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Research Article

Using a Novel Fractal-Time-Series Prediction Model to Predict Coal Consumption

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Currently, coal is still the main energy source for China's economic development, and the environmental issues caused by coal consumption have aroused widespread concern. Predicting and analyzing coal consumption will help to formulate a higher level of energy consumption planning and economic development strategy. The main purpose of this study is to develop a new fractal time-series prediction (FTSP) model to predict coal consumption, providing reference for formulating effective energy consumption planning and economic development strategies. Hurst index is an important indicator of whether time-series data have long memory and fractal characteristics. This paper uses the rescaled range (R/S) method to calculate Hurst index of the coal consumption per-10000-Yuan-GDP (CC/GDP). The Hurst index is 0.8025, exceeding 0.5, indicating that the time-series data CC/GDP has a long memory and fractal characteristic. Based on this, this paper uses the FTSP model to predict China's coal consumption (CC/GDP). The prediction results show that the FTSP model accurately predicted China's coal consumption with a relative error rate (RER) of less than 5% and a mean absolute percentage error (MAPE) of 6.62%. The model predicts a decrease in China's coal consumption from 0.25 tons of standard coal in 2021 to 0.11 tons of standard coal in 2030, a decrease of 44%. To sum up, the FTSP model provides a new and accurate way to predict coal consumption, and the results suggest that China's coal consumption is sustainable and will decrease significantly in the coming years. This study has important implications for energy consumption planning and economic development strategies.

1. Introduction

1.1. Research Background and Significance. Coal, as one of the main sources of energy, is a nonrenewable fossil fuel that has been used since ancient times. Huge consumption of coal could be the main cause of air pollution; today, environmental issues are of global concern and this is one of the serious problems that coal will face in the future and threaten its sustainability [1, 2]. Energy consumption structure with coal as its core is the key source of serious air pollution in China. For an example, coal consumption produces PM2.5 pollution, which seriously affects public health [3, 4]. What is more, a large amount of carbon dioxide has led to a sharp increase in greenhouse gases, posing a threat to the human life system, while emission of carbon dioxide mainly comes from the combustion of fossil fuels such as coal, oil, and natural gas in industrial production. Therefore, coal consumption has aroused human concern [5–7]. In China, coal reserves are relatively rich, and coal will dominate the energy consumption structure for a long time in the future [8]. As a basic energy and industrial raw material, coal provides an effective guarantee for China's social and economic development and national energy security [9]. In China's energy consumption structure, although the proportion of coal has a downward trend, it has been operating at a high level [10]. In order to achieve sustainable economic development and optimize the energy consumption structure, in 2020, China proposed for the first time that China would increase its independent contribution, adopt more powerful policy measures, and strive to achieve the peak of carbon dioxide emissions by 2030 and carbon neutrality by 2060, which is referred to as China's "double carbon" goal. Under adverse conditions such as regional conflicts and global energy crisis, balancing environmental protection and energy security, meeting coal consumption demand and resource and environmental constraints, and realizing "double carbon" goal are urgent issues for China [11–13]. Though the world has endured great technological promotions, fossil fuels (such as natural gas, coal, and oil) are the major energy source of the world [14]. Up to now, the position of coal in economic development is still irreplaceable. Coal consumption is a comprehensive indicator of national production and domestic energy consumption levels over a period of time. It not only reflects changes in coal demand but also has an important impact on changes in the energy consumption structure. Reasonable coal consumption can promote the organic unity of environmental friendliness and economic development. Therefore, the analysis and prediction of coal consumption has important theoretical and practical significance for relevant departments to formulate reasonable coal resource development policies.

