluate the model [32]. The definition of indicators is shown in Table 1.

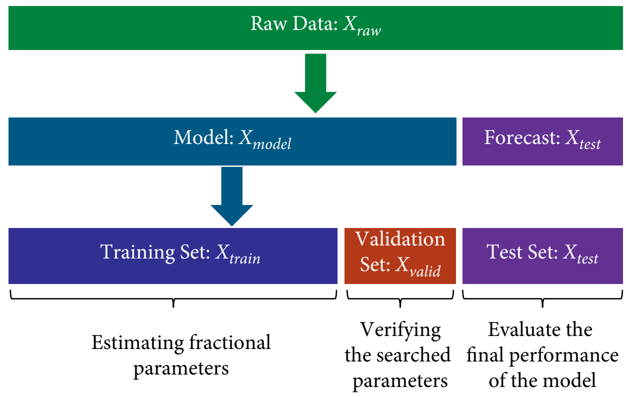

Figure 1: Schematic diagram of data set division.

(1) Input the original data sequence X, need to search for the optimal parameter model mdl, parameter optimization interval S, iteration number $n_{\text{iteration}}$
(2) Divide the data set into two parts: training set X_{train} and validation set X_{valid}
(3) Define the objective function $\min_{x_i \in X_{\text{valid}}} W$
(4) Initialize the objective function judgment value as $\text{MAE}_{\min}$
(5) for $i = 1$; $i \le n_{\text{iteration}}$; $i = i + 1$ do
(6) For mdl, randomly select a set of parameter values $\text{value}_{\text{params}}$ with uniform distribution in the interval S
(7) Pass the training set X_{training} into this model to train the mdl and predict the time series node where the validation set $X_{\text{validation}}$ is located to get the forecast result $\widehat{X}$
(8) Calculate MAE of the forecast result $\widehat{X}$ and the verification set $X_{\text{validation}}$ as $\text{MAE}_{\text{validation}}$
(9) if ($\text{MAE}_{\text{validation}} < \text{MAE}_{\min}$) do
(10) params = $\text{value}_{\text{params}}$
(11) Update judgment value $\text{MAE}_{\min} = \text{MAE}_{\text{validation}}$
(12) end
(13) end
(14) return params
(15) Output optimal parameter params

Algorithm 1: The process of optimizing parameters by random search algorithm.

4.2. Forecasting Method. 44 months of data on natural gas consumption in the US power sector (from Jan 2017 to Aug 2020) are collected. The results of the analysis of the data are shown in Figure 2, and it can be seen that the data presents a clear quarterly trend. The consumption is the most in the autumn period of each year, and it shows an upward trend year by year. Under the influence of this quarter, the traditional direct modelling and forecasting method obviously cannot achieve better results. In our work, we use a rolling forecasting method for time series data [33]. The specific process is shown in Figure 3. Such methods are widely used in the research of various forecasting models.

To illustrate the forecasting method represented by this figure, we label the data set of natural gas consumption in the US power sector as $X = \{x(1), x(2), \ldots, x(n), n = 44\}$, set $\tau = 12$ as the number of rolling window for rolling forecasting, and divide X into group $n - \tau$ data subsets: the first subset is $T_1 = \{x(1), x(2), \ldots, x(\tau)\}$, the second subset is $T_2 = \{x(2), x(3), \ldots, x(\tau + 1)\}$, and the last subset is $T_{n-\tau} = \{x(n - \tau), x(n - \tau + 1), \ldots, x(n - 1)\}$. In each forecasting step, the first ten data points are included in the training subset, and the last two data points form the validation subset. In each subset $T_i (i = 1, 2, \ldots, n - \tau)$, last time series node x_n in the original data set X is predicted by the randomly optimized model.

The first step time node of each subset is used to form the one-step forecasting result of the rolling forecast, and the second step time node of each subset prediction corresponds to the result of the two-step prediction, and so on. According to the above description, the forecasting result of each step is a prediction value composed of $n - \tau + 1 - \zeta_{step}$ subsets of model parameters adjusted by random search.

With the forecasting method, the overall prediction scheme in this work is shown in Figure 4.

