Research on the Prediction of Total City Energy Consumption Based on Grey Prediction Model

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Abstract. The research on the relationship between City energy consumption and economic development is of important significance in formulating our country’s energy policies and economic development strategies. Based on the historical energy consumption data of Beijing, we set about to study the grey prediction model GM (1, 1) and forecast the energy consumption in the coming years of Beijing in the paper. For the energy consumption and economic growth of the developing countries, we make simple study and expectation to the related research on the relationship between energy consumption and economic development by means of predicted energy consumption value and historical GDP in the way of causal and co-integration analysis. We forecast that Beijing’s energy consumption can to some extent provide helpful reference for its energy policies and economic development.

1. Introduction
The prediction of energy consumption based on the grey prediction model GM (1, 1) and the analysis on the internal relation between energy consumption and economic growth can enable the Government to have a certain assurance in the future energy consumption and economic development closely related to it. Energy is the foundation of social and economic development in the present world, which is crucial to the economic sustainable development and safety of a country [1]. The interrelation and interaction between energy and economy, society & environment determine to a large extent the coordinated development state of economy, society and environment [2].

The research on the prediction of our country’s energy consumption is mainly divided into two categories: one is prediction in a single method, including ARMA model, grey prediction model, multivariate statistics and CDM model; the other is prediction by using combined model, including combined non-linear regression & optimized grey prediction model, combined AR and GM (1, 1) model, combined AHP and GM (1, 1) model, combined input-output and scenario analysis model and combined ANN and GM (1, 1) optimized prediction model etc. The energy consumption of Beijing during 2018-2020 is predicted herein by using the grey prediction model.
2. Analysis on Factors Affecting Consumption

2.1. Factors Affecting Energy Consumption

Energy demand is determined jointly by multiple factors, and the influence factors of energy consumption mainly include three aspects: production effect caused by the variation in the scale of production; structure effect caused by the adjustment of economic structure; strength effect caused by technological progress. Due to the differences in social institutions and economic development patterns, the influences of economic growth, energy price and economic structure on energy consumption are various in different countries and regions.

2.2. Analysis on Grey Correlation between Energy Consumption and Influence Factor

Energy price has the largest influence on energy consumption structure among all factors, indicating that energy price has an extremely important impact on the adjustment of energy consumption structure. Energy supply in our country is coal dominated, and such energy consumption structure cannot be changed in a short period.

Industrial structure also has a very significant impact on the energy consumption structure, and the factors such as Cityization rate, scientific & technological level, carbon emission intensity and marketization rate similarly have an obvious impact on such structure. Firstly, with the continuous improvement of Cityization level, the demand for energy consumption stays at a high level and the degree of association with such structure is also strengthened. Secondly, the continuous use of the energy-saving technology in the production and life is able to effectively reduce the total energy consumption, particularly in the high energy consumption industries such as smelting, steel and machinery etc. It stands to reason that there is apparent correlation between the scientific & technological level and the energy consumption structure. Secondly, in the circumstance of the established total energy consumption and coal-dominated energy consumption structure, such structure will affect energy consumption strength and carbon emission intensity. Finally, the constant improvement of marketization degree and the formation of price mechanism will affect the energy consumption of enterprises and individuals.

The growth rate of GDP, energy efficiency and energy consumption structure also have a greater degree of association. In the process of economic development, the growth rate of GDP and that of energy consumption basically keep the same trend. In the circumstance of established economic environment and policies, the growth rate of GDP and the energy consumption structure form a relatively stable degree of association. In terms of energy efficiency, it is continuously improved in our country with the constant innovation of the energy-saving & cost-reducing technology and the limitation of high energy-consuming industries, thereby manifesting that the energy efficiency and the coal-dominated energy consumption structure have a greater degree of association.

The degree of association between labor productivity and energy consumption structure is apparently inferior to that of other factors. The average number of employees and the energy consumption structure cannot reveal obvious association, which may indicate that the degree of association between labor productivity and energy consumption structure is inferior to that between other factors and it.

