Research on distributed photovoltaic power generation prediction based on grey model for energy Internet of city

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Abstract. Power load forecasting is one of the basic tasks of power system dispatching coordination and rational arrangement of energy production. Reasonable power load forecasting can ensure safe, continuous and stable energy supply, and provide reasonable guarantee for the safe and economic operation of power system. Based on Beijing’s new energy and renewable energy online monitoring system, this paper collects power generation data, environmental data and equipment working condition data, and uses gray model prediction method to predict the load of XXXXX photovoltaic power station, and obtain more accurate power load data, which is complex fluctuation. The photovoltaic power generation project provides the basis for post-generation planning.

1. Introduction
The purpose of power load forecasting is to predict the temporal and spatial distribution of power load and ensure the stability and reliability of power energy. The equipment of distributed photovoltaic power generation is distributed. And the power data is affected by natural environment and fluctuates greatly. So, it is necessary to provide the power load forecasting model to establish a reliable renewable energy power system [1]. Since the 1950s, the research on power load forecasting has been carried out abroad. With the rapid increase of electricity consumption and the integration of various energy types into the grid, power load forecasting methods developed rapidly in China. From the initial traditional statistical analysis method, elastic coefficient method, to the later grey forecasting method, neural network and wavelet analysis method and other power load forecasting methods emerged [2].

The grey load forecasting method is based on the trend of development and has low requirements on the sample size. Therefore, it is not limited by the extensive distribution of photovoltaic power stations, complex data representation and other factors.

In this paper, photovoltaic power generation data collected in Beijing renewable energy monitoring system were processed, and the load forecast of power station was carried out by using grey model prediction method. The prediction results are consistent with the actual data and the prediction accuracy is high. This is of great significance for the rational development of renewable energy generation/consumption plans, as well as the planning of market and customer relations, security and economic use of electricity.
2. The grey model method

2.1. Grey generated

Grey system determines the unknown information of the system by the development and generation of the known information. Since it does not have excessive requirements on the number of samples, grey system theory has been widely applied in many fields of research, such as sample index data processing, research object analysis, evaluation, prediction, control and system optimization, etc. [3]. The commonly used grey generation methods include accumulation and subtraction generation, step ratio generation, mean generation, etc. This paper mainly uses the grey generation method generated by accumulation.

Accumulative Generating Operation (AGO) is a mathematical processing method that generates a new accumulative data sequence by successively phasing the data in the same sequence. The sequence before accumulation is called the original sequence, and the sequence after accumulation is called the generated sequence. After the chaotic and irregular original data is generated by accumulation, it becomes an increasing sequence with exponential growth law.

Let \( x(0) \) and \( x(1) \) be the original sequence and the generated sequence respectively:

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

2.2. Grey modelling process

2.2.1. The mechanism of grey prediction model. According to Grey prediction Model theory, the random variable with no rule is generated by Grey, and the original data sequence is changed into a series with exponential growth rule. The first-order exponential equation can be used to establish a differential equation model for the generated series, which is called Grey Model [4-5] and denoted as GM (Grey Model). GM(1,1) model, as a special case of GM(1,n) model, is a useful load forecasting tool in power system load. It is composed of a first-order differential equation containing only a single variable.

The theory of grey prediction model mainly includes three links: first, the original data sequence is regarded as the grey process of change in a certain range and time area, and the original discrete data is generated by accumulation to make it into a series of Numbers with exponential growth law. Then, the discrete grey differential equation model can be estimated by least square method. Finally, according to the initial value, the corresponding function of time is solved, and the predicted data obtained by the data model is generated by accumulation, which is then reduced to the original load data satisfying the actual application.

2.2.2. grey prediction (GM) model. To build GM(1,1) model, only one sequence \( x(0) \) is needed. Let the original data sequence with single variable \( x(0) \) be:

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

Generate a sequence of first order accumulation using 1-AGO

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

\[
x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)
\]
Among them, the original sequence of Numbers is generated by accumulation to become a more regular sequence of Numbers, and then the model is built for \( x(1) \) First order linear differential equation is constructed:

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

(5)

According to the definition of derivative, it is expressed in discrete form as follows:

\[
\frac{\Delta x}{\Delta t} = \frac{x^{(1)}(k+1)-x^{(1)}(k)}{k+1-k} = x^{(1)}(k + 1) - x^{(1)}(k) = x^{(0)}(k + 1)
\]

(6)

The \( x \) value is taken as the mean value of \( k \) and \( k + 1 \) at the moment, and the above results are written in matrix form as follows:

\[
Y_n = BA
\]

(7)

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

(8)

In the above equations, the vectors \( Y_n \) and \( B \) are known quantities, and the vector \( A \) is the parameter to be solved. Because the variables are ‘a’ and ‘u’. The ‘a’ is the development coefficient of the model, which reflects the development trend of data sequence; The ‘u’ is the coordination coefficient of the model, which reflects the changing relationship between the data. The least square method is used to solve the parameter column \( A \), where \( E \) is the error term.