1.2. Research on Prediction Methods. Many domestic and foreign scholars have developed various prediction methods to predict the economic prospect, reserve level, production of coal, and impact of coal consumption on the environment. Jalaee et al. [2] proposed a novel hybrid method for predicting coal consumption in Iran based on socioeconomic variables using the bat and grey wolf optimization algorithm with an artificial neural network (BGWAN). Mengshu et al. [15] proposed a combined algorithm using self-adaptive differential evolution algorithm and support vector machine (SVM) optimization algorithm for coal consumption forecasting. The forecast shows that by 2030, China's coal consumption will be between 2.2 billion tons and 3.7 billion tons. Hou et al. [16] combined with the new normal of economy and the current situation of energy structure adjustment, and based on the range of control parameters, made a Monte Carlo simulation prediction to forecast China's coal demand. The results showed that China's coal demand would rise first and then decline from 2016 to 2025 and reach the peak demand of 4.025 billion tons in 2020. Xie et al. [17] predicted that China's energy consumption demand will be 5.5 billion~5.6 billion tons of standard coal in 2025 by using the elasticity coefficient method. The proportion of coal decreased from the highest 72.5% in 2007 to 59% in 2018 and further decreased to 50%~52% in 2025. The proportion of nonfossil energy will increase from 14.3% in 2018 to 18% in 2025. Jebara et al. [18] improved the classical time-series model and established a neural network model to predict coal consumption. The results showed that the total coal consumption of India in 2010, 2020, and 2030 is predicted to be 695518, 890143, and 1594844 thousand tons, respectively. Jalaee et al. [14] investigated coal consumption up to 2030 using a new hybrid method of WOANFIS (whale optimization algorithm and adaptive neuro-fuzzy inference system); the results demonstrate that WOANFIS is a suitable method for estimating worldwide coal consumption. Jia et al. [19] predicted the coal consumption of Gansu Province from 2020 to 2035 by using the Grey-Markov chain model. The results show that the coal demand of Gansu Province will maintain an upward trend in the next 15 years. Wahid et al. [20] used the results of autoregressive integrated moving average (ARIMA) to predict Pakistan's coal consumption. Results show that an increasing trend from 2016 to 2030 and the response of coal consumption to income and price are inelastic. Wang [21] takes the linear fitting of the ARIMA model and the nonlinear fitting of the BP model as independent variables and takes the per capita coal consumption sequence as the dependent variable. Through multiple-linear regression, a new combined model was constructed to improve the accuracy of coal consumption prediction. Jiang et al. [22] used ARIMA method to predict China's coal price, consumption, and investment from 2016 to 2030. The results show that the average annual growth rate of coal consumption and investment will decrease except that the coal price fluctuates during the forecast period. Liu et al. [23] constructed a methodology for studying the path of mandatory coal consumption control using aggregate reduction indicators based on scenario combination and system dynamics (SD) prediction analysis. Based on this, the optimal scenario model for future coal consumption in Shandong Province was developed. Benalcazar et al. [24] proposed a multilayer perceptron neural network (MLPNN) to predict the global coal consumption from 2020 to 2030. The results show that global coal consumption will decelerate in 2020 (39.32 billion tons of oil equivalent), 2025 (40.69 billion tons of oil equivalent) and 2030 (41.82 billion tons of oil equivalent). Tang et al. [25] analyzed the key factors driving the change of China's coal consumption by using the Logarithmic Mean Divisia Index (LMDI) method and believed that, since 2007, the positive changes in energy intensity and energy structure have directly led to the decline of coal consumption; since 2012, the positive changes in the industrial structure have directly promoted the significant reduction of coal consumption. Dong et al. [26] used LMDI method to decompose the main influencing factors of changes in China's total coal consumption into economic effects, structural effects, and intensity effects. Nguyen et al. [27] used autoregressive distribution lag model to study for the impact of globalization on coal consumption in Vietnam. The results show that the great improvement of Vietnam's globalization level has increased its coal consumption capacity, and rapid economic growth has promoted more coal consumption. Duan and Luo [28] proposed a new multivariable grey model based on grey information differences (MVGM (1, N)). The research results show that MVGM (1, N) is superior to other models and can effectively predict coal consumption. Li et al. [29] proposed a novel time-series prediction method, and the coal consumption data of Poland from 1965 to 2018 was used to predict the coal consumption of Poland from 2019 to 2030 with a 95% confidence interval. The results show that Poland was likely to fulfill its commitments under the current policy. Kumar and Jain [30] applied three time-series models, namely, Grey-Markov model, Grey model with rolling mechanism, and singular spectrum analysis to forecast India's conventional energy consumption. Considering the structure of time-series, the above three models were, respectively, used to predict the consumption of crude oil, coal, electricity (utilities), and natural gas. Their prediction accuracy was 99.2%, 97.9%, 96.9%, and 98.6%, respectively.

The existing researches, mainly including SVM, Monte Carlo simulation prediction, elastic coefficient method, WOANFIS, MVGM (1, N), Grey-Markov chain model, LMDI, ARIMA model, and MLPNN model, use different methods to predict the future development trend of China's coal consumption from different perspectives and have achieved high-quality prediction results. However, the seemingly simple coal consumption data actually contains a lot of economic development information, such as the speed and quality of economic development, the energy competition between regions, and the relationship between economic development and the natural environment. Therefore, exploring the laws behind the coal consumption data and selecting a more appropriate model to accurately predict the development trend of China's coal consumption is still a huge challenge. In this study, a novel fractal-time-series prediction (FTSP) model is proposed, which can use the variable fractal dimension of time-series-data to predict the development trend of coal consumption.

1.3. Research Theme and Innovation. The concept of fractal was first proposed by a Polish born American mathematician Mandelbrot, B. B, of which the basic idea is to find order from disorder and revealed the laws contained in the extremely irregular complex phenomena such as chaos and fragmentation and fractal has wide applications in physics, biology, chemistry, materials science, and other fields [31, 32]. Fractal theory provides a research means for studying various complex economic phenomena and the competition and coordination of various fractal elements in complex social systems [33–36]. In particular, in the field of natural science and social science, statistical analysis and modeling prediction based on the fractal theory have also been widely used [37–40]. Dimension of traditional fractal methods is invariant integer, which is helpful for simplifying and analyzing problems. However, some complex phenomena cannot be solved in the space of integer dimensions. Fractional fractal dimension greatly enriches the traditional theory that the dimension is an integer [41]. Long-memory (persistence) of time series is a non-linear feature of time-series [42]. The persistence of random generation process is measured by the *Hurst* index (H). When $0.5 < H < 1$, it shows that the time-series has the characteristics of long memory, which is called fractal time-series [43]. Fractal theory provides an effective tool for proposing the FTSP model. Overall, our work mainly is in the following three highlights:

(1) The FTSP model was based on the fact that time-series is a series with fractal characteristics. The rescaled range (R/S) analysis method was introduced to calculate the *Hurst* index of the time-series, according to which, whether the time-series is a fractal-time-series with long memory is determined. In order to eliminate the impact of sudden change on the prediction results at a certain time point, the original time-series was transformed into a new series (TNS) by first-order or second-order or higher-order accumulative transformation.

