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Medium and Long-term Power Load Forecasting Based on Grey Markov Correction Model

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Abstract: *Medium and long-term load forecasting is a necessary prerequisite for distribution network planning, and is of great significance for the improvement of economic and social benefits of the power system. Aiming at the defects of low prediction accuracy and poor applicability of traditional grey forecasting model, a medium and long-term load forecasting method of power system based on Markov residual correction and improved grey theory is proposed. Based on the classical grey forecasting GM(1,1) model, this method first divides the state according to the relative residuals, calculates the Markov residual transition matrix, and then uses the equal-dimensional innovation method to construct the grey Markov correction forecast. Model, and finally use residual processing method to revise the prediction results. The simulation results based on an actual example of load forecasting of annual power consumption in Guangxi Province show that compared with the traditional grey forecasting model, the grey Markov residual correction model proposed in this paper has significant advantages in forecasting accuracy and applicability.*

Keywords: *Load forecasting; Grey model; Markov chain; Equal-dimensional innovation*

1. Introduction

Power system load forecasting is based on the historical data of power load, economy, society and meteorology, etc., to explore the influence of historical data changes of power load on future load, in order to seek the internal relationship between power load and various related factors, so as to predict the future load. Scientific forecasting of the power load and accurate load forecasting are beneficial to reduce the cost of power generation, ensure the demand for electricity, and enhance the reliability of power supply, thereby improving the economic and social benefits of the power system[1-2].

2. Manuscript Preparation

2.1. Trend Analysis

Trend analysis is also known as trend curve analysis, curve fitting or curve regression. Trend analysis is by far the most studied and most popular quantitative forecasting method. The trend analysis method is to fit a curve according to the previous relevant data, and this curve can reflect the growth and development trend of the load, and then estimate the load value in a certain time period in the future according to the growth trend of the curve. There are many trend models commonly used, among which it is relatively simple to select a trend model, but in the process of fitting the curve, the accuracy and the consistency of the fitting interval are required. The limitation of this method is that it needs to choose a suitable curve model, and the error of different curve models is relatively large; it needs to have a better statistical law and a clear development trend[3].

2.2. Regression Analysis

Regression analysis, also known as statistical analysis, is one of the most widely used quantitative prediction methods. Regression analysis method is to determine the functional relationship between the power consumption and the impact factor through statistical analysis of the impact factor value and the historical data of electricity consumption, so as to realize the prediction. This method not only depends on the accuracy of the model, but also on the accuracy of the predicted value of the impact factor itself.

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The shortcomings of this method are: high requirements for historical data; difficult model initialization; there may be a phenomenon that the quantitative results do not match the qualitative analysis results[4].

2.3. Neural Network Method

Neural network is an artificial neuron network, which is a network composed of a large number of neurons connected to each other. It is an abstraction and simulation of several characteristics of the human brain or natural neural network. The important role of neural network in the field of load forecasting is mainly reflected in the fact that it is easy to deal with various factors that affect load changes in the modeling process. In particular, using the improved Newton learning algorithm and genetic algorithm combined with the neural network method for daily load forecast has more reliable accuracy and faster convergence speed. There are many existing neural network models, which describe and simulate different levels of biological systems from different perspectives. The neural network method used by scholars [5], through the simulated human brain nervous system with strong learning ability, using historical data training, the load model is used, and then the model is used to carry out load prediction, although there is a strong self-study and Adaptive ability, but this method is only applicable to short-term load predictions for sample space.

