

## Research Article

# Forecast of Energy Consumption Based on FGM(1, 1) Model

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Received 17 October 2020; Revised 25 January 2021; Accepted 1 February 2021; Published 15 February 2021

Academic Editor: Bo Zeng

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The normal supply of energy is related to the stable development of the economy and society. Forecasting energy consumption helps prepare for the normal supply of energy. In the study of energy consumption forecasting, different scholars have used different forecasting models. This paper uses five-year energy consumption data in the Beijing-Tianjin-Hebei region and uses the grey fractional FGM(1, 1) model to analyze the next six years. Then, the energy consumption of three places is predicted. The advantage of the grey score FGM(1, 1) model is that it can get more accurate prediction results based on a small amount of information. In this study, relatively outdated information affects the accuracy of prediction results. However, other prediction models have great limitations on data. Choosing the grey number fractional model for prediction research can get a more reasonable prediction result. We use the FGM(1, 1) model to make predictions and get the prediction results. In Beijing, the growth rate of natural gas consumption has slowed down and will be basically stable by 2023. The average annual deceleration of coal consumption is 32%. The average annual deceleration of coke consumption is 10%. Crude oil consumption decreased by 6.3% annually. Gasoline consumption is slowly increasing. The consumption of kerosene increased about 8% annually. Diesel consumption is slowly decreasing. Fuel oil consumption is reduced by 17% annually. The average annual growth rate of power consumption exceeds 6%. In Tianjin, the annual growth rate of natural gas consumption is about 5%. Coal consumption is reduced by about 8% every year. The average annual deceleration of coke consumption is 7%. Crude oil consumption decreased by 2.4% annually. Gasoline consumption is slowly decreasing. The consumption of kerosene has increased by about 20% annually. Diesel consumption is slowly decreasing. Fuel oil consumption is reduced by 20% annually. Electricity consumption is slowly increasing. In Hebei Province, the annual growth rate of natural gas consumption is about 15%. Annual coal consumption is reduced by about 3%. Coke consumption remained stable. Crude oil consumption is reduced by 3% annually. Gasoline consumption is slowly increasing, and kerosene consumption has increased by about 31% annually. Diesel consumption is reduced by about 3% annually. Fuel oil consumption remained stable. Electricity consumption is slowly increasing.

## 1. Introduction

Energy is an important material basis for human progress and social and economic development. The development and utilization of energy has greatly promoted the development of the world economy and human society. And the increase in energy consumption is the inevitable result of economic and social development. The rapid development of China's economy is also inseparable from the normal supply of energy. In the year 2000, China's GDP was 10,028 trillion RMB ¥ and the total national energy consumption was 1469.6 million tons of standard

coal. In 2017, China's GDP was 832.35 billion RMB ¥ and the total national energy consumption was 4,455.2 million tons of standard coal. It should be noted that with the rapid economic development and rapid energy consumption, economic development and environmental pollution have become the main contradictions that currently exist. It is under this background that the Chinese government has proposed the scientific development concept to accelerate the development of modern energy. Industries adhere to the basic national policy of saving resources and protecting the environment. While developing the economy, we should also pay attention to

the issue of energy consumption. While improving energy supply capacity, we should pay attention to energy efficiency and energy conservation and emission reduction.

As an important part of China's economy, the Beijing-Tianjin-Hebei region is also an important issue of concern to scholars in terms of economic development, energy consumption, and environmental protection. Especially with the acceleration of the integration of Beijing-Tianjin-Hebei and the construction of Xiong'an New Area, the economic development of the Beijing-Tianjin-Hebei region has ushered in new development opportunities. And the demand for energy for economic and social development will further increase. Research on the prediction of energy consumption has become a necessary research topic. Accurate prediction will help the government and enterprises do a good job of energy planning ahead of time.

There are many methods for data forecasting [1–4]. Different forecasting methods have different requirements for raw data. One of the characteristics of grey model is that it can forecast small data and poor information. The grey system model can be used for forecasting.

The grey system is a relatively new theory developed by Julong in the 1980s [5, 6]. In this theory, information that is clearly known is defined as white information and information that is completely unknown is defined as black information. Information that falls between completely known and completely unknown is defined as grey information. In the real world, situations with incomplete information are ubiquitous. For example, agricultural yield, stock returns, and unemployment rates can be affected by uncertainties. Thus, problems related to these issues can be solved using grey system theory.

Many researchers use the first-order single variable grey forecasting model, GM(1, 1) [7–10], to make predictions. But the model has relatively large errors in the prediction of specific problems. Under certain conditions, the fractional grey model, FGM(1, 1) [11–14], has a higher accuracy than the GM(1, 1) model. The FGM(1, 1) model performs the calculation using the time series of the predicted object itself and only needs a small amount of data to achieve a better prediction.