(2) Traditional time-series-prediction models imply a basic assumption that the spatial dimension is an integer. In the FTSP model, for improving the prediction accuracy, the variable fractal dimension was used for prediction. FTSP model provides a new reference for improving time-series prediction.

(3) The *Hurst* index of CC/GDP calculated by R/S analysis method is 0.8025, indicating that CC/GDP is a series with fractal characteristics. The prediction results showed that the mean absolute percentage error (MAPE) is 6.62%, less than 10%, reaching the high accuracy and that China's coal consumption is sustainable. From 2021 to 2030, China's CC/GDP will decrease from 0.25 tons of standard coal in 2021 to 0.11 tons of standard coal in 2030, a decrease of 44%.

1.4. Introduction to Research Content. The rest of this paper is arranged as follows: In second part, the principles and steps of establishing the FTSP model are described, including the basic concepts of time-series data, several important transformations, calculation of the Hurst index (R/S calculation method steps), basic principles of the FTSP model and prediction accuracy standards, etc. In third part, China's coal consumption is predicted by using the FTSP model, and the prediction results are described. In fourth part, constant fractal dimension, variable fractal dimension, the limitation of FTSP model, and other explanations (how this article can be used for long-term planning) are discussed. The fifth part is the main conclusion, including the long memory and fractal characteristics of time-series-data CC/GDP, the calculation of fractal dimensions, the prediction of coal consumption development trends, and the significance of establishing the FTSP models.

2. FTSP Model

2.1. Basic Concepts of Time-Series-Data. Time-series is data collected at different time points. This kind of data is collected in time order and is used to describe the state or degree of a certain thing or phenomenon with time. For example, China's GDP data from 2010 to 2020 is time-series data. If t is taken as the time number, and suppose 2010 year is $t = 1$, corresponding *GDP* is x_1, and suppose 2011 year is $t = 2$, corresponding *GDP* is $x_2, \ldots$, and 2020 year is $t = 11$, corresponding *GDP* is x_{11}, then, the time-series $X = (x_1, x_2, \ldots, x_{11})$ can be obtained.

2.2. Several Important Transformations of Time-Series-Data

2.2.1. Translation Transformation. For a time-series $X = (x_1, x_2, \ldots x_n)$, if sequence $X^+ = (x_1^+, x_2^+, \ldots, x_n^+)$ satisfies equation (1), then sequence X^+ is called the translation transformation of X, which is abbreviated as $Tt\ (\lambda)$, among them, λ is a constant.

$$x_r^+ = x_r + \lambda\,(r = 1, 2, \ldots, n). \tag{1}$$

2.2.2. Accumulative Transformation. The so-called accumulative transformation is the first-order or second-order or higher-order accumulative summation of the original sequence. For a time-series $X = (x_1, x_2, \cdots x_n)$, if sequence $X^{(1)} = (x_1^{(1)}, x_2^{(1)}, \ldots\ldots, x_n^{(1)})$ satisfies equation (2), then sequence $X^{(1)}$ is called the one-time-accumulative transformation of X, which is abbreviated as $T\ (oat)$.

$$x_r^{(1)} = \sum_{i=1}^{r} x_i\,(r = 1, 2, \ldots, n). \tag{2}$$

Similarly, if sequence $X^{(1)} = (x_1^{(1)}, x_2^{(1)}, \ldots\ldots, x_n^{(1)})$ is transformed $(T\,(\mathrm{oat}))$, then sequence $X^{(2)}$ can be obtained. Sequence $X^{(3)}$ and $X^{(4)}$ can be obtained in turn.

2.3. Fractal Characteristics of Time-Series. Memory is one of the most interesting aspects of many processes in nature and society. In economics, a random shock in the past or present would have a significant long-term effect on future events. If the attenuation degree of the time-series follows the power law, there is no cut-off for the past impact. In this case, time-series are said to have long-term memory or persistence, and the long-term memory (persistence) is a non-linear feature of time-series [42, 43]. The *Hurst* index is widely used for all time-series, because it is particularly robust and requires few assumptions for the system under study. The persistence of random generation process is measured by the *Hurst* index (H). In the 1940s, the British hydrologist Hurst discovered that many statistical results in nature can be well characterized by biased random walks. Based on this, he proposed using the rescaled range (R/S) analysis method to construct the Hurst index as a criterion for determining whether a time-series follows a Brownian motion or a biased random walk. The Hurst index is widely used, initially to study natural phenomena, but later widely used by scholars to study the behavioral characteristics of financial markets such as stocks and exchange rates. The *Hurst* index of the time-series is between 0 and 1 and is divided into three intervals with an interval of 0.5. The following time-series show different characteristics in different intervals: when $0 \leq H < 0.5$, it indicates that time-series belongs to medium memory process; when $H = 0.5$, it shows that the time-series is a random series, showing short memory characteristics; when $0.5 < H < 1$, the time series has a positive effect, indicating that the future trend is consistent with the past. The closer H is to 1, the stronger its persistence is. The time series has a positive effect, indicating that the future trend is consistent with the past. The closer H is to 1, the stronger its persistence. Time-series satisfying $0.5 < H < 1$ have the characteristic of long memory, that is, stochastic processes have persistence. At this time, time-series is also called fractal time-series. A time series with the Hurst statistical (long memory) characteristics is the result of a long series of interconnected events, what happens today will affect the future and what happened in the past will also affect the present. This is precisely the theory and method we need to analyze data sequences, which is difficult to do with traditional probability statistics. This is also the basis of the FTSP model. In this study, *R/S* (rescaled range) analysis was used to calculate the *Hurst* index [44–47]. The specific steps are as follows:

For a time-series $X = (x_1, x_2, \ldots x_n)$ with uniform time interval, its mean value satisfies the following equation:

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} x_i. \tag{3}$$

For time-interval T ($\mathrm{T} = 2, 3, \ldots n$), the cumulative deviation of time-series at time t can be calculated by equation (4) and define the range as $R\ (T)$ by equation (5) and as $S\ (T)$ by equation (6).

$$v(t) = \sum_{i=1}^{t} x_i - t\overline{X}\,(1 \leq t \leq T), \tag{4}$$

$$R(T) = V_{\max}(T) - V_{\min}(T), \tag{5}$$

$$\mathrm{S}(T) = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(x_t - \overline{X}\right)^2 T}\,(T = 2, 3, \ldots n). \tag{6}$$

We Took the natural logarithm on both sides of equation (7) and then conducted regression to obtain the *Hurst* index to determine whether the time-series is a sequence with fractal characteristics. Among them, C is constant and H is the *Hurst* index.

$$\left(\frac{R}{S}\right)_T = \frac{R(T)}{S(T)} = CT^H. \tag{7}$$

2.4. Fractal Prediction of Time-Series. The *Hurst* index is economy-physics concepts that inform the characteristics of the time-series. If $0.5 < H < 1$, it shows that time-series is a sequence with fractal characteristics. Therefore, based on fractal theory, we propose a FTSP model to predict the time-series.

2.4.1. Summary of Fractal Theory. Using power exponent distribution [48, 49], the fractal model can be described as follows:

$$N(r) = \frac{C}{r^D} = C \cdot r^{-D}, \tag{8}$$

where r is the characteristic line degree, $N(r)$ represents the magnitude of the measured object; D represents the fractal dimension; and C is a parameter.

In traditional geometry, dimension is an integer, but in fractal theory, dimension is not an integer, which enriches the traditional theory. As to usual fractal theory, the dimension is invariable, which will help simply analyzing question [41]. It has been found that many complex phenomena are not suitable for constant dimensional fractal models; therefore, many scholars bring forward variable dimension fractal model [49, 50].

We substituted any two points (r_i, N_i) and (r_j, N_j) into equation (8) and sorted out the calculation formulas of constants D and C as follows:

$$D = \frac{\ln N_i - \ln N_j}{\ln r_j - \ln r_i}, \tag{9}$$

$$C = N_i r_i^D. \tag{10}$$

The variable fractal dimension can be determined by equations (9) and (10) and then the fractal dimension required for prediction can be finally selected through repeated trial calculation according to the prediction accuracy.

2.4.2. Prediction Processing. We can take logarithms on both sides of equation (8) and obtain the average (constant) fractal dimension by linear regression, but the effect is not perfect. In addition, the study found that the direct prediction of the original data has poor prediction accuracy. Therefore, we can transform the original data to form a good variable dimension fractal model [51, 52]. The specific steps are as follows:

The first step: *Transformation of Time-Series Data.* In order to eliminate the impact of the sudden change of the series at a certain time point on the prediction, a series of transformations are required for the time-series. For a time-series$X = (x_1, x_2, \ldots x_n)$, assume that the characteristic degree r is a uniform time span and set $N(1) = x_1$, when $r = 1$, and $N(2) = x_1 + x_2$, when $r = 2, \ldots,$ that is, according to the transformation of equation (2), sequence $X^{(1)}$ is obtained. Similarly, by $T(oat)$ transformation, sequence $X^{(2)}$ and $X^{(3)}$ are obtained correspondingly (Table 1).

The second step: *Calculation of Fractal Dimension.* For the sequence $X^{(1)}$, the variable fractal dimension D can be calculated by equations (9) and (10). At the same time, according to the prediction accuracy requirements, select the fractal dimension D and calculate the corresponding constant C. So do sequence $X^{(2)}$ and sequence $X^{(3)}$. Generally, for the same sequence, the value of stable fractal dimension is selected as the predicted fractal dimension.

The third step: *Determination of Fractal Dimension*. For sequence $X^{(1)}, X^{(2)}$ and $X^{(3)}$, substituting the fractal dimensions D and C calculated in the third step into the corresponding sequence, the predicted value of the real value of series X could be obtained by iteration back according to the order of transformation. Furthermore, compare the prediction results under the above three conditions according to the prediction accuracy requirements, and finally, determine the fractal dimension D and constant C.

The fourth step: Substituting the fractal dimensions D and C determined in the fourth step into the corresponding sequence and assigning a value to time span r, the predicted value of original series X could be obtained by iteration back according to the order of transformation.

To sum up, (a) we used the Hurst index to determine whether the time series is a fractal time series. (b) A cumulative transformation is performed on the time series to obtain a new time series, and different fractal dimensions are calculated using equation (9). (c) We predicted the original data, calculated the prediction accuracy, and determined the value of the fractal dimension to be used through comparison. (d) We predicted the future development trend based on the determined fractal dimension.