2.4. Grey Forecasting

Grey forecasting method is a method of forecasting power demand by using grey system theory, which can be divided into series forecasting, catastrophe forecasting, topological forecasting and comprehensive forecasting. Sequence forecasting method is generally used in the forecasting of electricity demand. The specific method is to convert the original data of electricity consumption into generated data, obtain a generating function with strong regularity through the generated data, and establish a differential equation model to predict the future electricity demand. The grey model method treats the uncertain factors in the power load as a grey system to study. Grey forecasting technology is widely used in short-term, medium-term and long-term power load forecasting due to its small sample size and high forecasting accuracy[6].The gray prediction method has the following characteristics: use gray mathematics to deal with uncertain quantities and make them quantified; make full use of known information to seek the motion law of the system; and can deal with poor information systems. Grey forecasting is a useful tool for projects with only a few observations.Although the traditional grey forecasting model has significant advantages over other methods in medium and long-term load forecasting, for data with large randomness and volatility, due to the influence of some disturbance factors, with the passage of time, the data fitting is poor, and the forecasting accuracy is poor. There will be a more obvious decline with the increase of the data gray level, and the applicability is not strong. Therefore, there are many researches on applying the improved grey forecasting technology to forecast the load on this basis.Sun et al.[7] uses the three-point moving average method for preprocessing and optimization, thereby weakening the random fluctuation characteristics of the data series, reducing the impact of frequent data fluctuations on the results, and enhancing the anti-interference ability of gray forecasting to fluctuating load data series. Ren et al.[8-9] introduce the concept of equal-dimensional innovation, continuously add new data, and remove the earliest innovation, so as to reflect the impact of future random disturbances on the gray system. Scholars such as He and Liu[10-11] not only used the equal-dimensional innovation prediction model, but also added the residual error correction gray prediction model to superimpose the residual error between the model value and the actual value on the traditional gray model value, and corrected the model value. However, the example analysis proves that the prediction of Grey Markov GM(1,1) prediction model [12-14] has certain accuracy and applicability.

This paper combines the GM(1,1) model and the Markov chain method to predict the power load, that is, the gray model is used to explain the development trend of the power load, and the Markov chain is used to improve the residual error of the gray prediction model, so as to improve the medium and long-term The accuracy of power load forecasting.

3. Introduction to Grey Prediction Theory

3.1. GM (1,1) Model Principle Introduction

In 1982, Professor Deng Julong proposed the grey system theory. In the study of grey system theory, various systems are divided into white, black and grey systems. "White" means that the information is

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completely known, "black" means that the information is completely unknown; "grey" means that the information is partially known and partially unknown, or the information is incomplete. The research object of grey system theory is the uncertain system with "some information is known, and some information is unknown, poor information, small sample". For the power load system, the power supply unit, power grid capacity, etc. are known, but other factors affecting the load, such as weather conditions, regional economic activities, etc., are difficult to know exactly. Therefore, the power load is a gray system, and the predicted load conforms to the gray system. Predictive model usage conditions. The commonly used gray prediction models are GM(1,1) and GM(1,n) models. The principle is to first perform an accumulation and generation process on the original data sequence, convert it into a regular sequence, and then establish a GM (1,1) model, thereby obtaining the differential equation. By solving this differential equation, the parameter values of the equation can be derived. Finally, the gray prediction model of the cumulative sequence is obtained, and the prediction is carried out [15-16]. The specific modeling process is as follows.

The original data of the electricity load in previous years is recorded as:

$$\mathrm{x}^{(0)} = \left[\mathrm{x}^{(0)}(1), \mathrm{x}^{(0)}(2), \dots, \mathrm{x}^{(0)}(\mathrm{n})\right] \tag{1}$$

One accumulation generates a sequence (1-AGO) as

$$\mathrm{x}^{(1)} = \left[\mathrm{x}^{(1)}(1), \mathrm{x}^{(1)}(2), \dots, \mathrm{x}^{(1)}(\mathrm{n})\right] \tag{2}$$

In the formula, the original sequence and the one-time accumulation generated sequence satisfy the following relationship:

$$\mathrm{x}^{(1)}(\mathrm{k}) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{x}^{(0)}(\mathrm{k}) \tag{3}$$

The inverse operation generated by an accumulation is called an accumulation reduction, that is:

$$\mathrm{x}^{(0)}(\mathrm{k}+1) = \mathrm{x}^{(1)}(\mathrm{k}+1) - \mathrm{x}^{(1)}(\mathrm{k}) \tag{4}$$

Since the sequence $x(1)$ has an exponential growth law, we think that the $x^{(1)}$ sequence satisfies the first-order linear differential equation with the exponential growth form as the general solution:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \tag{5}$$

In the formula, a is the development gray number; μ is the endogenous control gray number.