Many scholars have made predictions on energy consumption using other models. Electric load forecasting is done by complete ensemble empirical mode decomposition adaptive noise and support vector regression with quantum-based dragonfly algorithm by Zhang and Hong [15]. Combining the PEM, LSSVR model, and CCPSO algorithm, a hybrid forecasting method for SMTS, PEM, and LSSVR-CCPSO, is developed by Li et al. [16]. Forecasting electric by seasonal recurrent SVR (support vector regression) with chaotic artificial bee colony algorithm was done by Hong [17]. There are many scholars based on the improved GM (1,1) model for forecasting, or GM (1,1) model combined with

other models for forecasting [18–32]. The research draws on the related research results of predecessors. This paper uses energy consumption data from 2013 to 2017 in the Beijing-Tianjin-Hebei region [33] and uses the FGM(1, 1) model to predict energy consumption. Through prediction, the result of the research is to use less original data to obtain 6-year forecast data of energy consumption in Beijing, Tianjin, and Hebei. At the same time, compared with the traditional FM(1, 1) model, the prediction error of the fractional FGM(1, 1) model is smaller in most cases.

## 2. Model Introduction of FGM(1, 1)

The execution of GM (1, 1) model is done through data accumulation, grey model, and inverse accumulation of data. The advantage is that it can process grey information and sparse data. However, the model has disadvantages. Namely, the errors are large for certain problems. FGM(1, 1) addresses this deficiency of the GM(1, 1) and reduces the errors by judiciously selecting the accumulation order number. With this approach, better prediction results can often be achieved. The basic process of FGM(1, 1) is given by the following equations.

For a non-negative sequence,  $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$ , the FGM(1, 1) model is constructed as follows:

Step 1: by the accumulation generation operator,  $x^{(r)} = \sum_{i=1}^k C_{k-i+r-i}^{k-i} x^{(0)}(i)$ , the  $r$ th-order accumulation sequence is

$$X^{(r)} = x^{(r)}(1), x^{(r)}(2), \dots, x^{(r)}(n), \quad (1)$$

where  $C_{r-1}^0 = 0$ ,  $C_k^{k+1} = 0$ , and  $C_{k-i+r-1}^{k-i} = ((k-i+r-1)(k-i+r-2) \cdots (r+1)r/(k-i)!)$ .

Note that a superscript (0) indicates an original sequence and a superscript (r) indicates an  $r$ th-order accumulation sequence.

Step 2: establish the differential equation as

$$\frac{dx^{(r)}(t)}{dt} + ax^{(r)}(t) = b, \quad (2)$$

where  $a$  is the development grey number and  $b$  is the endogenous control grey number.

The solution of the equation is an exponential function:

$$x^{(r)}(t+1) = \left[ x^{(0)}(1) - \frac{b}{a} \right] e^{-at} + \frac{b}{a}. \quad (3)$$

Using the least-squares method,  $\hat{a}$  and  $\hat{b}$  are solved by

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y,$$

where

$$B = \begin{bmatrix} -0.5(x^{(r)}(1) + x^{(r)}(2)) & 1 \\ -0.5(x^{(r)}(2) + x^{(r)}(3)) & 1 \\ \vdots & \vdots \\ -0.5(x^{(r)}(n-1) + x^{(r)}(n)) & 1 \end{bmatrix},$$

$$Y = \begin{bmatrix} x^{(r)}(2) - x^{(r)}(1) \\ x^{(r)}(3) - x^{(r)}(2) \\ \vdots \\ x^{(r)}(n) - x^{(r)}(n-1) \end{bmatrix}.$$

Step 3: obtain the corresponding time function as

$$\hat{x}^{(r)}(k+1) = \left[ x^{(0)}(1) - \frac{\hat{b}}{a} \right] e^{-\hat{a}k} + \frac{\hat{b}}{a}, \quad (4)$$

where  $\hat{x}^{(r)}(k+1)$  is the value at time  $k+1$ .

Step 4: for sequence  $\hat{X}^{(r)} = \{\hat{x}^{(r)}(1), \hat{x}^{(r)}(2), \dots, \hat{x}^{(r)}(n)\}$ , the restoring sequence is

$$\alpha^{(r)} \hat{X}^{(r)} = \{ \alpha^{(1)} \hat{x}^{(r)(1-r)}(1), \alpha^{(1)} \hat{x}^{(r)(1-r)}(2), \dots, \alpha^{(1)} \hat{x}^{(r)(1-r)}(n) \}, \quad (5)$$

where  $\alpha^{(1)} \hat{x}^{(r)(1-r)}(k) = \hat{x}^{(r)(1-r)}(k) - \hat{x}^{(r)(1-r)}(k-1)$ . Then, the predicted value is

$$\{ \hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \dots, \hat{x}^{(0)}(n) \}. \quad (6)$$

Step 5: there are many testing methods for grey forecasting models. And the average absolute percentage is a commonly used testing method in grey forecasting. This paper uses this method for model testing. Grey systems are often evaluated by using the mean absolute percentage error (MAPE = 100% × 1/n ∑<sub>k=1</sub><sup>n</sup> |x<sup>(0)</sup>(k) - x̂<sup>(0)</sup>(k)/x<sup>(0)</sup>(k)|).