2.5. Accuracy Tests on the FTSP Model. Regarding the prediction accuracy of the model, Liu and Lin [53] believed that the prediction accuracy of the model could be measured by the relative error rate (RER). The calculation formulas of the residual error between the estimated value and the true value of the original data and the relative error rate (RER) are as follows:

$$\varepsilon(r) = \hat{x}_r - x_r; \mathrm{RER} = \frac{|\varepsilon(r)|}{x_r} \times 100\%. \tag{11}$$

Hu [54] believed that the mean absolute percentage error (MAPE) could be used. MAPE is more stable than the average absolute error and root mean square error. MAPE formula is as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{r=1}^{n} \frac{|x_r - \hat{x}_r|}{x_r} \times 100\%. \tag{12}$$

The accuracy grade confirmation of a model is shown in Table 2.

3. Results

3.1. Data and Variables. The data required for this research include during the period from 2006 to 2020, China's GDP (100 million Yuan), annual total coal consumption (10000 tons of standard coal), and other statistical data. The above statistical data are all from China Statistical Yearbook (2007–2021). The variable predicted is the coal consumption per 10000 yuan GDP (CC/GDP).

Table 1: Box counting method for calculating the magnitude of the measured object.

r	$X^{(1)}/N_1(r)$	$X^{(2)}/N_2(r)$	$X^{(3)}/N_3(r)$
1	$x_1^{(1)} = x_1$	$x_1^{(2)} = x_1^{(1)}$	$x_1^{(3)} = x_1^{(2)}$
2	$x_2^{(1)} = x_1 + x_2$	$x_2^{(2)} = x_1^{(1)} + x_2^{(1)}$	$x_2^{(3)} = x_1^{(2)} + x_2^{(2)}$
3	$x_3^{(1)} = x_1 + x_2 + x_3$	$x_3^{(2)} = x_1^{(1)} + x_2^{(1)} + x_3^{(1)}$	$x_3^{(3)} = x_1^{(2)} + x_2^{(2)} + x_3^{(2)}$
...	...	...	...
n	$x_n^{(1)} = \sum_{i=1}^n x_i$	$x_n^{(2)} = \sum_{i=1}^n x_i^{(1)}$	$x_n^{(3)} = \sum_{i=1}^n x_i^{(2)} x_n^{(3)} = \sum_{i=1}^n x_i^{(2)}$

Table 2: Standards for model accuracy tests.

Accuracy grade	RER	MAPE
(I) High	< 1%	< 10%
(II) Good	≥ 1%~ < 5%	≥ 10%~ < 20%
(III) Reasonable	≥ 5%~ < 10%	≥ 20%~ < 50%
(IV) Weak	≥ 10%~ < 20%	≥ 50%
(V) Needs to be revised	≥ 20%	

Coal consumption is an overall quantity. Due to the different scale of economic development each year, if the time-series-data of coal consumption are directly used to predict future development trends, the impact of the scale of economic development cannot be excluded. Therefore, using CC/GDP to predict future development trends can accurately reflect the changing laws of coal consumption's impact on economic development.

Considering the characteristics of China's GDP and actual coal consumption (CC) in different years, the coal consumption (CC) is expressed by the actual total coal consumption per unit GDP. Since, there is a production price factor when calculating the "output value," the actual coal consumption per unit GDP can be divided into "energy consumption per unit output value at current price" and "energy consumption per unit output value at comparable price." When studying on the change of the actual coal consumption per unit of GDP over a period, the actual coal consumption per unit of GDP at comparable prices could be used by [10]. The formula for calculating the comparable price output value of GDP is as follows:

$$GDP_t = \frac{(GDP_{t-1} \times I_t)}{100}, \qquad (13)$$

where I_t is the GDP index of t^{th} year (calculated at comparable prices, the previous year was equal to 100) and GDP_{t-1} is the GDP of $(t-1)^{\text{th}}$ year.

CC/GDP index (Unit: tons of standard coal/ten thousand Yuan GDP) can be obtained by dividing the annual total coal consumption (ten thousand tons of standard coal) by the GDP of the year. The original data are shown in Table 3.

From Table 3 and Figure 1, it can be seen that from 2006 to 2020, China's CC/GDP data showed a downward trend, from 0.9824 in 2006 to 0.2792 in 2020, with a decrease of 71.6%, fully demonstrating the significant effect of "energy conservation and emission reduction" in China.

3.2. Hurst Index of the Original Time-Series-Data. The R/S analysis method for calculating the Hurst index can first calculate the parameters R (range), S (standard deviation),

Table 3: CC/GDP of China (2006~2020).

Year	CC/GDP
2006	0.9824
2007	0.9010
2008	0.7737
2009	0.6891
2010	0.6475
2011	0.6014
2012	0.5232
2013	0.4840
2014	0.4426
2015	0.4022
2016	0.3733
2017	0.3462
2018	0.3136
2019	0.2887
2020	0.2792

Unit: tons of standard coal/10000 Yuan GDP.

and R/S for different T values according to equations (3)–(6). The calculation results are shown in Table 4. Then, according to equation (7), take the natural logarithms of R/S and T and regress to obtain equation (14), from which the Hurst exponent of the time-series CC/GDP can be obtained.

$$\ln\left(\frac{R}{S}\right)_T = \underset{t(-2.6706)}{-0.370047} + \underset{t(12.0347)}{0.802484} \ln T + e_i. \qquad (14)$$

Among them, $R^2 = 0.9235$, $F = 144.83$. At the 5% significance level, the equation and coefficient passed the significance test. Therefore, it can be obtained that the *Hurst* index of the original time-series (CC/GDP) is 0.8025, which indicates that the series CC/GDP is a sequence with fractal characteristics.