The differential term in discrete form can be expressed as $x^{(0)}(k+1)$, and $x^{(1)}$ generally takes the average value of k and $k+1$ times,Therefore, the original equation (5) can be transformed into:

$$\mathrm{x}^{(0)}(\mathrm{k}) + \frac{1}{2}\mathrm{a}\left[\mathrm{x}^{(1)}(\mathrm{k}) + \mathrm{x}^{(1)}(\mathrm{k}+1)\right] = \mathrm{u} \tag{6}$$

The above result can be written in matrix form as:

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(2) + x^{(1)}(3)\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x^{(1)}(n-1) + x^{(1)}(n)\right] & 1 \end{bmatrix} \begin{bmatrix} a \\ u \end{bmatrix} \tag{7}$$

Abbreviated as $\mathrm{Y_n} = \mathrm{B} \cdot \mathrm{A}$, the solution equation is $\mathrm{A} = (\mathrm{B^T B})^{-1}\mathrm{B^T Y_n} = \begin{bmatrix} \hat{\mathrm{a}} \\ \hat{\mathrm{u}} \end{bmatrix}$, and bringing the parameters back to the original equation has:

$$\hat{\mathrm{x}}^{(1)}(\mathrm{k}+1) = \left[\mathrm{x}^{(0)}(1) - \frac{\hat{\mathrm{u}}}{\hat{\mathrm{a}}}\right] \mathrm{e}^{-\mathrm{ak}} + \frac{\hat{\mathrm{u}}}{\hat{\mathrm{a}}} \tag{8}$$

Equation (8) is the time response function model of the GM(1,1) model.

This is a forecasting equation for the $x^{(1)}$ time series. To get the forecasting equation for the $x^{(0)}$ time series, make

$$\begin{aligned} \hat{x}^{(0)}(k+1) &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{\hat{u}}{a}\right] \cdot \left[e^{-\hat{a}k} - e^{-\hat{a}(k-1)}\right] \\ &= (1 - e^{\hat{a}}) \left[x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right] \cdot e^{-\hat{a}k} \end{aligned} \tag{9}$$

It can be seen from the above principle formula that the traditional gray GM(1,1) model requires less historical data, does not need to consider the distribution law and change trend, the model is simple and easy to implement, and the prediction results are highly verifiable, which is considered to be It is one of the most effective methods for medium and long-term load forecasting.

3.2. *Model Verification*

3.2.1. Residual Test

There are two absolute errors and relative errors. $\hat{X}^{(0)}(i)$ is calculated according to formula (8), and then calculate the absolute residual sequence of the original sequence $X^{(0)}(i)$ and $\hat{X}^{(0)}(i)$, that is

$$\Delta^{(0)}(\mathrm{i})=\left|\mathrm{x}^{(0)}(\mathrm{i})-\hat{x}^{(0)}(i)\right|(i=1,2,\ldots,n) \tag{10}$$

$$\varphi(i)=\frac{\Delta^{(0)}(i)}{x^{(0)}(i)}\times 100\%(i=1,2,\ldots,n) \tag{6}$$

Calculate the average relative residual:

$$\overline{\Phi}=\frac{1}{n}\sum_{i=0}^{n}\varphi(i) \tag{12}$$

Given α, when $\overline{\Phi}<\alpha$ and $\varphi_n<\alpha$ is set up, the model is called the residual test qualified model. It is usually taken by α of 0.01, 0.05 and 0.10, and the corresponding model is excellent, qualified, and barely qualified.

3.2.2. Posterior-variance-test

(1)Calculate the standard deviation of the original series:

$$S_1=\sqrt{\sum[x^{(0)}(i)-\bar{x}^{(0)}]^2 \Big/ (n-1)} \tag{13}$$

(2)Calculate the standard deviation of absolute error sequences:

$$S_2=\sqrt{\sum[\Delta^{(0)}(i)-\bar{\Delta}^{(0)}]^2 \Big/ (n-1)} \tag{14}$$

(3) Calculate the variance ratio:

$$C=\frac{S_1}{S_2} \tag{15}$$

(4) Calculate small error probability:

$$P=p\left|\Delta^{(0)}(i)-\bar{\Delta}^{(0)}\right|<0.6745S_1 \tag{16}$$

Set $e_i=\left|\Delta^{(0)}(i)-\bar{\Delta}^{(0)}\right|, S_0=0.6745S_1$,then $P=p\{e_i<S_0\}$.