4.3. Forecasting Results of FNGM with Different Steps. In this section, the forecasting results of the first three steps of the FNGM after random search and tuning parameters are used for comparative analysis, as shown in Table 2. The MAE, MAPE, and RMSE of the one-step forecasting are 24.45, 2.58%, and 35.26, and all of them are smaller than other step forecasting. It is worth noting that the metrics values of one-step forecasting are smaller than two-step forecasting, and

Table 1: Definition of the evaluation metrics.

Metrics	Definition	Expression
MAE	Mean absolute error	$\mathrm{MAE} = (1/n)\sum_{i=1}^{n} \lvert x(i) - \hat{x}(i)\rvert$
MAPE	Mean absolute percentage error	$\mathrm{MAPE} = (1/n)\sum_{i=1}^{n} \lvert (x(i) - \hat{x}(i))/x(i)\rvert \times 100\%$
RMSE	Root mean squared error	$\mathrm{RMSE} = \sqrt{(1/n)\sum_{i=1}^{n} (x(i) - \hat{x}(i))^2}$

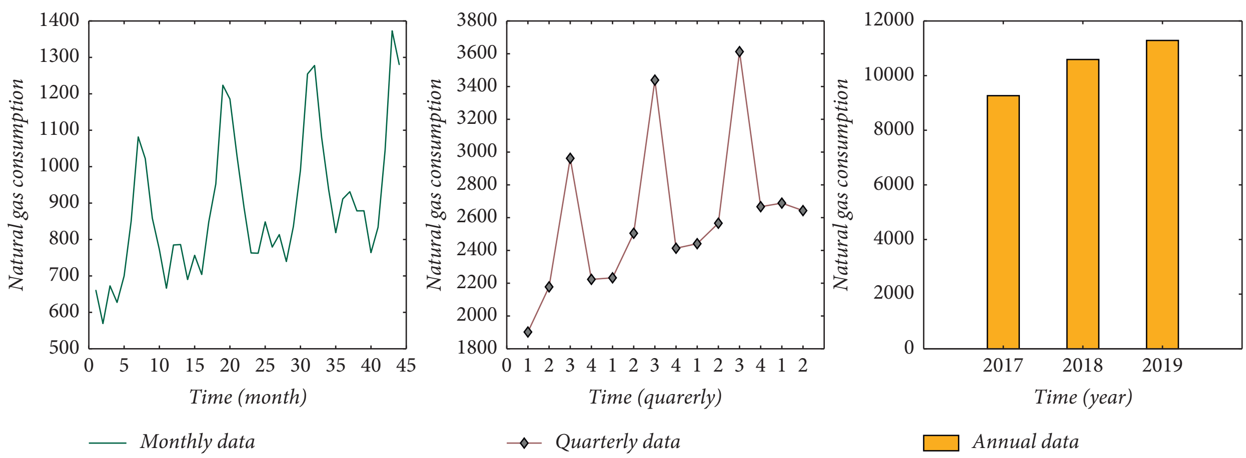

Figure 2: Raw data on natural gas consumption in the power sector.