3. Basic Theory and Prediction Model of System

3.1. Grey Generation

Grey system determines the unknown system information by virtue of the development and generation of given information, thereby realizing the process of changing the system from grey to white. On account of no numerous requirements on the number of samples, grey system theory has been widely applied in the research on many fields such as handling of sample index data, analysis, evaluation, prediction, control of research objects and system optimization etc. The commonly used grey generation modes cover accumulated and inverse accumulated generating operation, stepwise ratio generation and mean value generation etc. Accumulated generating operation is mainly introduced herein [3].
As the base of grey modeling, Accumulated Generating Operation, AGO is a mathematical treatment method in which the data in the same sequence are added successively to generate new accumulated data sequence. The data sequence before accumulation is called original sequence and that after accumulation called generated sequence. After the irregular original data are accumulated, they will turn into ascending sequence with the law of exponential increase.

\[
X^{(0)} \text{ and } x^{(1)} \text{ are respectively original sequence and generated sequence:}
\]
\[
x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)], x^{(1)} = [x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)]
\]

\[
X^{(0)} \text{ and } x^{(1)} \text{ satisfy the following formula:}
\]
\[
x^{(1)}(k) = \sum_{j=1}^{k} x^{(0)}(j)
\]

\{x^{(1)}\} is the accumulated generating operation sequence of \{x^{(0)}\}, generally donated as 1-AGO.

3.2. Grey Modeling Process

3.2.1. Modeling Mechanism of Grey Prediction Model
The theory of the grey prediction model is changing the original data sequence to the sequence with the law of exponential increase after grey generation is made to the irregular random variable. A differential equation model is established for the generated sequence by using the first order exponential equation, called grey model [4], donated as GM (Grey Model). GM (1, 1) model is a particular case of GM (1, n) model, a useful load prediction tool in the electric system, and it is composed of a first order differential equation containing single variable only.

Establishing the differential equation model by using the theory of grey prediction model mainly includes three links: firstly, the original data sequence is used as the grey process changed in a certain range and time zone, and the original discrete data turn into the sequence with the law of exponential increase after accumulated generation; secondly, due to the form of first order differential equation being that of exponential increase, parameter estimation can be made to the discrete grey differential equation model with the least square method; finally, the time response functions can be solved based on the initial values, and the predicted data obtained by the accumulated generating operation data model revert to original load data meeting actual application after inverse accumulated generating operation.

3.2.2. Grey Prediction Model (GM)
A sequence x^{(0)} is needed only to establish GM (1, 1) model. Assuming that the single variable is the original data sequence of x^{(0)}:

\[
x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)]
\]

The first order AGO sequence is generated with 1-AGO.

\[
x^{(1)} = [x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)]
\]

\[
x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)
\]

After AGO is made to the original sequence, modeling is made after the original sequence turns into more regular generation sequence. The linear first order differential equation is constructed to x(1):

\[
\frac{dx^{(1)}}{dt} + ax^{(1)} = u
\]

According to the definition of differential coefficient, it is expressed as below in a discrete form:
\[ \frac{\Delta x}{\Delta t} = \frac{x^{(1)}(k+1) - x^{(1)}(k)}{k+1-k} = x^{(1)}(k+1) - x^{(1)}(k) = x^{(0)}(k+1) \] (6)

The mean value of moment k and k+1 is taken for x value. The result above is written as matrix form:

\[ Y_n = BA \] (7)

Where:

\[ Y_n = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix}, A = \begin{pmatrix} a \\ u \end{pmatrix}, B = \begin{pmatrix} -\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2)], 1 \\ -\frac{1}{2}[x^{(1)}(2) + x^{(1)}(3)], 1 \\ \vdots \\ -\frac{1}{2}[x^{(1)}(n-1) + x^{(1)}(n)], 1 \end{pmatrix} \] (8)

In the equation set above, vector quantities Yn and B are known, and vector quantity A is the parameter to be solved. There are a and u variables only, of which a is development coefficient of model and reflects the development trend of data sequence; u is the coordination coefficient of model and reflects the variation relation between data. The parameter A is solved with the least square method, and E in the equation is error term.

\[ Y_n = B \hat{A} + E \] (9)

To make \[ \min \| Y_n - B \hat{A} \|^2 = \min (Y_n - B \hat{A})^\top (Y_n - B \hat{A}) \]

The equation is derived by using the matrix, attaining:

\[ \hat{A} = (B^\top B)^{-1} B^\top Y_n = \begin{pmatrix} \hat{a} \\ \hat{u} \end{pmatrix} \] (10)

The obtained \( \hat{a}, \hat{u} \) are substituted into the original first order differential equation, attaining:

\[ x^{(1)}(k+1) = [x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}]e^{-\hat{a}t} + \frac{\hat{u}}{\hat{a}}, (k = 1, 2, \cdots) \] (11)

The equation above is called time response function model of GM (1, 1), and it is the specific calculation formula of grey prediction model. IAGO reduction is made again to the equation, thereby attaining the grey prediction model of original sequence x (0):

\[ \hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1 + e^{\hat{a}})x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}e^{-\hat{a}t}, (k = 1, 2, \cdots) \] (12)