The evaluation criteria of the model MAPE are shown in Table 1. When MAPE < 10%, it means that the model fitting effect is better and the prediction result is more reliable. When 10% < MAPE < 20%, the model fit has a certain degree of credibility. When MAPE > 20%, the fitting effect of the model is average and the prediction result has little reference value.

In particular, for the fractional FGM(1, 1) model, at that time  $r = 1$ , the FGM(1, 1) model is the GM(1, 1) model. The traditional grey GM(1, 1) model can be regarded as a special case of the fractional model.

### 3. Validation Study and Analysis Results

This article predicts the energy consumption of Beijing, Tianjin, and Hebei in China. The energy consumption data come from the National Statistical Yearbook of China, including the consumption data of coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel, natural gas, and electricity (data source website: <http://www.stats.gov.cn/tjsj/ndsj/>). By querying the five-year data of the Statistical Yearbook, the trend of energy consumption in the three places is obtained.

Regarding energy consumption in Beijing, natural gas consumption is on the rise. Coal consumption is showing a decreasing trend. Coke consumption is showing a decreasing trend. The consumption of crude oil fluctuates. Gasoline consumption shows an increasing trend. The consumption of kerosene is showing an increasing trend. Beijing's diesel consumption is showing a decreasing trend. Fuel oil consumption shows a decreasing trend. Electricity shows an increasing trend.

Regarding energy consumption in Tianjin, natural gas consumption is on the rise. Coal consumption is showing a decreasing trend. Coke consumption is showing a decreasing trend. The consumption of crude oil fluctuates. Gasoline consumption shows an increasing trend. The consumption of kerosene is showing an increasing trend. Tianjin's diesel consumption is relatively stable. Fuel oil consumption shows a decreasing trend. Electricity shows an increasing trend.

Regarding energy consumption in Hebei Province, natural gas consumption is on the rise. Coal consumption is showing a decreasing trend. Coke consumption is showing a decreasing trend. Crude oil consumption shows an increasing trend. Gasoline consumption shows an increasing trend. The consumption of kerosene is showing an increasing trend. Consumption in Hebei Province is showing a decreasing trend. Fuel oil presents a fluctuating trend. Electricity shows an increasing trend.

This paper firstly models and predicts natural gas in Tianjin. Other energy sources use the same process to obtain fitting and prediction results.

**3.1. Natural Gas Consumption Forecast.** This paper establishes an FGM(1, 1) model for natural gas consumption in Tianjin. In particular, it is the traditional grey GM(1, 1) model when  $r = 1$ .

The original columns are obtained from the original data:

$$X^{(0)} = \{32.27, 45.09, 63.62, 74.06, 82.31\}. \quad (7)$$

The cumulative sequence of order 0.1 is

$$X^{(0.1)} = \{x^{(0.1)}(1), x^{(0.1)}(2), x^{(0.1)}(3), x^{(0.1)}(4), x^{(0.1)}(5)\} \\ = \{32.27, 48.32, 69.90, 84.14, 95.91\}. \quad (8)$$

Establish a whitening differential equation :

$$\frac{dx^{(r)}(t)}{dt} + ax^{(r)}(t) = b. \quad (9)$$

Solve the unknown parameters by the least-squares method :

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y = \begin{bmatrix} 0.1142 \\ 23.5183 \end{bmatrix}. \quad (10)$$

Here, the two unknown parameters  $a$  and  $b$  are solved by using the following equation:

TABLE 1: MAPE evaluation criteria.

MAPE (%)	Predictive performance
<10	Excellent
10 ~ 20	Good
20 ~ 50	General
>50	Difference

$$\hat{x}^{(0.1)}(k+1) = \left[ 32.27 - \frac{23.5183}{0.1142} \right] e^{-0.1142k} + \frac{23.5183}{0.1142}. \quad (11)$$

We obtain the 0.1-order accumulation sequence as

$$\begin{aligned} \hat{X}^{(0.1)} &= \{ \hat{x}^{(0.1)}(1), \hat{x}^{(0.1)}(2), \dots, \hat{x}^{(0.1)}(7), \hat{x}^{(0.1)}(8) \} \\ &= \{ 32.27, 51.01, 67.73, 82.65, 95.95, 107.82, 118.41, 127.86 \}. \end{aligned} \quad (12)$$

Then, perform 0.9-order accumulation on the 0.1-order accumulation sequence to obtain the first-order accumulation sequence.

$$\begin{aligned} \hat{X}^{(1)} &= \{ \hat{x}^{(0.1)(0.9)}(1), \hat{x}^{(0.1)(0.9)}(2), \dots, \hat{x}^{(0.1)(0.9)}(7), \hat{x}^{(0.1)(0.9)}(8) \} \\ &= \{ 32.27, 80.06, 141.23, 213.89, 296.41, 387.42, 485.73, 590.33 \}. \end{aligned} \quad (13)$$