\[
Y_n = BA + E
\]

(9)

To make them \( \min \| Y_n - BA \|^2 = \min \left( Y_n - BA \right)^T(Y_n - BA) \)

By using the matrix derivative formula, the following equation can be obtained:

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

(10)

The solution will be:

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

(11)

The above formula is called the time response function model of GM (1,1) model, which is the specific calculation formula of the grey prediction model. By reducing and restoring this formula, the grey prediction model of the original series \( x(0) \) can be obtained as follows:

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

(12)

3. Numerical examples validate

3.1. original pv power load prediction data of Beijing

The photovoltaic power generation of Beijing new energy and renewable energy power monitoring platform in the last four years was selected as the basic data of power load prediction, and on the basis of the original collected data, the vacancy data in the same period was filled up with the mean value. The power load data from January 2015 to May 2019 are shown in table 1.
Table 1. Load data of Beijing photovoltaic power station in recent 4 years.

| data/kwh | 2015    | 2016    | 2017    | 2018    | 2019    |
|----------|---------|---------|---------|---------|---------|
| M1       | 1992112 | 2201820 | 1629024 | 2171540 | 1966064 |
| M2       | 2037091 | 2133440 | 1904864 | 2336108 | 1773952 |
| M3       | 2424721 | 2319668 | 2322300 | 2384972 | 2071944 |
| M4       | 2709700 | 2179292 | 1605848 | 2215868 | 1717136 |
| M5       | 2825400 | 2049248 | 2029748 | 1934536 | 2133152 |
| M6       | 1714100 | 1914464 | 1512188 | 2207952 |
| M7       | 2302194 | 988616  | 1734036 | 1494476 |
| M8       | 1897313 | 1643956 | 2225704 | 1822280 |
| M9       | 1511235 | 162652  | 2181256 | 2237032 |
| M10      | 2593865 | 1170912 | 1151892 | 2054400 |
| M11      | 1805829 | 1668768 | 1958344 | 1790376 |

3.2. The grey method predicts the photovoltaic power generation of Beijing from June 2019 to June 2020

According to the above grey prediction steps, historical data is input and the prediction result is obtained with the corresponding prediction deviation, which can initially maintain the error of grey prediction method in a certain range. The predicted photovoltaic power generation data of Beijing from June 2019 to June 2020 are shown in table 2.

Table 2. Beijing's predicted photovoltaic power generation from June 2019 to June 2020

|        |        |        |        |        |
|--------|--------|--------|--------|--------|
| 2019M6 |        | 1946768 |        |        |
| 2019M7 |        | 1945223 |        |        |
| 2019M8 |        | 1943680 |        |        |
| 2019M9 |        | 1942139 |        |        |
| 2019M10|        | 1940598 |        |        |
| 2019M11|        | 1939059 |        |        |
| 2019M12|        | 1937520 |        |        |
| 2020M1 |        | 1935983 |        |        |
| 2020M2 |        | 1934448 |        |        |
| 2020M3 |        | 1932913 |        |        |
| 2020M4 |        | 1931380 |        |        |
| 2020M5 |        | 1929848 |        |        |

3.3. The error analysis

This article will also be the last ten months of the error of predicted value and the historical data, see table 3. Its absolute value error is limited within 15, analyzes its error sources, because the extent of the photovoltaic power generation is affected by meteorological conditions is larger, the fluctuation of meteorological environment bring complex fluctuations in output, but grey prediction results can reveal eliminates the meteorological environment after the influence factors such as law of photovoltaic power generation.
Table 3. Model errors from August 2018 to May 2019

| Years   | The historical data: kwh | Model values: kwh | Relative error: % |
|---------|--------------------------|-------------------|-------------------|
| 2018M8  | 1822280.0                | 1962278.3         | 7.68              |
| 2018M9  | 2237032.0                | 1960721.7         | 12.35             |
| 2018M10 | 2054400.0                | 1959166.34        | 4.63              |
| 2018M11 | 1790376.0                | 1957612.2         | 9.34              |
| 2018M12 | 1889712.0                | 1956059.31        | 12.35             |
| 2019M1  | 1966064.0                | 1954507.64        | 0.59              |
| 2019M2  | 1773952.0                | 1952957.2         | 10.09             |
| 2019M3  | 2071944.0                | 1951408.0         | 5.82              |
| 2019M4  | 1717136.0                | 1949860.02        | 13.55             |
| 2019M5  | 2133152.0                | 1948313.27        | 8.66              |

4. Conclusion
In this paper, the grey model is used to predict the photovoltaic power generation of Beijing from June 2019 to June 2020, which proves the effectiveness of the model method. In view of the advantages of various intelligent algorithms in improving operational efficiency and the performance of prediction models, their application in existing energy consumption prediction methods should be further expanded. Intelligent algorithms should be used to optimize the parameters of the gray model, and the optimal combination prediction model can be established according to actual needs to further improve the prediction accuracy [6].

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