3.3. Pretreatment of the Original Data CC/GDP. In order to eliminate the impact of the sudden change of the series at a certain time point on the prediction, after repeated trial and error, data CC/GDP are implemented Tt (λ) transformation to obtain sequence X. Following the steps of the prediction processing, we obtain the sequence $X^{(1)}$, $X^{(2)}$, and $X^{(3)}$ and then the corresponding fractal dimensions are obtain by equation (9). The above calculation results are shown in Table 5, and the stable fractal dimension value of the shaded part in Table 3 has been emphasized according to the second step of the prediction processing.

After repeated trial and error, it is found that the FTSP model has higher accuracy (Table 6) when the fractal dimension D and the corresponding constant C are −1.7936 and 1.55385, respectively.

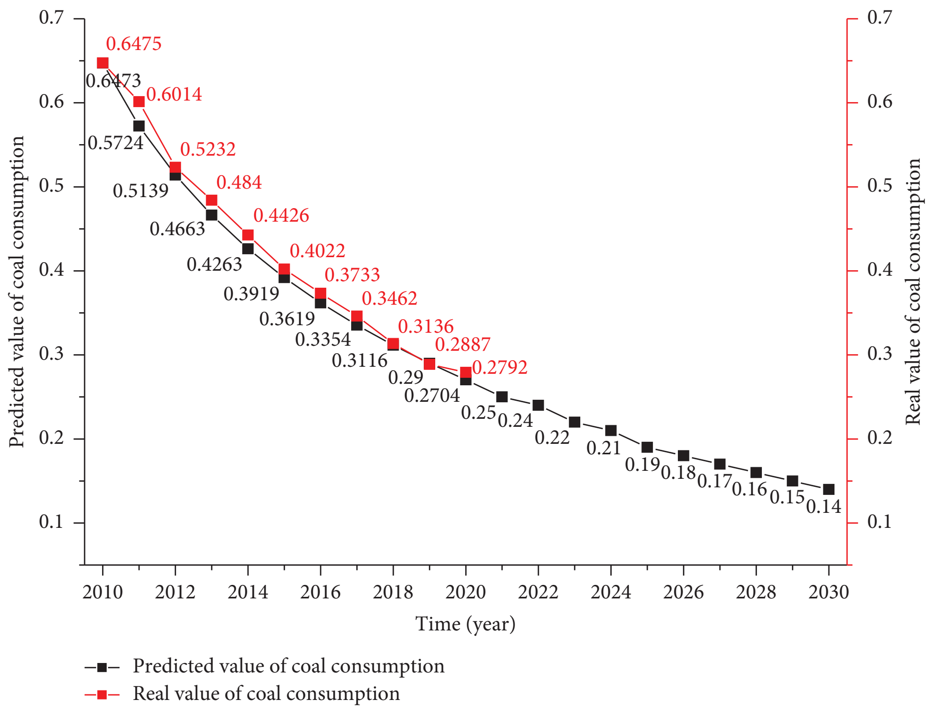

Figure 1: Prediction result of CC/GDP (2021~2030).

Table 4: Calculation results of the Hurst index.

T	R	S	R/S
2	0.3645	0.4072	0.8950
3	0.6016	0.3596	1.6732
4	0.7542	0.3206	2.3524
5	0.8651	0.2910	2.9728
6	0.9300	0.2670	3.4834
7	0.9300	0.2472	3.7618
8	0.9300	0.2320	4.0086
9	0.9300	0.2209	4.2088
10	0.9300	0.2139	4.3481
11	0.9300	0.2098	4.4331
12	0.9300	0.2083	4.4661
13	0.9300	0.2094	4.4412
14	1.1185	0.2124	5.2666
15	1.3759	0.2157	6.3795

Table 5: Pretreatment of CC/GDP and calculated fractal dimension.

r	X	$X^{(1)}$	$X^{(2)}$	$X^{(3)}$	$D(1)$	$D(2)$	$D(3)$
1	1.98	1.98	1.98	1.98			
2	1.90	3.88	5.87	7.85	−0.9701	−1.5651	−1.9851
3	1.77	5.66	11.52	19.37	−0.9278	−1.6652	−2.2283
4	1.69	7.35	18.87	38.24	−0.9082	−1.7144	−2.3641
5	1.65	8.99	27.86	66.10	−0.9068	−1.7467	−2.4528
6	1.60	10.60	38.46	104.56	−0.8988	−1.7676	−2.5151
7	1.52	12.12	50.58	155.14	−0.8714	−1.7769	−2.5594
8	1.48	13.60	64.18	219.32	−0.8651	−1.7838	−2.5927
9	1.44	15.04	79.22	298.54	−0.8558	−1.7881	−2.6183
10	1.40	16.45	95.67	394.21	−0.8458	−1.7904	−2.6384
11	1.37	17.82	113.49	507.70	−0.8414	−1.7922	−2.6546
12	1.35	19.17	132.66	640.36	−0.8370	−1.7934	−2.6679
13	1.31	20.48	153.14	793.50	−0.8282	−1.7936	−2.6788
14	1.29	21.77	174.91	968.40	−0.8234	−1.7935	−2.6880
15	1.28	23.05	197.95	1166.36	−0.8276	−1.7942	−2.6958

3.4. Accuracy Test on the FTSP Model. Therefore, we set up a novel FTSP model as follows:

$$N(r) = x_r^{(2)} = \frac{1.55385}{r^{-1.7936}}. \tag{15}$$

Substituting $r = 2, \ldots, 15$ into equation (15), the prediction values of CC/GDP from 2007 to 2021 are obtained by iteration back according to the order of transformation and inverse translation transformation. According to equations (11) and (12), the RER and MAPE are calculated. Table 6 shows that since 2010, the relative error rate is less than 5%, and the accuracy grade is grade II; the relative error rate of some years is smaller, and the accuracy grade is grade I. MAPE is 6.62%, less than 10%, reaching the high accuracy standard.