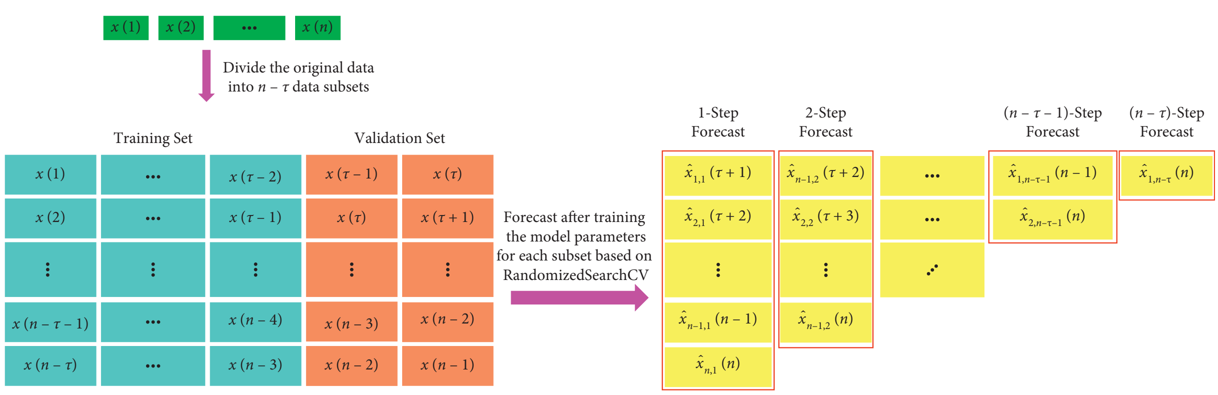

Figure 3: Rolling forecast mechanism.

the metrics values of two-step forecasting is smaller than three-step forecasting.

We compared the forecasting results under different step sizes in Table 2, and detailed plots are shown in Figure 5 which illustrate thatthe forecasted curve are farther from the original data with the step sizes increasing. It can be concluded that the shorter the step size, the higher the prediction accuracy obtained in the rolling prediction mechanism.

4.4. Forecasting Results in Comparison with Other Grey System Models. In order to further evaluate the accuracy of the rolling forecast of the FNGM with random search, we selected the remaining 11 models mentioned in Section 3 for comparative analysis. It should be mentioned that the GM, NGM, DGM, and NDGM are used for forecasting with the rolling forecasting without optimized nonlinear parameters.

In such 12 forecasting models, the prediction performances of the FNGM, FGM, FDGM, NIPGM, and NIPDGM are better than others. The forecasting results of these five models are shown in Figure 6. And it includes the prediction comparison of three kinds of different step sizes. It can be clearly observed that the forecasting results represented by the FNGM are better than the other four models in every step size.

To visually show the prediction performance of the rolling prediction mechanism after random search, the evaluation metrics mentioned in Section 4.2 are used to quantify the effectiveness of the forecasting results of the models. Table 3 shows the different evaluation metrics of all models in the first three steps of prediction. In the one-step

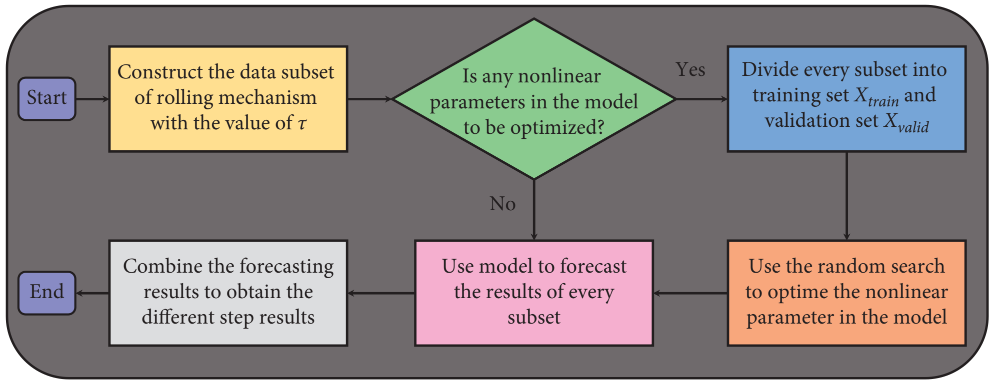

FIGURE 4: The process of the application of natural gas consumption in the US power sector.

TABLE 2: Forecasting results of the FNGM under different step sizes in the power sector's natural gas consumption.

