ABSTRACT

Aims: As a basic energy source, coal occupies a leading position in the production and consumption of energy. If a reasonable coal energy production policy is to be formulated, effective forecasting is essential. Due to the lack of data, effective prediction with small samples has become the key to research.

Study Design: A nonlinear grey Bernoulli Simpson model based on new information priority accumulation method is developed in this work to forecast the coke production in the Anhui China. The introduction of non-linear parameters makes the new model constructed with universality.

Place and Duration of Study: School of Science, Southwest University of Science and Technology, Mianyang, between April 2021 and June 2021.

Methodology: This paper has established the nonlinear grey Bernoulli Simpson model with new information priority accumulation. Based on the grid search optimization, the data is divided by the leave-out method to construct a nonlinear problem to solve the nonlinear parameters of the model. Finally, the new model established was applied to the forecast of coke production in Anhui Province, China.

Results: The MAPE and RMSPE of the nonlinear grey Bernoulli Simpson model based on new
1. INTRODUCTION

As the world's most abundant and widely distributed conventional energy, coal energy is used in power production, steel manufacturing and residential areas. Coke produced with coal as a raw material can make up for the high volatility of coal that is not conducive to transportation [1] and can be used as a raw material for iron smelting and steelmaking. The production of coke uses coal energy in a relatively clean way [2]. In some areas of China, coal energy is still used as the raw material for thermal power generation [3]. Forecasting coal energy production in some regions of China is an effective means to adjust resource allocation promptly. China is a major coal producer, and coal production is related to the country's national development strategy. For this reason, accurately predicting coal production is conducive to the country's rational formulation of energy policies, improving production efficiency, and benefiting the country's economic development and social stability. At present, scholars at home and abroad have also conducted much research on coal production forecasting. The main methods are Univariate Linear regression, Autoregressive model, Intervention Analysis model, Exponential Smoothing method and Grey state Markov model [4,5]. The literature shows that the coal output predicted based on the improved grey mathematical model is very close to the actual output and has a high reference value [6]. Therefore, this paper makes further improvements to the grey prediction model to obtain higher prediction accuracy. Since the introduction of the grey system by Professor Deng [7], it has been widely used in the prediction of energy, economy, environment, and other fields with the advantages of small samples and simple calculation methods. Driven by the research of many scholars, the grey system theory has developed more maturely. In the work of Xie et al., a discrete grey model was constructed [8]. Cui et al. established an inhomogeneous grey model based on the characteristics of the nonlinear index sequence [9]. Chen et al. introduced Bernoulli’s equation to change the grey input and adjusted the new model by controlling the exponential power to let the new model have good adaptability [10]. In terms of background value construction, Wei et al. used the integral median theorem to optimize the background value in the grey model [11]. Ma et al. used the Simpson integral formula to optimize, and a series of examples proved that the new model has excellent predictive performance [12]. Wu et al. defined the grey model of the fractional accumulation method, which made the model have the characteristics of eliminating the randomness of the original data [13]. To meet the new information principles in the grey system, Zhou et al. designed a method of accumulating the priority of new information [14]. The improvements of these scholars have greatly enriched the modelling methods of grey systems and made the application scope of grey models wider. This paper intends to establish a nonlinear grey Bernoulli Simpson model based on the new information priority accumulation method and apply it to energy forecasting. In the second section, the construction of the grey Bernoulli model under the Simpson integral formula is introduced in detail. The required parameters of the new model are solved in Section 3. Section 4 presents the application of the coke production in Anhui Province, China, with the new model. Moreover, Section 5 gives the conclusion of this paper.

2. METHODS

2.1 The establishment of the Grey Model

For a set of time series \( Y^{(0)} = \{y^{(0)}(k) | k = 1, 2, ..., n\} \), the set \( Y^{(1)} = \{y^{(1)}(k) | k = 1, 2, ..., n\} \) obtained by the accumulative generation operation is defined as follows:
Using the Simpson integration, the integral on
\[ y^{(1)}(k) = \sum_{i=1}^{n} y^{(0)}(i) \] (1)

Then use the accumulation set to establish the
grey differential equation:
\[ \frac{dy^{(1)}(t)}{dt} + \alpha_i y^{(1)}(t) = \beta_i \] (2)

where \([\alpha_i, \beta_i]^T\) is the grey parameter of the model.