3.5. Prediction Results. The above analysis fully shows that it is feasible to predict CC/GDP by equation (15). According to the above FTSP model (equation (15)), China's CC/GDP in the next 10 years (2021–2030) is predicted (Figure 1). The prediction results show that, based on 2021, CC/GDP will decline at an annual average rate of 5.52% in the next 10 years and that when reaching the "carbon peak" in 2030, CC/GDP in China will decrease from 0.25 tons of standard coal in 2021 to 0.11 tons of standard coal, with a decrease of 44%.

In fact, the Chinese government issued China's energy policy as early as 2012: China will promote the transformation of energy production and utilization modes, build

Table 6: Prediction results of CC/GDP.

Year	Predictive value	Real value	RER (%)
2007	1.2567	0.9010	39.48
2008	0.9086	0.7737	17.43
2009	0.7498	0.6891	8.82
2010	0.6473	0.6475	0.03
2011	0.5724	0.6014	4.83
2012	0.5139	0.5232	1.78
2013	0.4663	0.4840	3.66
2014	0.4263	0.4426	3.68
2015	0.3919	0.4022	2.55
2016	0.3619	0.3733	3.03
2017	0.3354	0.3462	3.13
2018	0.3116	0.3136	0.66
2019	0.2900	0.2887	0.48
2020	0.2704	0.2792	3.12

a safe, stable, economic, and clean modern energy industrial system and strive to support sustainable economic and social development with sustainable energy development by adhering to eight energy development guidelines, including "saving first." After that, the Chinese government launched a series of energy reform policies. Relevant data show that the proportion of nonpetrochemical energy consumption in China's total energy consumption has increased from 7.4% in 2006 to 16.1% in 2021, with an increase of 117.6% and that the proportion of coal consumption in total energy consumption has decrease from 72.4% in 2006 to 56% in 2021, with a decrease of 22.7% (Statistical Yearbook 2022) [55]. The above forecast research fully demonstrates that a series of investment portfolio policies issued by the Chinese government in the past have played an important role in achieving the "dual carbon" goal.

4. Discussion

4.1. Constant Fractal Dimension. In order to improve the prediction accuracy, the variable fractal dimensions are used in the prediction process. In addition, we took the natural logarithm on both sides of equation (8) and then conducted linear regression to obtain the constant fractal dimensions of sequence $X^{(1)}$, $X^{(2)}$ and $X^{(3)}$, which are 0.8989, 1.7204, and 2.4065, respectively (Figure 2).

The regression results showed that the goodness of fit (R^2) was high, and the coefficients and equations passed the significance test. Compared with Table 5, the constant fractal dimension has the same order of magnitude as the fractal dimension under $D(1)$, $D(2)$, and $D(3)$ (Table 5).

4.2. Variable Fractal Dimension. In the prediction research of the FTSP model, the variable fractal dimension D and the parameter C should be finally determined by repeated trial calculation according to the accuracy requirements. The calculation of fractal dimension is not complicated, but the workload is large. Therefore, it should be considered to compile computer programs for calculation (machine learning).

In the calculation of fractal dimension, the data used are the coordinates of two adjacent points (Table 3). After repeated trial and error, it is found that the fractal dimension of the coordinate calculation of not adjacent two points fluctuates greatly.

4.3. FTSP Model. The observation of the prediction accuracy depends on the development trend; generally, the prediction accuracy of the first several time points of the time-series is poor and the accuracy is higher from a certain time point (Table 6). The difficulty of the FTSP model is to determine the fractal dimension of the sequence, and there is no more effective standard to determine the fractal dimension. When the fractal dimension is determined, a series of transformations are required; when the original sequence is predicted, the corresponding inverse transformation is needed. The above process will inevitably lead to prediction errors, which need to be reduced by repeated trial and error.

The FTSP model is proposed based on the time-series-prediction model and is only an improvement on the method of time-series-prediction model; therefore, the characteristics of time-series prediction can be reflected in FTSP model. There are the following two elements constituting the time-series: one is time and the other is the variable value corresponding to time. The time-series of real data can show the development and change laws of the research object in a certain period. Therefore, the characteristics and development laws of variable changes can be found out from the time-series and the future changes of variables can be effectively predicted [56]. Time-series prediction implies the following basic assumptions: it is assumed that the development and change of things are continuous in time and the past trend of things will extend to the future [57]. Temporarily, the causal relationship between changes in variables and external specific factors is not considered and only the decisive role of time factors in time-series prediction is considered. In a statistical sense, we can calculate the *Hurst* index of time-series to measure whether time series have fractal characteristics, but the reality is relatively complex. In fact, the future development of things often has great uncertainty, for example, some major historical events faced by human society (e.g., earthquakes and plagues) may cause the development and change of things to show great leaps in a certain period of time. Based on this, the external specific factors affecting the development of things cannot be ignored [58, 59]. Therefore, when the FTSP model is used for prediction, the medium and short-term prediction may be more reliable. When studying the prediction results, it is not necessary to adhere to the prediction results, but to dialectically analyze and apply them in combination with the development laws of things.