Time	Raw data	1-step	2-step	3-step
Jan-18	786.11	773.98		
Feb-18	690.11	673.68	659.19	
Mar-18	756.62	741.09	733.16	725.96
Apr-18	703.99	695.79	686.30	677.71
May-18	848.15	840.66	838.13	835.82
Jun-18	952.64	839.44	835.73	832.34
Jul-18	1223.67	1268.89	1331.45	1389.46
Aug-18	1185.67	1281.92	1311.53	1336.84
Sep-18	1029.91	1037.77	1041.93	1044.49
Oct-18	887.94	863.76	858.65	852.15
Nov-18	763.07	736.87	725.98	714.24
Dec-18	762.34	740.79	726.83	712.69
Jan-19	848.45	832.11	819.91	808.37
Feb-19	779.24	760.05	743.59	728.36
Mar-19	813.45	798.35	786.73	776.22
Apr-19	739.62	726.20	711.73	698.74
May-19	836.02	826.66	820.33	814.52
Jun-19	990.47	918.34	911.44	905.09
Jul-19	1254.53	1240.49	1285.34	1325.15
Aug-19	1277.77	1336.42	1371.14	1400.80
Sep-19	1080.68	1086.31	1089.51	1091.38
Oct-19	936.59	912.01	906.20	899.03
Nov-19	818.80	792.02	780.41	768.00
Dec-19	911.44	894.51	882.68	870.95
Jan-20	931.23	915.78	904.74	894.26
Feb-20	878.63	862.20	847.75	834.35
Mar-20	878.83	862.71	850.29	839.02
Apr-20	763.96	746.91	727.89	710.84
May-20	833.70	823.40	813.30	804.09
Jun-20	1045.39	1028.14	1022.43	1017.07
Jul-20	1372.90	1375.74	1460.99	1542.94
Aug-20	1280.55	1281.02	1273.93	1282.90
MAE		24.45	40.34	55.63
MAPE		2.58%	4.17%	5.64%
RMSE		35.26	51.51	71.21

forecasting, all the metrics of the FNGM are smaller than other models' one-step results, the MAPE values of several models are slightly smaller, such as FGM, FDGM, and NIPDGM, but are still much greater than three times that of FNGM. And the prediction results of the FNGM with other steps are also reliable. In particular, the performance of FNGM in three-step performance is better than other models' one-step performance.

Considering the prediction results obtained by different accumulation, in the forecasting results of the NGM under three accumulations, the FNGM achieves the best prediction effect but the prediction accuracy of the NGM and NIPNGM

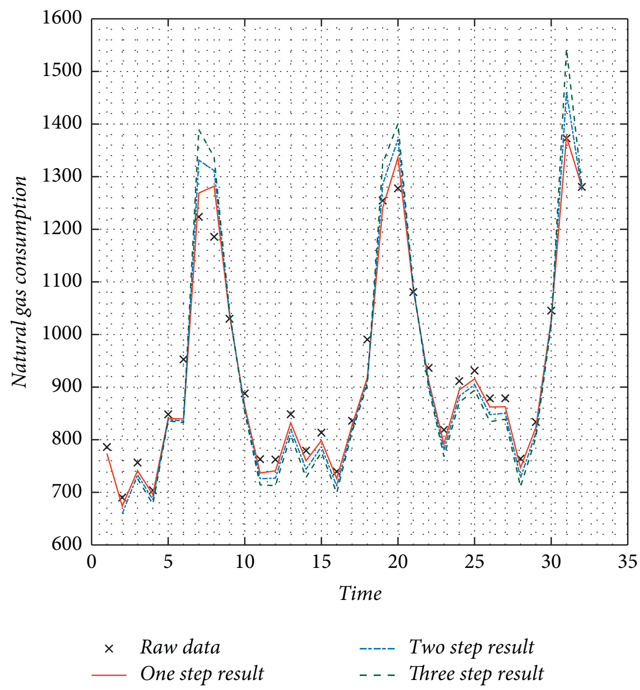

FIGURE 5: The forecasting results of the FNGM with different step sizes in the power sector's natural gas consumption.