Integrate the equation to obtain the discrete form
of GM satisfies:
\[ y^{(0)}(k) + \alpha_1 z^{(1)}(k) = \beta_1 \] (3)

where \( z^{(1)}(k) = \frac{1}{2} \left( y^{(1)}(k) + y^{(1)}(k - 1) \right) \) is the
integral \( \int_{k-1}^{k} y^{(1)}(t) \) approximated by the
trapezoidal rule.

Then the grey parameter can be solved by the
least square estimation:
\[ [\alpha_i, \beta_i]^T = \left( \theta^T \theta \right)^{-1} \theta^T \Psi_1 \] (4)

where:
\[ \Psi_1 = \begin{pmatrix} y^{(0)}(2) \\ y^{(0)}(3) \\ \vdots \\ y^{(0)}(n) \end{pmatrix}, \theta_1 = \begin{pmatrix} -z^{(k)}(2) \\ -z^{(k)}(3) \\ \vdots \\ -z^{(k)}(n) \end{pmatrix} \] (5)

The time response of the GM is:
\[ \hat{y}^{(1)}(k + 1) = \left( y^{(0)}(1) - \frac{\beta_1}{\alpha_i} \right) e^{-\alpha_i k} + \frac{\beta_1}{\alpha_i} \] (6)

And the first-order inverse accumulation
generates forecasting results are:
\[ \hat{y}^{(0)}(k + 1) = \hat{y}^{(1)}(k + 1) - \hat{y}^{(1)}(k) = \\
\left( 1 - e^{\alpha_i} \right) \left( y^{(0)}(1) - \frac{\beta_1}{\alpha_i} \right) e^{-\alpha_i k} \] (7)

2.2 The Nonlinear Grey Bernoulli
Simpson Model Based on New
Information Priority Accumulation
Method

In the work of this paper, the Bernoulli equation
is introduced to improve the grey input. Then the
Simpson integration is used to improve the grey
discretization process. The new model is called
the nonlinear grey Bernoulli Simpson model(NGBSM). This paper also uses the new
information priority accumulation method to
improve prediction accuracy further to meet the
new information principle. This section will
introduce the new information priority accumulation method first, and the construction
of the NGBSM is given in the next section.

2.2.1 The new information priority
accumulation

To make the incoming data of the grey model
satisfy the new information principle, this paper
inducts the accumulative generation parameter \( \lambda \)
to adjust the weight of the sequence generation.
The generated sequence under the accumulation of new information can be expressed as:
\[ y^{(\lambda)}(k) = \sum_{i=1}^{k} \lambda^{k-i} y^{(0)}(i), \lambda \in (0,1) \] (8)

and the new information priority inverse accumulation satisfies:
\[ y^{(\lambda)}(k) = \begin{cases} y^{(\lambda)}(k) - \lambda \cdot y^{(\lambda)}(k-1), k = 2,3, ..., n, \lambda \in (0,1) \\ y^{(\lambda)}(1), k = 1 \end{cases} \] (9)

2.2.2 The establishment of the NIPNGBSM

The differential equation of the NIPNGBSM is:
\[ \frac{dy^{(\lambda)}(t)}{dt} + \alpha_2 y^{(\lambda)}(t) = \beta_2 \left( y^{(\lambda)}(t) \right)^\gamma \] (10)

where \( y^{(\lambda)} \) is the new information priority
accumulation sequence introduced in Section
2.2.1, and \( \gamma \) is the Bernoulli parameter.