4. Gray System Improvements

4.1. Gray Markov Correction Model

For each fixed t, function $x(t)$ is a random variable, and $x(t)$ is a random process. The Markov process is defined as: When the random process is known at the time $t=i$, the process is only related to the t_i timing state at time $t=i+1$, and is not related to the state of t_i. Also known as there is no effect. The discrete Markov process is called the Markov Chain. First, according to the GM (1, 1) model, the power load is predicted, and the state transfer matrix of the residual loss of the known year can be obtained according to the Markov chain method. Comparing the predictive value with the actual value, the residual is the specific magnitude of the actual value, divides the residual amplitude into several states, calculates one of the probability of the state to all other states, and then obtains a state transfer matrix of residual transfer, according to the residual transfer matrix This situation is corrected to the gray prediction result, resulting in a more accurate model prediction result. The specific calculation process is as follows.

4.1.1. State Division

First, state division is performed, and the predicted value $\hat{\mathrm{x}}^{(0)}(\mathrm{k})$ of the original sequence is obtained according to the GM (1, 1) model, and the residual value $\Delta(\mathrm{k}) = \mathrm{x}^{(0)}(\mathrm{k}) - \hat{\mathrm{x}}^{(0)}(\mathrm{k})$, the residual relative value $\varepsilon(\mathrm{k}) = \frac{\Delta(\mathrm{k})}{\mathrm{x}^{(0)}(\mathrm{k})}$, then utilize the distribution of the predicted value, divide the data sequence into a number of states The interval, record $\otimes_{\mathrm{i}} = [\otimes_{\mathrm{i}1}, \otimes_{\mathrm{i}2}]$ is the i-th state, where $\otimes_{\mathrm{i}2} = \hat{\mathrm{x}}^{(0)}(\mathrm{k}) + \mathrm{B_i}, \mathrm{A_i} = \mathrm{a_i}\mathrm{x}^{(0)}(\mathrm{k}), \mathrm{B_i} = \mathrm{b_i}\mathrm{x}^{(0)}(\mathrm{k})$, the value of a_i, and b_i is determined according to the specific situation.

4.1.2. Build state transfer matrix

The basic idea of the Markov chain prediction method is to estimate future change trends based on the state transfer matrix through the state transfer matrix. One-step state transition matrix form is:

$$P_1 = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & & P_{2n} \\ \vdots & \vdots & \ldots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \tag{17}$$

It describes the probability distribution of n state mutual transfer. Among them, the P_{ij} is the probability of transferring the Markov chain state S_i to the state S_j, and $0 \le p_{ij} \le 1$. In actual calculations, we can use state-shifted frequencies as the probability of state shift. It is assumed that the number of times the state S_i appears as m_i according to the sample data, and the number of times the state S_i is transferred to the state S_i is m_{ij} at this time:

$$P_{ij} \approx \frac{m_{ij}}{m_j} \tag{18}$$

The Markov predictive method is shown as $S^{(k+1)} = S^{(k)} \cdot P_1$, where $\mathrm{S}^{(k)}$ is a state vectuation of the predicted object at $t = k$.

4.1.3. Markov Correction Factor

When the transfer matrix of the time series is determined, $k > n$, according to the state interval, the gray predicted value is corrected according to the state interval. To this end, the Markov correction coefficient is introduced. Let R_i be the correction coefficient of Markov prediction method for GM(1,1) prediction data, $i = 1, 2, 3 \ldots, n$. Since $\varepsilon(\mathrm{k}) = \frac{\Delta(\mathrm{k})}{\mathrm{x}^{(0)}(\mathrm{k})}$, so

$$\mathrm{x}^{(0)}(\mathrm{k}) = \frac{\hat{\mathrm{x}}^{(0)}(\mathrm{k})}{1 - \varepsilon(\mathrm{k})} \tag{19}$$