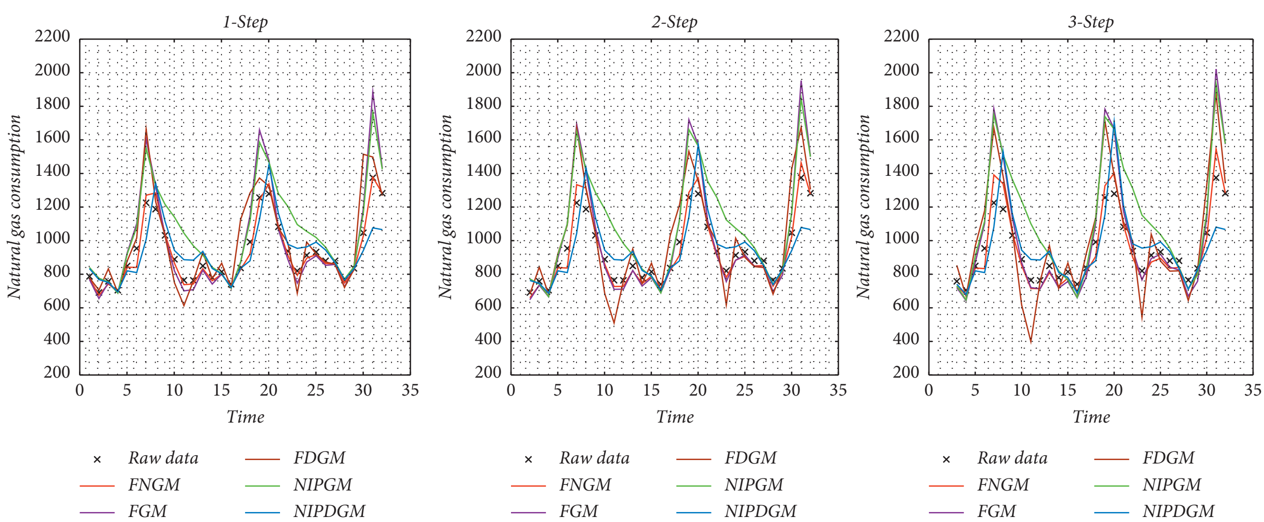

FIGURE 6: The forecasting results' comparison of the FNGM, FGM, FDGM, NIPGM, and NIPDGM under different step sizes in the natural gas consumption of power sector.

is not good enough. It illustrates that the fractional-order accumulation forecasting models are suitable in the application of natural gas consumption in the US power sector. In addition, results in Table 3 indicated that the longer the step size is, the worse the prediction accuracy is.

4.5. Forecasting Results in Comparison with Different Benchmarking Models. To further validate the performance of fractional nonhomogeneous grey model in the application of natural gas consumption, the autoregressive model (AR) [34] and artificial neural networks (ANN) [35] are selected as the benchmarking models to compare with FNGM. The metrics are calculated by the forecasting results illustrated in Figure 7. The MAE, MAPE, and RMSE of AR are 839.91, 90.23%, and 1172.76; they are much worse than the FNGM, and this shows that the AR is not appropriate for this application. Although the ANN has achieved satisfactory prediction results, the FNGM still retains its superiorities in short-term prediction.

4.6. Brief Summary. According to the above results, first of all, the FNGM is more complex than the other fractional-

Table 3: Evaluation metrics of the forecasting models

	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step
		FNGM			GM			NGM	
MAE	**24.45**	40.34	55.63	210.44	285.39	343.63	1.82 E + 12	1.91 E + 13	2.15 E + 14
MAPE	**2.58%**	4.17%	5.64%	21.68%	29.37%	35.44%	1.49 E + 11	1.61 E + 12	2.09 E + 13
RMSE	**35.26**	51.51	71.21	254.75	342.68	396.63	9.59 E + 12	1.06 E + 14	1.18 E + 15
		DGM			NDGM			FGM	
MAE	208.05	282.17	340.31	1.19 E + 23	5.69 E + 26	5.23 E + 30	93.66	113.47	137.90
MAPE	21.34%	28.93%	34.98%	1.00 E + 20	5.52 E + 23	5.89 E + 27	8.68%	10.42%	12.57%
RMSE	254.33	341.44	394.63	6.71 E + 23	3.17 E + 27	2.86 E + 31	153.10	183.19	219.73
		FDGM			FNDGM			NIPGM	
MAE	88.90	117.24	150.52	1.41 E + 12	1.49 E + 14	2.25 E + 16	134.41	167.94	205.14
MAPE	9.17%	12.00%	15.26%	1.13 E + 09	1.19 E + 11	1.79 E + 13	13.67%	16.81%	20.23%
RMSE	148.13	163.90	203.60	7.98 E + 12	8.30 E + 14	1.23 E + 17	172.17	214.40	261.96
		NIPNGM			NIPDGM			NIPNDGM	
MAE	3.33 E + 06	1.04 E + 07	3.23 E + 07	84.82	95.12	105.74	5.36 E + 08	8.36 E + 09	1.60 E + 11
MAPE	4.15 E + 03	1.29 E + 04	4.05 E + 04	8.40%	9.34%	10.24%	7.03 E + 05	1.10 E + 07	2.10 E + 08
RMSE	1.30 E + 07	4.01 E + 07	1.24 E + 08	110.79	123.73	144.06	3.03 E + 09	4.65 E + 10	8.78 E + 11