We consider the integral of equation on \([k - 1, k + 1]\), we have:
\[ \int_{k-1}^{k+1} y^{(\lambda)}(t) dt = \beta_2 \int_{k-1}^{k+1} \left( y^{(\lambda)}(t) \right)^\gamma dt \] (11)

Using the Simpson integration, the integral on \([k - 1, k + 1]\) can be approximated by the following as:
\[ \int_{k-1}^{k+1} x(t) dt = \frac{(k + 1) - (k - 1)}{6} \times [x(t - 1) + 4x(t) + x(t + 1)] \] (12)
3.2 The Definition of Objective Function in Parameter Optimization

3. THE PARAMETER OPTIMIZATION BASED ON GRID SEARCH

calculating the following nonlinear problem:

\[ y^{(\lambda)}(k + 1) - y^{(\lambda)}(k - 1) + \frac{a_2}{3} s(k) = \frac{\beta_2}{3} s_y(k) \]  

Set:
\[
\psi_2 = \begin{pmatrix}
    y^{(\lambda)}(3) - y^{(\lambda)}(1) \\
    y^{(\lambda)}(4) - y^{(\lambda)}(2) \\
    \vdots \\
    y^{(\lambda)}(n) - y^{(\lambda)}(n - 2)
\end{pmatrix}, \quad \Theta_2 = \begin{pmatrix}
    -\frac{1}{3} s(2) & \frac{1}{3} s_y(2) \\
    -\frac{1}{3} s(3) & \frac{1}{3} s_y(3) \\
    \vdots & \vdots \\
    -\frac{1}{3} s(n - 1) & \frac{1}{3} s_y(n - 1)
\end{pmatrix}
\]

Then the grey parameter \([a_2, \beta_2]\) can be obtained by the least squares estimate:
\[
[a_2, \beta_2]^T = (\Theta_2^T \Theta_2)^{-1} \Theta_2^T \psi_2
\]

The time response of the NIPNGBSM is:
\[
y^{(\lambda)}(k + 1) = \left[ y^{(\mu)}(1)^{(1-\gamma)} - \frac{\beta_2}{\alpha_2} e^{-\alpha_2(1-\gamma)k} + \frac{\beta_2}{\alpha_2} \right]^{1-\gamma}
\]

And the prediction result generated by the new information priority inverse accumulation can be obtained by equation (9).

3. THE PARAMETER OPTIMIZATION BASED ON GRID SEARCH

3.1 The Division of Raw Data

To ensure that the optimized parameters are reliable, dividing the raw data by the hold-out method in machine learning so that the original data is divided into three mutually exclusive subsets: training set \(Y_t^{(0)}\), validation set \(Y_v^{(0)}\) and forecasting set \(Y_f^{(0)}\):

\[
Y_t^{(0)} = \{ y^{(0)}(k) | k = 1, 2, \ldots, \mu \} \\
Y_v^{(0)} = \{ y^{(0)}(k) | k = \mu + 1, \mu + 2, \ldots, \mu + \nu \}, \mu + \nu + \rho = n \\
Y_f^{(0)} = \{ y^{(0)}(k) | k = \nu + 1, \nu + 2, \ldots, \nu + \rho \}
\]

where the \(Y_t^{(0)}\) is used to initialize the model, the \(Y_v^{(0)}\) is ordered to achieve the purpose of optimizing the parameters and the \(Y_f^{(0)}\) is used to quantify the predictive performance of the model.

3.2 The Definition of Objective Function in Parameter Optimization

In the process of the model’s parameter optimization, the searched parameters(new information priority accumulation parameter\(\lambda\), Bernoulli parameter \(\gamma\)) need to be evaluated to measure whether they are fair-wether parameters. In our work, measure the effectiveness of the search parameters by calculating the following nonlinear problem:

\[
\min \Phi(\lambda, \gamma) = \frac{1}{V} \sum_{i=1}^{V} \left| \frac{y^{(0)}(i) - y^{(0)}(i)}{y^{(0)}(i)} \right| \times 100\%
\]
3.3 The Optimization of Grid Search

This paper uses a simple way to solve the nonlinear problem constructed in Section 3.2. First, for the two parameters $\lambda$, $\gamma$, separating their parameter spaces at equal intervals to obtain the sets of different parameter values. The sets of $\lambda$ and $\gamma$ are respectively denoted as $\Lambda$ and $\Gamma$. Then use the Cartesian product $\Lambda \times \Gamma$ to approximate all parameters value of the NGBSM. It can be seen the tinier interval is, the more situation of search parameters is obtained. The division and combination of grid search can be represented by Fig. 1.