3.3. Posterior Variance Test

Posterior variance test is an inspection method according to the statistics of the predicted value and actual value of the prediction model [5]. The calculation steps are as follows:

Assuming that historical load sequence is \( x^{(0)}(k) \) and the predicted value sequence is \( x^{(0)}(k) \), of which k=1,2,...,n. The difference between the actual value \( x^{(0)}(k) \) and predicted value \( x^{(0)}(k) \) of k moment is \( \varepsilon(k) \), called residual error of k moment. The average value \( \bar{\varepsilon} \) of the residual error is:
The average value $\bar{x}$ of the historical data thereinto is:

$$\bar{x} = \frac{1}{n} \sum_{k=1}^{n} x^{(0)}(k)$$

(14)

The variances of the historical data and residual error are donated as $S_1^2$ and $S_2^2$ respectively, and the posterior variance ratio $C$ and small error probability $P$ are defined as follows:

$$C = \frac{S_1}{S_2}$$

$$P = P \{ |e(k) - \bar{e}| < 0.6745 S_1 \}$$

(15)

The precision of the prediction model is evaluated comprehensively as per $C$ and $P$ indicators. See Table 1.

**Table 1.** Comprehensive Evaluation on Small Error Probability ($P$) and Posterior Variance Ratio ($C$) of Prediction Model

| Prediction Precision Grade | $P$  | $C$  | Prediction Precision Grade | $P$  | $C$  |
|----------------------------|------|------|----------------------------|------|------|
| Good (Grade 1)             | >0.95| <0.35| Marginal (Grade 3)         | >0.7 | <0.45|
| Qualified (Grade 2)        | >0.8 | <0.5 | Unqualified (Grade 4)      | $\geq$0.7 | >0.65 |

4. Prediction of Beijing’s Energy Consumption Based on Grey Prediction Model

4.1. Load Prediction Based on GM(1,1) Model

The historical data of energy consumption of Beijing area during 2010-2017 are collected herein[14] and used as sample. By using grey model and prediction model, prediction is made to Beijing’s energy consumption data during 2018-2020, and comparison is made to such data and the historical data, thereby calculating the relative error and absolute error of the actual values and predicted values of every year. See Table 2, in which the numerical value of parameter $a=-0.06$, $u=3833.07$.

**Table 2.** Comparison between Predicted Value and Error of Grey Prediction Model

| Years | Historical Data | Model Value | Relative Error (%) | Absolute Error |
|-------|----------------|-------------|--------------------|---------------|
| 2010  | 6359.43        | 6359.4      | 0                  | 0             |
| 2011  | 6397.30        | 6406.9      | 0.15               | 9.6           |
| 2012  | 6564.10        | 6476.14     | -1.34              | -87.96        |
| 2013  | 6723.90        | 6533.75     | -2.96              | -190.15       |
| 2014  | 6831.23        | 6890.66     | 0.87               | 59.43         |
| 2015  | 6852.55        | 6906.00     | 1.78               | 53.45         |
| 2016  | 6961.70        | 7115.55     | 2.21               | 153.85        |
| 2017  | 7132.84        | 7108.50     | -3.41              | -24.34        |
| 2018  | 7198.87        |             |                    |               |
| 2019  | 7265.09        |             |                    |               |
| 2020  | 7378.90        |             |                    |               |

It can be seen from the table that the error of GM (1, 1) model is relatively small in the prediction of Beijing’s long-term energy consumption, the maximum relative error among the predicted values of every year is controlled within 3.41% and the average relative error is relatively small, with a very high precision. Therefore, it is a feasible method.
4.2. Posterior Variance Test
After the establishment of grey prediction model and to ensure the accuracy of the predicted result of such model, an accuracy test can be carried out to such model with the posterior variance test method. According to the calculation result, the posterior variance ratio $C=0.0819$ and the small error probability $P>0.95$. It can be judged that the prediction result of the grey model is better and it can be determined that the precision of such model is Grade 1.

5. Conclusion and Expectation
The total energy consumption of Beijing during 2018-2020 is predicted by using the grey model, proving the effectiveness of the model method. In view of the advantages of various intelligence algorithms in enhancing operation efficiency and improving prediction model performance, the application of such algorithms in the existing energy consumption prediction methods shall be further expanded, and parameter optimization shall be made to the grey model by using the intelligence algorithm. Moreover, the preferred combined prediction models can be established according to the actual needs, thereby further improving prediction precision.

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