Then, the predicted value is

$$\begin{aligned} \hat{X}^{(0)} &= \{ \hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \dots, \hat{x}^{(0)}(7), \hat{x}^{(0)}(8) \} \\ &= \{ 32.27, 47.79, 61.18, 72.66, 82.52, 91.00, 98.31, 104.60 \}. \end{aligned} \quad (14)$$

When  $r=1$  in FGM(1, 1), the fitting and prediction results of the GM(1, 1) model can be obtained. The fitting results of the two models are shown in Table 2. Generally, the MAPE of the fractional FGM(1, 1) model is smaller, and the fractional FGM(1, 1) model is selected for prediction. Otherwise, when the MAPE of GM(1, 1) is less than FGM(1, 1), select the GM(1, 1) model where  $r=1$  in the fractional model to predict.

Comparing the results in Table 2, it can be found that the MAPE of the fractional FGM(1, 1) model and the MAPE of the traditional GM(1, 1) model both meet the requirements. The order of FGM(1, 1) is calculated by the particle swarm algorithm. As the fitting effect is the best at 0.1, the prediction is more accurate. The MAPE of FGM(1, 1) is 2.4 which is less than 4.8 of the traditional grey GM(1, 1) model. From the comparison of the fitted values, we can also find the fitted value of the FGM(1, 1) model is closer to the true value than the fitted value of the GM(1, 1) model, which also shows that the FGM(1, 1) model is more accurate than the traditional GM(1, 1) model.

Using the data from 2013 to 2017 and using the FGM(1, 1) model, the fitted values of natural gas consumption in Beijing, Tianjin, and Hebei from 2013 to 2017 are shown in Table 3.

It can be seen from Table 3 that for natural gas consumption in Beijing, when  $r=0.3$ , the MAPE of FGM(1, 1) is 3.25. For natural gas consumption in Hebei Province, when

$r=0.9$ , the MAPE of FGM(1, 1) is 4.9. And the model's MAPE is less than 10%, indicating that the model prediction is relatively accurate. The model can be used to predict the natural gas consumption of the three places. The prediction results are shown in Table 4. The forecast results show that in the next few years, natural gas consumption in the three places will continue to increase rapidly. By 2023, natural gas consumption in Beijing will reach 19.1 billion cubic meters, that in Tianjin City will reach 11.9 billion cubic meters, and that in Hebei Province will reach 23.1 billion cubic meters. It also reflects the preference for clean energy.

Through the same process, select the optimal order and use the FGM(1, 1) model to fit and predict other energy consumption; we can get the fitting value of other energy, and judge whether the prediction result based on the value of MAPE is credible.

**3.2. Coal Consumption Forecast.** As a traditional energy source in production and life, coal consumption in Beijing, Tianjin, and Hebei still accounts for a large proportion of energy consumption. According to data in recent years, it has been found that coal consumption has shown a downward trend year by year. We use FGM(1, 1) model to build models, and the fitting results are shown in Table 5.

It can be seen from Table 5 that for coal consumption in Beijing, when  $r=1$ , the MAPE of FGM(1, 1) is 3.46. For coal consumption in Tianjin, when  $r=1$ , the MAPE of FGM(1, 1) is 0.47. For coal consumption in Hebei Province, when  $r=1$ , the MAPE of FGM(1, 1) is 0.08. And the model prediction accuracy is less than 10%. The FGM(1, 1) model prediction is relatively accurate. The model can be used to predict coal consumption in the three places. In these three cases, the order  $r$  is equal to 1, and then the FGM(1, 1) model is the GM(1, 1) model.

Table 6 shows the predicted value of coal consumption in the three places from 2018 to 2023. From the forecast results, the coal consumption in the three places has shown a decreasing trend. Specific to the three places, Beijing's coal consumption will decrease rapidly and it will be reduced to 530,000 tons by 2023. Tianjin's coal consumption will be at a moderate rate and will be reduced to 23.13 million tons by 2023. Hebei's coal consumption the decline is the smallest. And 234.14 million tons will still be consumed by 2023.

**3.3. Coke Consumption Forecast.** As an important industrial raw material, Tianjin City and Hebei Province consume more coke while Beijing consumes less coke. This also reflects the characteristics of the industrial structure of the three places. Hebei Province and Tianjin City have a higher industrial share. Using the same process as above, the fitting results are shown in Table 7.

It can be seen from Table 7 that for coke consumption in Beijing, when  $r=0.8$ , the MAPE of FGM(1, 1) is 6.89. For coke consumption in Tianjin, when  $r=0.9$ , the MAPE of FGM(1, 1) is 0.93. For coke consumption in Hebei Province, when  $r=0.1$ , the MAPE of FGM(1, 1) is 1.18. And the model prediction accuracy is less than 10%. The model prediction is

TABLE 2: Fitted value of Tianjin natural gas model.