4. APPLICATION OF THE COKE PRODUCTION IN ANHUI CHINA

4.1 Metrics to Measure Predictive Performance

This paper not only established the prediction model of the NGBSM but also used the other five prediction models: Grey model (GM) [7], discrete Grey model (DGM) [8], nonlinear Grey Bernoulli model (NGBM) [10], NGBSM, new information priority nonlinear Grey Bernoulli model (NIPNGBM) as the comparison models. The model’s prediction performance is quantified from MAPE (Mean absolute percentage error) and RMSPE (Root mean squared percentage error) [15]. The mathematical expression is defined as:

$$
\text{MAPE} = \frac{1}{\rho} \sum_{j=x+1}^{v+p} \left| \frac{y^{(0)}(j) - y^{(0)}(j)}{y^{(0)}(j)} \right| \times 100\%
$$

$$
\text{RMSPE} = \sqrt{\frac{1}{\rho} \sum_{j=x+1}^{v+p} \left( \frac{y^{(0)}(j) - y^{(0)}(j)}{y^{(0)}(j)} \right)^2} \times 100\% \quad (19)
$$
http://www.stats.gov.cn/）， and the parameters of the data division are set as follows: $\mu = 16, \nu = 16$.

Table 1. The forecasting results and metrics of each grey models

| Year | Raw data | GM | DGM | NGBM | NGBSM | NIPNGBM | NIPNGBSM |
|------|----------|----|-----|------|-------|----------|-----------|
| 1995 | 293.45   | 293.45 | 293.45 | 293.45 | 293.45 | 293.45 | 293.45 |
| 1996 | 295.59   | 260.25 | 261.26 | 58.94 | 59.05 | 119.60 | 221.21 |
| 1997 | 299.90   | 281.13 | 282.17 | 70.52 | 70.67 | 149.61 | 259.15 |
| 1998 | 292.44   | 303.68 | 304.75 | 84.27 | 84.47 | 182.83 | 299.29 |
| 1999 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2000 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2001 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2002 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2003 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2004 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2005 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2006 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2007 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2008 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2009 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2010 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2011 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2012 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2013 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2014 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2015 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2016 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2017 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2018 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| 2019 | 304.18   | 328.05 | 329.14 | 100.53 | 100.79 | 219.03 | 341.40 |
| MAPE | 25.40%   | 25.42% | 14.93% | 15.12% | 2.39% | 1.86% |
| RMSPE | 25.81% | 25.83% | 15.61% | 15.83% | 2.79% | 2.58% |

Fig. 2. The forecasting results of coke production in Anhui Province
The forecasting results and metrics of each model are shown in Table 1. And the values of the parameters are $\lambda = 0.9999$, $\gamma = 0.7177$. As shown in the table, the MAPE and RMSPE of the NIPNGBSM are 1.86% and 2.58%. It proves that the NIPNGBSM has excellent predictive capabilities.

To further observe the effectiveness of the NIPNGBSM, this paper has made a prediction comparison chart, as shown in Fig. 2. In the prediction stage of the model, the NIPNGBM, after parameter optimization, shows excellent generalization ability, which shows that the model we constructed can be used as a practical tool to observe data in advance of the energy areas.

5. CONCLUSION

In this paper, a nonlinear grey Bernoulli model based on the Simpson integral formula is established, which improves the standard input of background values. The new information priority accumulation improves the model's prediction accuracy further in the data processing. The novel model is named NGBSM. Then use a practical and straightforward grid search approach to optimize the parameters of the model. Due to the introduction of non-linear parameters, the new model will reduce the limitation. Applying NGBSM to the prediction of coke production in Anhui Province, China, the calculation results show that our new model has the best prediction performance, proving that the method proposed in this paper can bring a new and reliable tool for energy prediction.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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