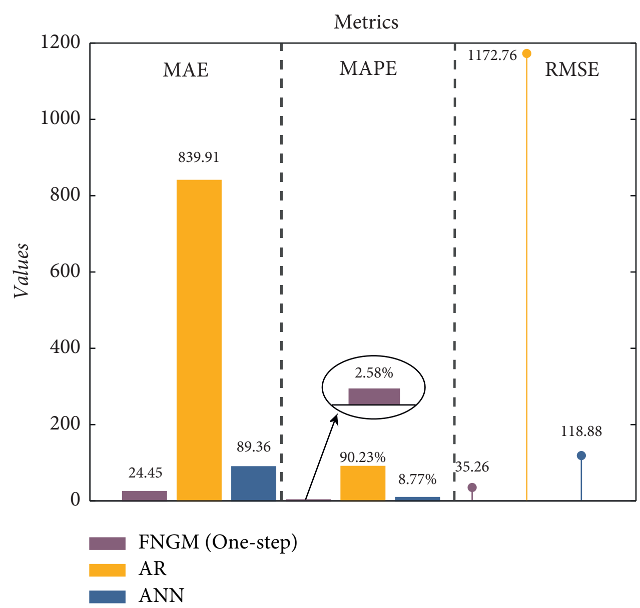

Figure 7: The comparison of the evaluation metrics values of the FNGM, AR, and ANN.

order accumulation model because it is nonhomogeneous withfractional-order accumulation. Such properties of FNGM make it nonlinear and more flexible. The flexibility of the model can be reflected in the more general form of FNGM described in Section 2.2. These improvements make the model have a stronger description ability for complex data.

On the generalization performance of the model, the in-sample cross-validation improves the fitting performance, so the effective prediction results can be obtained. But for other grey system models, they may not have better formulation or adopt a better optimization algorithm. For the benchmarking models, they may not have the in-sample cross-validation to improve the performance.

To sum up, the model used in this paper is more flexible and has stronger nonlinear properties; the use of data division and verification set makes it have stronger generalization performance; random optimization enables FNGM to obtain fully accurate nonlinear parameters. According to the description of the application results, the FNGM has the best prediction performance on the data sets of natural gas consumed by the US power sector. It implies that the research in this paper can be extended to similar natural gas energy prediction.

5. Conclusions

This paper uses a random search algorithm to estimate the parameters of the forecasting model and applies the rolling forecasting modelling mechanism to achieve accurate forecasting of time series data. First, we transform the optimization parameter problem into a nonlinear programming problem by constructing the nonlinear objective function reflecting the performance of the proposed model on the validation subset. Secondly, the rolling forecast modelling mechanism is used to forecast the natural gas consumption of the US power sector. By comparing the other eleven forecasting models, the results show that the step size influences the forecasting accuracy, and the accuracy becomes lower with more forecasting steps. The FNGM obtained by random search has an excellent performance in forecasting natural gas consumption, which illustrates that the FNGM can be used as a reliable tool for studying clean energy consumption.

Limitations of this work should also be mentioned. First, the random optimization only has weak convergence, and thus the preconditions (such as initial points and bound for the variables) may require more prior knowledge. However, such limitations widely exist in the heuristic algorithms. Second, the structure of the fractional nonhomogeneous grey system model is not complicated enough, which may limit its flexibility to deal with more complex time series.

Data Availability

All the data sets are available in the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was supported by the Humanities and Social Science Fund of Ministry of Education of China (19YJCZH119) and Southwest University of Science and Technology University Student Innovation Fund Project (CX21-100).

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