According to the state division method, $\mathrm{a_i} = \frac{\otimes_{\mathrm{i}1} - \hat{\mathrm{x}}^{(0)}(\mathrm{k})}{\mathrm{x}^{(0)}(\mathrm{k})}, \mathrm{b_i} = \frac{\otimes_{\mathrm{i}2} - \hat{\mathrm{x}}^{(0)}(\mathrm{k})}{\mathrm{x}^{(0)}(\mathrm{k})}$, so substituting a_i and b_i into equation (19), the correction coefficient of the i-th state is $\mathrm{R_i} = \frac{1}{2}\left(\frac{1}{1-\mathrm{a_i}} + \frac{1}{1-\mathrm{b_i}}\right)$.Therefore, when $k > n$, it is necessary to use the initial state vector and the state transition matrix to determine the state of the time series, and then multiply the gray prediction value by the Markov correction coefficient to obtain the revised prediction value, that is, $\hat{\mathrm{y}}(\mathrm{k}) = \hat{\mathrm{x}}^{(0)}(\mathrm{k}) \cdot \mathrm{R_i} = \hat{\mathrm{x}}^{(0)}(\mathrm{k}) \cdot \frac{1}{2}\left(\frac{1}{1-\mathrm{a_i}} + \frac{1}{1-\mathrm{b_i}}\right)$, $k \geqq 2$, i is the number of states.

4.2. Add Equal Dimension and New Information

The traditional GM (1, 1) model uses the past data up to $k = n$ when modeling. However, in the development process of any gray system, as time goes by, some random disturbance factors will enter the system continuously, which will affect the development of the system. Therefore, using the traditional GM (1, 1) model to predict, only the most recent data with higher accuracy, the more the future develops, the smaller the prediction significance. In order to reflect the impact of future random disturbances on the gray system and improve the prediction accuracy, new data are continuously added while using the gray Markov model. The process is:In the original data sequence $\mathrm{x}^{(0)} = (\mathrm{x}^{(0)}(1), \mathrm{x}^{(0)}(2), \ldots, (\mathrm{x}^{(0)}(\mathrm{n}))$, the latest information $\mathrm{x}^{(0)}(\mathrm{n}+1)$ is added, the oldest information $\mathrm{x}^{(0)}(1)$ is deleted, and the new data sequence is obtained: $\mathrm{x}'^{(0)} = (\mathrm{x}^{(0)}(2), \mathrm{x}^{(0)}(3), \ldots, (\mathrm{x}^{(0)}(\mathrm{n}+1))$, an improved grey prediction model based on $\mathrm{x}'^{(0)}$ is established. Then, Divide the state according to the relative error of the predicted value to determine the state transition matrix and Markov correction coefficient. The formula $\mathrm{S}^{(\mathrm{k}+1)} = \mathrm{S}^{(\mathrm{k})} \cdot \mathrm{P_1}$ and $\mathrm{p_{ij}} = \max_{\mathrm{k}} \mathrm{p_{ik}}$ are used to determine the state of the predicted value. Finally, the state correction coefficient is used to improve the future gray forecast

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value, and continuously obtain a series of forecast data.

5. Case Simulation

5.1. Building a Grey Markov Model

In this paper, the annual electricity consumption of Guangxi Province from 1996 to 2015 is selected as the historical data, as shown in Table 1. The electricity consumption data from 2016 to 2018 is used as the standard to test the pros and cons of the model. The GM (1, 1) and grey Markov models were established, the data were collected from the National Bureau of Statistics, and the simulation experiments were implemented in the Matlab2019 environment.The trend graph of the original sequence and the sequence after the accumulation is calculated by Matlab as shown in Figure 1. It can be found that the trend after accumulation tends to increase exponentially, which can be predicted by GM(1,1).

Table 1: Electricity consumption in Guangxi Province from 1996 to 2015 (unit: billion kwh)

Year	Consumption	Year	Consumption	Year	Consumption	Year	Consumption
1996	241.73	2001	331.92	2006	579.46	2011	1112.21
1997	266.95	2002	356.95	2007	681.14	2012	1153.9
1998	273.58	2003	414.93	2008	753.39	2013	1237.7
1999	289.06	2004	456.86	2009	856.35	2014	1307.99
2000	314.44	2005	510.15	2010	993.24	2015	1334.32