4.4. Other Instructions. The research found that the time-series-data applied to coal consumption prediction in this paper have long memory and fractal characteristics, laying a theoretical foundation for the prediction of the FTSP

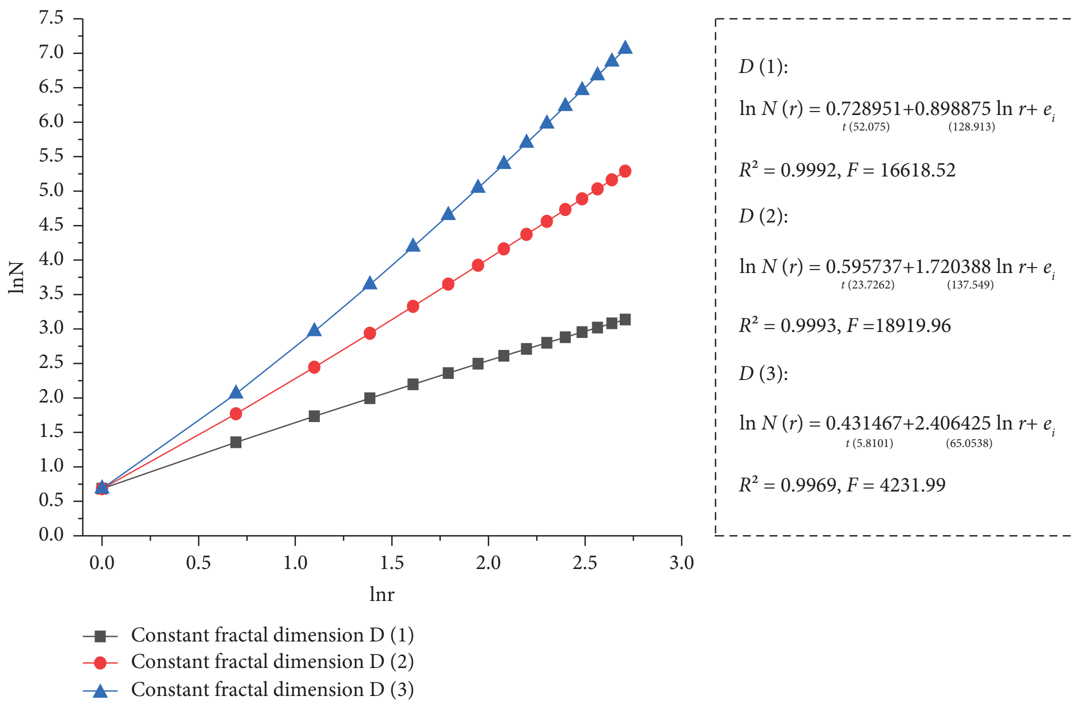

Figure 2: Constant fractal dimension of sequences $X^{(1)}$, $X^{(2)}$, and $X^{(3)}$.

model. Research on statistical theory indicates that data reflecting objective phenomena contains a lot of information and can be used to predict the future through time-series prediction models. Coal consumption data with long memory and fractal characteristics inherently contains a large amount of information. For example, important information such as past development strategies, implementation paths, information feedback, and behavior correction are contained. The prediction results of the FTSP model present the future trend of China's coal consumption (a significant downward trend). More importantly, the Chinese government can explore the domestic and foreign background of a series of policies hidden behind past coal consumption data, which is the basis for formulating long-term plans, the so-called "historical experience, realistic response, and future trend." Therefore, predicting and analyzing coal consumption by the FTSP model will help to formulate a higher level of energy consumption planning and economic development strategy.

5. Conclusions

In this paper, the *Hurst* index of the original time-series CC/GDP is found to be 0.8025 greater than 0.5 by using the *R/S* analysis method, which shows that the series is a long-term memory process of a nonlinear system and a series with fractal characteristics. Based on this, a novel FTSP model is established to predict China's coal consumption.

The variable fractal dimension of the new series is calculated and the "appropriate" fractal dimension is selected for prediction. The research shows that the new sequence obtained by the second-order accumulative transformation with the fractal dimension of 1.736 has the best prediction result.

Statistical analysis shows that from 2006 to 2020, the coal consumption (CC/GDP) has a significant downward trend. The prediction accuracy of the FTSP model is high and the MAPE is 6.62%, less than 10%, which meets the high accuracy standard. The forecast results show that when the "carbon peak" is reached in 2030, CC/GDP will drop by 0.11 tons of standard coal from 0.25 tons of standard coal in 2021, with a drop of 44%.

In coal consumption prediction, there are two important results that need attention, including the optimal fractal dimension and MAPE. Using the constant fractal dimension in Figure 2 for prediction, the comparability is poor. Therefore, it is necessary to find the optimal fractal dimension among the calculated variable fractal dimensions. How to find the best fractal dimension? You need to use MAPE for filtering. The above content is the core content of this study.

Coal consumption plays an important role in the sustainable coal industry. This paper uses a novel FTSP model to predict the development trend of China's coal consumption, which provides a new idea for promoting sustainable economic development and optimizing energy consumption structure.

Data Availability

The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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