Year	Actual value (100 million cubic meters)	GM(1,1)	FGM(1,1)
2013	32.27	32.27	32.27
2014	45.09	49.73	47.79
2015	63.62	59.39	61.18
2016	74.06	70.93	72.66
2017	82.31	84.70	82.52
<i>r</i>		1	0.1
MAPE		4.8	2.4

TABLE 3: Fitted value of natural gas model.

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2013	98.81	98.81	32.27	32.27	49.86	49.86
2014	113.70	121.07	45.09	47.79	56.08	56.14
2015	146.88	140.67	63.62	61.18	72.97	67.08
2016	162.31	155.65	74.06	72.66	70.45	79.22
2017	164.56	166.89	82.31	82.52	96.70	92.94
<i>r</i>		0.3		0.1		0.9
MAPE		3.25		2.4		4.9

TABLE 4: Natural gas model prediction value (100 million cubic meters).

Year	Beijing	Tianjin	Hebei
2018	175.21	91.00	108.63
2019	181.25	98.31	126.63
2020	185.49	104.60	147.37
2021	188.30	110.02	171.30
2022	189.97	114.67	198.93
2023	190.75	118.67	230.86

TABLE 5: Coal fitting value (10,000 tons).

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2013	2019.23	2019.23	5278.67	5278.67	31663.27	31663.27
2014	1736.54	1722.70	5027.28	4997.59	29635.54	29657.17
2015	1165.18	1169.16	4538.83	4587.63	28943.13	28888.4
2016	847.46	793.49	4230.16	4211.31	28105.65	28139.56
2017	490.46	538.53	3875.61	3865.85	27417.13	27410.13
<i>r</i>		1		1		1
MAPE		3.46		0.47		0.08

TABLE 6: Forecast value of coal consumption (10,000 tons).

Year	Beijing	Tianjin	Hebei
2018	365.49	3548.73	26699.60
2019	248.05	3257.63	26007.50
2020	168.35	2990.40	25333.34
2021	114.25	2745.10	24676.65
2022	77.542	2519.92	24036.98
2023	52.63	2313.21	23413.90

relatively accurate. The model can be used to predict coal consumption in the three places.

Table 8 shows the coke consumption in the three places from 2018 to 2023. From the forecast results, the coke consumption in the three places shows a decreasing trend. Specific to the three places, the base of coke consumption in Beijing is relatively small, showing a decreasing trend. The coke consumption in Tianjin has fallen by a large margin, and by 2023, the coke consumption in Tianjin will be

TABLE 7: Fitting value of coke (ten thousand tons).

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2013	0.79	0.79	955.48	955.48	8339.85	8339.85
2014	0.64	0.63	954.39	951.90	8127.20	7987.29
2015	0.44	0.40	904.69	915.99	7726.45	7963.64
2016	0.21	0.26	887.29	868.13	8079.49	7996.31
2017	0.18	0.18	808.70	816.57	8040.78	8034.78
$r$		0.8		0.9		0.1
MAPE		6.89		0.93		1.18

TABLE 8: Forecast value of coke consumption (ten thousand tons).

Year	Beijing	Tianjin	Hebei
2018	0.13	764.70	8065.47
2019	0.11	714.15	8085.05
2020	0.09	665.72	8093.61
2021	0.08	619.82	8092.41
2022	0.07	576.62	8083.03
2023	0.06	536.15	8067.02

reduced to 5.36 million tons. At the same time, it can be seen that coke consumption in Hebei Province will remain relatively stable in the next few years.

**3.4. Crude Oil Consumption Forecast.** As a raw material for petroleum fuels, the consumption of crude oil in Beijing, Tianjin, and Hebei is very large. Observing the crude oil consumption data of the three places from 2013 to 2017, it is found that the change in crude oil consumption is relatively small. Using the same modeling process as above, the fitting results are shown in Table 9.

It can be seen from Table 9 that for crude oil consumption in Beijing, when  $r=1$ , the MAPE of FGM(1, 1) is 3.74. For crude oil consumption in Tianjin, when  $r=1$ , the MAPE of FGM(1, 1) is 3.42. For crude oil consumption in Hebei Province, when  $r=0.5$ , the MAPE of FGM(1, 1) is 5.6. The model whose prediction accuracy is less than 10% is more accurate. By comparing the fitted value and the actual value, it can also be observed that the fitting effect is better.

Table 10 shows the crude oil consumption in the three places from 2018 to 2023. From the forecast results, the crude oil consumption in the three places is showing a decreasing trend. Among them, the rate of decrease in Beijing is relatively fast, and the crude oil consumption will be 5.71 million tons by 2023. Tianjin's crude oil consumption has declined slowly and will be 13.44 million tons by 2023. Hebei's crude oil consumption has remained stable and shows a slight decrease.

**3.5. Gasoline Consumption Forecast.** With the rapid growth of the number of motor vehicles, the gasoline consumption in the Beijing-Tianjin-Hebei region from 2013 to 2017 also showed a trend of increasing year by year, especially in Hebei Province. Using the same process as above, the fitting results are shown in Table 11.