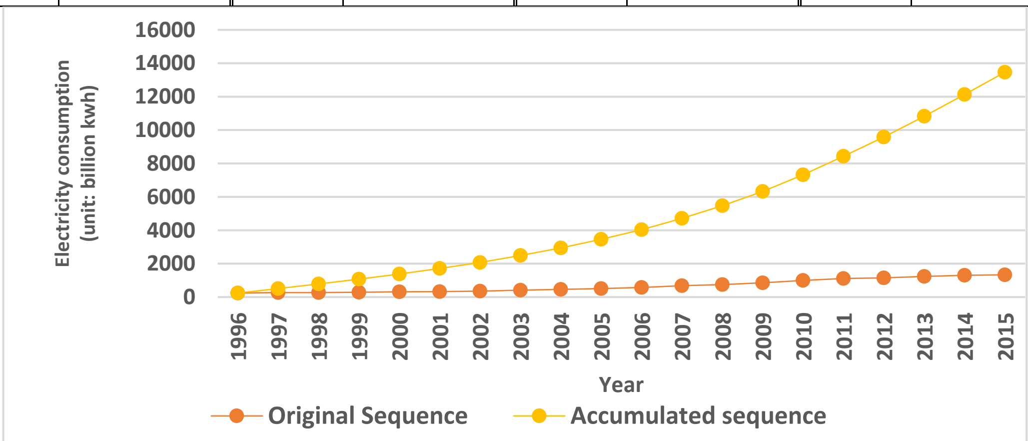

Figure 1: Original sequence and cumulative sequence trend graph

The calculation result is:

$$A = \begin{bmatrix} \hat{a} \\ \hat{u} \end{bmatrix} = \begin{bmatrix} -0.0988 \\ 217.0397 \end{bmatrix}$$

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right] e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}}$$

$$= 2438.488\, e^{0.0988k} - 2196.76$$

The gray prediction model of the original sequence obtained by the cumulative reduction of formula (10) is:

$$\hat{x}^{(0)}(k+1) = (1 - e^{-0.0988})243.488e^{0.0988k}$$

Table 2: Status Classification Criteria

Status	1	2	3	4
Divide the interval	$(\hat{x}^{(0)}(k) - 0.16x^{(0)}(k), \hat{x}^{(0)}(k) - 0.08x^{(0)}(k)]$	$(\hat{x}^{(0)}(k) - 0.08x^{(0)}(k), 0]$	$(0, \hat{x}^{(0)}(k) + 0.08x^{(0)}(k)]$	$(\hat{x}^{(0)}(k) + 0.08x^{(0)}(k), \hat{x}^{(0)}(k) + 0.16x^{(0)}(k)]$

According to the Markov chain state division standard and the actual distribution of the relative error of the gray prediction value, the system is divided into four state intervals, as shown in Table 2.

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Assuming that the gray predicted value is in the i-th state, the predicted value of the gray Markov model can take the following values:

$$y'(k) = \frac{\otimes_{i1}+\otimes_{i2}}{2} = \hat{x}^{(0)}(k) + \frac{a_i+b_i}{2} x^{(0)}(k) \tag{20}$$

From formula (9) and formula (20), the gray predicted value, Markov state, gray Markov predicted value and relative error of the two predicted values of the original sequence are obtained. The specific calculation results are shown in Table 3.

Table 3: Comparison of prediction results of two models for annual electricity consumption (billion kwh)

Year	Actual value	GM(1,1)Model		Status	Grey Markov Model	
		Predictive value	Relative residuals		Predictive value	Relative residuals
1996	241.73	241.73	0.00%	2	241.73	0.00%
1997	266.95	253.2182	5.14%	3	263.8962	1.14%
1998	273.58	279.5081	-2.17%	2	268.5649	1.83%
1999	289.06	308.5275	-6.73%	2	296.9651	-2.73%
2000	314.44	340.5597	-8.31%	1	302.8269	3.69%
2001	331.92	375.9177	-13.26%	1	336.0873	-1.26%
2002	356.95	414.9466	-16.25%	1	372.1126	-4.25%
2003	414.93	458.0276	-10.39%	1	408.236	1.61%
2004	456.86	505.5814	-10.66%	1	450.7582	1.34%
2005	510.15	558.0723	-9.39%	1	496.8543	2.61%
2006	579.46	616.0131	-6.31%	2	592.8347	-2.31%
2007	681.14	679.9694	0.17%	3	707.215	-3.83%
2008	753.39	750.5659	0.37%	3	780.7015	-3.63%
2009	856.35	828.4919	3.25%	3	862.7459	-0.75%
2010	993.24	914.5084	7.93%	3	954.238	3.93%
2011	1112.21	1009.455	9.24%	4	1142.921	-2.76%
2012	1153.9	1114.26	3.44%	3	1160.416	-0.56%
2013	1237.7	1229.946	0.63%	3	1279.454	-3.37%
2014	1307.99	1357.643	-3.80%	2	1305.323	0.20%
2015	1334.32	1498.597	-12.31%	1	1338.479	-0.31%

5.2. Markov Error Correction

(1)The residual proportion is between -16% and -8%, indicating that the predicted value of the power load is seriously underestimated, which is called state 1, and the frequency of this situation in the prediction is 7.(2)The residual proportion is in the range of -8% to 0, indicating that the predicted value of the power load is normally underestimated, which is called state 2, and the frequency of this situation is 5 in the prediction.(3)The residual proportion is in the range of 0 to 8%, indicating that the predicted value of the power load is normally overestimated, which is called state 3, and the frequency of this situation in the prediction is 8.(4)The residual proportion is between 8% and 16%, indicating that the predicted value of the power load is seriously overestimated, which is called state 4, and the frequency of this situation in the prediction is 1.

Since the transition of the last state of the original data sequence is uncertain, the total frequency is 19 after removing the electricity consumption in 2015.The corresponding state transition probability matrix is:

$$\mathrm{P}_1 = \begin{pmatrix} 6/7 & 1/7 & 0 & 0 \\ 1/4 & 1/4 & 1/2 & 0 \\ 0 & 2/7 & 4/7 & 1/7 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

Using the formula $\mathrm{R_i} = \frac{1}{2}(\frac{1}{1-\mathrm{a_i}} + \frac{1}{1-\mathrm{b_i}})$, find the Markov correction coefficient Ri of the i-th state, $R_i, i = 1,2,3,4.$ The specific calculation results are shown in Table 4.

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Table 4: Markov correction factor

Status	Relative error	Correction factor
1	(-16%,-8%]	0.894
2	(-8%,0]	0.963
3	(0,8%]	1.043
4	(8%,16%]	1.139

Taking the electricity consumption data in 2015 as the initial state, since the relative error is -12.31%, it belongs to the state E1, so the initial state vector $S^{(0)}$=(1,0,0,0), then the state of the system at any time in the future The transition vector $S^{(k)}$=S(0) $Ᵽ^{k}_{1}$.

5.3. Grey Markov Modified Model Test

Initial vectors and state transition matrices are used to predict the future state of the time series. For example: Let the system state in 2016 be $S^{(1)}$, then

$$S^{(1)} = (1,0,0,0)\begin{pmatrix} \frac{6}{7} & \frac{1}{7} & 0 & 0 \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{2} & 0 \\ 0 & \frac{2}{7} & \frac{4}{7} & \frac{1}{7} \\ 0 & 1 & 0 & 0 \end{pmatrix} = (0.8671 \quad 0.1429 \quad 0 \quad 0)$$

Therefore, in the state E1 in 2016, at this time the gray prediction value $\hat{x}^{(0)}(21) = 1654.186$ the correction coefficient $R_1 = 0.894$, then the Markov correction value $\hat{y}(21) = \hat{x}^{(0)}(21) * R_1 = 1478.838$, the actual data is 1359.65, obviously, the accuracy of the predicted data after Markov correction has been greatly improved.Remove the electricity consumption data in 1996, add the revised value of 1478.838 in 2016, and construct a new set of time series with these 20 data Remove the electricity consumption data in 1996, add the revised value of 1478.838 in 2016, and construct a new set of time series with these 20 data $x'^{(0)} = (266.95, 273.58, \ldots, 1478.838)$, establish gray model, get, establish gray model, get:

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right] e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}}$$
$$= 2910.68e^{0.0952k} - 2643.73$$

The state is divided according to the distribution of the relative error of the predicted value, and the new correction coefficient and state transition matrix P2 are determined by the above method. Taking the electricity consumption data in 2016 as the initial state, the formula $S^{(k+1)} = S^{(k)} \cdot P_2$ and $\hat{y}(k) = \hat{x}^{(0)}(k) \cdot R_i$, find the Gray Markov correction for 2017 as 1547.027. Through a similar method, continuous addition of other maintenance and innovation, the electricity demand in 2016-2018 is obtained, as shown in Table 5.