It can be seen from Table 11 that for gasoline consumption in Beijing, when  $r=0.9$ , the MAPE of FGM(1, 1) is 0.44. For gasoline consumption in Tianjin, when  $r=0.5$ , the MAPE of FGM(1, 1) is 1.82. For gasoline consumption in Hebei Province, when  $r=0.5$ , the MAPE of FGM(1, 1) is 7.53. The model prediction accuracy is less than 10%. The FGM(1, 1) model prediction is more accurate.

Table 12 shows the gasoline consumption in the three places from 2018 to 2023. From the forecast results, the gasoline consumption in Beijing and Hebei Province is showing an increasing trend. But the growth rate is gradually slowing down. The gasoline consumption in Tianjin is relatively stable and showing a slight decrease. According to the trend, by 2023, gasoline consumption in Beijing, Tianjin, and Hebei will reach 5.27 million tons, 2.62 million tons, and 6.83 million tons, respectively.

**3.6. Forecast of Kerosene Consumption.** As an important lighting fuel, the consumption of kerosene in Beijing is relatively large, while the consumption of kerosene in Tianjin and Hebei Province is relatively small. Using the same modeling process as above, the fitting results are shown in Table 13.

It can be seen from Table 13 that for kerosene consumption in Beijing, when  $r=1$ , the MAPE of FGM(1, 1) is 0.27. For kerosene consumption in Tianjin, when  $r=0.4$ , the MAPE of FGM(1, 1) is 2. For kerosene consumption in Hebei Province, when  $r=0.5$ , the MAPE of FGM(1, 1) is 31.68. The MAPE of Beijing and Tianjin is relatively small, and the fitting prediction effect is better. Because of the large fluctuation of the original data, the fitting effect of Hebei Province is relatively poor.

Table 14 shows the consumption of kerosene in the three places from 2018 to 2023. From the forecast results, the consumption of kerosene in the three places is showing an increasing trend. The rate of decrease in Beijing is relatively slow. The growth rate of Tianjin is relatively fast. And the consumption of kerosene in Hebei Province also shows a rapid growth trend. Due to the large fluctuation of the original data, the reliability of the forecast results is low.

**3.7. Diesel Consumption Forecast.** As an important engine fuel, diesel consumption is relatively large in Beijing, Tianjin, and Hebei. But the original data of kerosene are obvious. Using the same process as above, the fitting results are shown in Table 15.

TABLE 9: Crude oil fitting value (ten thousand tons).

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2013	870.92	870.92	1759.15	1759.15	1385.89	1385.89
2014	1034.62	1028.01	1603.17	1579.07	1356.61	1470.02
2015	991.54	963.00	1616.72	1583.23	1666.82	1568.02
2016	821.00	902.10	1433.60	1570.99	1761.93	1614.56
2017	892.54	845.05	1624.85	1548.71	1542.17	1624.91
<i>r</i>		1		1		0.5
MAPE		3.74		3.42		5.6

TABLE 10: Forecast value of crude oil consumption (10,000 tons).

Year	Beijing	Tianjin	Hebei
2018	791.60	1520.35	1611.41
2019	741.54	1488.22	1582.45
2020	694.64	1453.73	1543.73
2021	650.71	1417.82	1499.15
2022	609.56	1381.12	1451.41
2023	571.01	1344.07	1402.38

TABLE 11: Gasoline fitting value (ten thousand tons).

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2013	423.61	423.61	212.24	212.24	347.55	347.55
2014	440.62	440.08	226.82	233.83	314.64	370.18
2015	462.75	460.77	263.73	255.86	475.32	421.45
2016	470.37	475.63	274.49	269.38	494.86	468.20
2017	489.85	487.26	273.47	276.69	493.39	509.60
<i>r</i>		0.9		0.5		0.5
MAPE		0.44		1.82		7.53

TABLE 12: Forecast value of gasoline consumption (10,000 tons).

Year	Beijing	Tianjin	Hebei
2018	496.83	279.63	546.43
2019	504.98	279.48	579.43
2020	512.10	277.14	609.22
2021	518.42	273.26	636.27
2022	524.11	268.30	660.94
2023	529.30	262.61	683.53

TABLE 13: Kerosene fitting value (10,000 tons).

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2013	477.06	477.06	56.12	56.12	17.59	17.59
2014	507.58	505.10	59.85	56.54	17.59	14.92
2015	544.38	547.41	65.78	67.74	8.24	17.68
2016	594.27	593.27	82.02	82.63	29.46	22.32
2017	644.00	642.97	101.50	100.73	27.56	28.78
<i>r</i>		1		0.4		0.5
MAPE		0.27		2		31.68

It can be seen from Table 15 that for Beijing diesel consumption, when  $r = 0.1$ , the MAPE of FGM(1, 1) is 1.32. For Tianjin diesel consumption, when  $r = 0.5$ , the MAPE of

FGM(1, 1) is 1.03. For diesel consumption in Hebei Province, when  $r = 0.3$ , the MAPE of FGM(1, 1) is 3.47. The model prediction accuracy is less than 10%.