Table 5: Comparison of two methods for forecasting electricity consumption in 2016-2018

	2016	2017	2018
Actual value	1359.65	1444.95	1702.75
GM(1,1)	1654.186	1825.928	2015.502
Grey Markov Correction	1478.838	1547.027	1776.390

By comparing with the actual electricity demand, it can be seen that the revised forecast effect has been greatly improved. It can be seen that the modified gray forecasting method based on Markov theory can improve the forecasting accuracy and is suitable for the forecasting of mid- to long-term annual electricity demand. Figure 2 shows how the two methods fit the original data respectively.

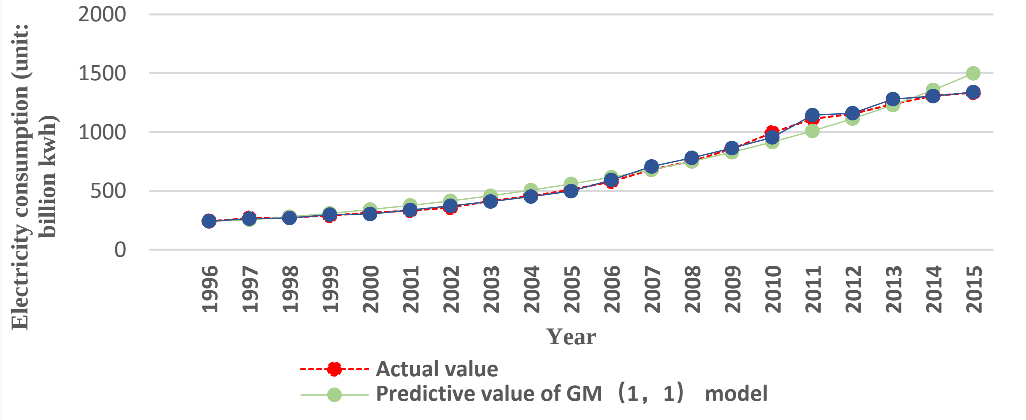

Figure 2: Fitting diagram of two methods for forecasting annual electricity consumption

5.4. Test Model

5.4.1. Residual Test Analysis

It can be seen from the data in Table 3 that the GM(1,1) modelΦ̅=0.064871785<0.1, while φ_20=0.1231>0.1, does not satisfy the residual test. The gray Markov correction model Φ̅=0.02105<0.05, and φ_20=0.0031<0.05, satisfy the residual test.

5.4.2. Posterior-Variance-Test

Substitute the data in Table 3 into equations (14) to (17), after calculation, C=0.101, P=1 for the GM(1,1) model, C=0.0322, P=1 for the gray Markov model, The posterior difference test prediction accuracy grades are all good. After inspection, the gray Markov correction model meets the requirements, and can be predicted by formula (9). The predicted power load values from 2016 to 2018 are shown in Table 7.

6. Conclusion

Power load is affected by many factors and belongs to the category of gray system. The residuals of the gray predictions are random, which meets the requirements for the use of Markov chains. Therefore, using the grey forecasting model to forecast the power load and using the Markov process to correct the residual can improve the forecasting accuracy of the model. This paper first introduces the basic principles of the grey forecasting model GM(1,1), and summarizes the defects of grey forecasting through literature review, so as to improve the traditional grey forecasting model based on Markov theory, using a curve parallel to the forecasting curve The data sequence is divided into several state intervals, and the correction coefficient of the forecast data is obtained, and the original data used for forecasting is further updated through isodimensional innovation. The research results show that the method has higher accuracy than the traditional gray forecasting model, and is suitable for the forecasting of medium and long-term power demand. It has good practicability, and established a gray Markov prediction model using the electricity demand load in Guangxi Province from 1996 to 2015, and predicted the electricity load from 2016 to 2018. Compared with the actual electricity load, the results verified The superiority of grey Markov model in improving the accuracy of medium and long-term power load forecasting. However, the grey prediction model with Markov correction transforms the prediction results from specific values into a combination of relative residual interval and probability. How to scientifically restore this combination to specific values in practical applications needs further study.

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