TABLE 14: Forecast value of kerosene consumption (10,000 tons).

Year	Beijing	Tianjin	Hebei
2018	696.83	122.29	37.43
2019	755.21	147.83	48.87
2020	818.48	178.04	63.92
2021	887.04	213.77	83.71
2022	961.35	256.01	109.67
2023	1041.89	305.98	143.73

TABLE 15: Diesel fitting value (ten thousand tons).

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2013	193.90	193.90	324.65	324.65	800.57	800.57
2014	196.46	191.91	334.43	337.08	788.80	783.89
2015	182.35	182.81	353.43	353.76	749.18	783.22
2016	172.69	176.47	370.35	359.03	843.59	768.24
2017	175.11	171.90	352.32	356.58	721.28	744.77
$r$		0.1		0.5		0.3
MAPE		1.32		1.03		3.47

Table 16 shows the diesel consumption in Beijing, Tianjin, and Hebei from 2018 to 2023. From the forecast results, the diesel consumption in the three places is showing a decreasing trend. The diesel consumption in Beijing is relatively stable. And the diesel consumption in Tianjin and Hebei is relatively stable. The drop is comparable.

**3.8. Fuel Oil Consumption Forecast.** The main use of fuel oil is in industrial production. The consumption of fuel oil in Tianjin and Hebei Province is relatively high. Using the same process, the fitting results are shown in Table 17.

It can be seen from Table 17 that for coal consumption in Beijing, when  $r=0.9$ , the MAPE of FGM(1, 1) is 7.27. For fuel oil consumption in Tianjin, when  $r=0.9$ , the MAPE of FGM(1, 1) is 13.91. For fuel oil consumption in Hebei Province, when  $r=0.2$ , the MAPE of FGM(1, 1) is 12.9. The MAPE of Tianjin and Hebei Province exceeds 10%. And the prediction effect of the model is relatively poor.

Table 18 shows the fuel oil consumption in the three places from 2018 to 2023. From the forecast results, the fuel oil consumption in the three places has shown a decreasing trend. Specifically, Tianjin's fuel oil consumption has fallen the fastest while fuel oil consumption of Beijing and Hebei has slowed down relatively. However, it should be noted that the forecast results of Tianjin and Hebei's fuel oil are less reliable.

**3.9. Power Consumption Forecast.** As an important secondary energy source, electricity is indispensable in today's social production and life. Observing the electricity consumption data of Beijing, Tianjin, and Hebei from 2015 to 2019, it can be found that the electricity consumption of the three places has shown a slight upward trend. Using the same process, the fitting results are shown in Table 19.

It can be seen from Table 19 that for the power consumption of Beijing, when  $r=0.9$ , the MAPE of FGM(1, 1) is 0.62. For the power consumption of Tianjin, when  $r=0.1$ , the MAPE of FGM(1, 1) is 0.79. For power consumption in Hebei Province, when  $r=0.1$ , the MAPE of FGM(1, 1) is 0.14. The FGM(1, 1) model whose prediction accuracy is less than 10% is more accurate.

Table 20 shows the power consumption of the three places from 2018 to 2023. From the forecast results, the power consumption of the three places is showing an increasing trend. The power growth reflects the expansion of the scale of production of enterprises and the improvement of people's living standards. And the slower increase in power consumption means that the efficiency of electricity consumption is continuously improving.

## 4. Results and Discussion

Through the prediction of energy consumption in Beijing, Tianjin, and Hebei, the flexible trend of energy consumption in the three places is obtained.

In Beijing, the growth rate of natural gas consumption has slowed down and will be basically stable by 2023. The average annual deceleration of coal consumption is 32%. The average annual deceleration of coke consumption is 10%. Crude oil consumption decreased by 6.3% annually. Gasoline consumption is slowly increasing. The consumption of kerosene increased about 8% annually. Diesel consumption is slowly decreasing. Fuel oil consumption is reduced by 17% annually. The average annual growth rate of power consumption exceeds 6%.

In Tianjin, the annual growth rate of natural gas consumption is about 5%. Coal consumption is reduced by about 8% every year. The average annual deceleration of coke consumption is 7%. Crude oil consumption decreased by 2.4% annually. Gasoline consumption is slowly decreasing. The consumption of kerosene has increased by



TABLE 16: Forecast value of diesel consumption (ten thousand tons).

Year	Beijing	Tianjin	Hebei
2018	168.37	349.34	717.85
2019	165.51	339.27	690.46
2020	163.10	327.62	664.19
2021	161.04	315.25	639.78
2022	159.22	302.70	617.48
2023	157.61	290.32	597.29

TABLE 17: Fuel oil fitting value (ten thousand tons).

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2013	8.30	8.30	86.93	86.93	35.18	35.18
2014	5.63	5.78	78.20	87.49	31.79	39.69
2015	4.91	4.83	94.14	70.57	51.73	43.68
2016	4.64	4.01	45.33	56.03	53.70	46.11
2017	2.81	3.33	40.68	44.35	43.13	47.40
<i>r</i>		0.9		0.9		0.4
MAPE		7.27		13.91		12.9

TABLE 18: Forecast value of fuel oil consumption (10,000 tons).

Year	Beijing	Tianjin	Hebei
2018	2.76	35.16	47.90
2019	2.30	28.01	47.83
2020	1.92	22.47	47.39
2021	1.60	18.18	46.68
2022	1.35	14.86	45.81
2023	1.14	12.28	44.82

TABLE 19: Power fitting value (100 million kWh).

Year	Beijing (actual value)	Beijing (fitted value)	Tianjin (actual value)	Tianjin (fitted value)	Hebei (actual value)	Hebei (fitted value)
2015	952.72	952.72	800.60	800.60	3175.68	3175.68
2016	1020.27	1016.85	807.93	797.06	3264.52	3260.24
2017	1066.89	1079.12	805.59	822.08	3441.74	3452.72
2018	1142.38	1128.55	855.14	850.64	3665.66	3657.37
2019	1166.40	1171.16	878.43	878.04	3856.06	3855.98
<i>r</i>		0.9		0.1		0.1
MAPE		0.62		0.79		0.14

TABLE 20: Forecast value of power consumption (100 million kWh).

Year	Beijing	Tianjin	Hebei
2020	1209.64	903.01	4043.28
2021	1245.40	925.25	4217.74
2022	1279.29	944.79	4379.21
2023	1311.83	961.80	4528.09
2024	1343.38	976.49	4665.00
2025	1374.21	989.10	4790.67

about 20% annually. Diesel consumption is slowly decreasing. Fuel oil consumption is reduced by 20% annually. Electricity consumption is slowly increasing.

In Hebei Province, the annual growth rate of natural gas consumption is about 15%. Annual coal consumption is reduced by about 3%. Coke consumption remained stable. Crude oil consumption is reduced by 3% annually. Gasoline consumption is slowly increasing, and kerosene consumption has increased by about 31% annually. Diesel consumption is reduced by about 3% annually. Fuel oil consumption remained stable. Electricity consumption is slowly increasing.

Of course, in terms of judging the usability of the model, when the MAPE is greater than 20, the prediction accuracy of the model is low, and the reliability of the prediction is relatively low. The reason for this is that the original data

have a relatively large disturbance, and the larger the model, the better the forecast.

According to energy consumption data and forecast results, it can be found that as the country promotes environmental protection policies, the consumption of high-polluting energy is showing a decreasing trend, and the proportion of clean energy consumption such as natural gas and electricity is increasing. For government and enterprises, environmental protection policies should be adjusted accordingly. On the one hand, the government should limit the use of high polluting energy. On the other hand, the government should encourage the use of clean energy.

## 5. Conclusion

Energy supply directly affects the normal economic and social development and the normal work and life of residents. Analysis of energy consumption can help us not only to understand the economic and social development status but also to make plans for the supply of energy for government departments through prediction. We study the energy consumption situation in the Beijing-Tianjin-Hebei region and use the fractional FGM(1, 1) model to predict the energy consumption of the three places; compared with the traditional grey GM(1, 1) model, the prediction accuracy of fractional FGM(1, 1) model is higher. Compared with other prediction models, the fractional FGM(1, 1) model has obvious advantages and lower model requirements. It only needs a small amount of data in recent years to make predictions. At the same time, the prediction accuracy of the submodels is higher and the amount of calculation is relatively high.

Through the forecast research in this article, it can be found that in the next few years, the consumption of highly polluting energy sources such as coal and coke will show a decreasing trend. The consumption of clean energy such as natural gas and electricity is showing an increasing trend. This is inseparable from the government's environmental protection policy.

The Beijing-Tianjin-Hebei region is a region with a large population and relatively insufficient resources. To achieve sustainable economic and social development, we must first take the path of saving resources. We should strengthen industrial energy conservation by advancing structural adjustments. Secondly, we should improve energy supply capacity, rationally use coal, actively promote power development, accelerate the popularization of low-pollution energy such as natural gas, and vigorously develop renewable energy such as wind, geothermal, and solar energy.

At the enterprise level, it is necessary to strengthen guidance, increase the enthusiasm of enterprise R&D and technological innovation, vigorously organize the research and development, promotion, and application of advanced energy technologies, and guide enterprises to accelerate technological progress and improve energy efficiency through market mechanisms. Local governments should strengthen the training and introduction of energy technology talents through policies and regulations to create a good atmosphere for the development of energy technology.

Finally, from a national perspective, China has a large population and low energy per capita. It should actively expand international energy trade and actively promote energy imports to fill the current situation of domestic energy shortages.

## Data Availability

The data used to support the finding of this study are included within the article.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

## Acknowledgments

This study was supported by the National Natural Science Foundation of China (71871084), Scientific Research Projects of Colleges and Universities in Hebei Province (Z2020221), and Research Project of Social Science Development in Hebei Province (20200302050).

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