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The middle-long-term Grey Elman Network Electric Load Forecasting Model based on MATLAB

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ABSTRACT

A good load forecasting model can accurately and quickly calculate the predicted value, which is conducive to reasonable planning and distribution of electric energy and improving the stability of power grid operation. In this paper, we built the gray Elman neural networks electro-load forecast model based on MATLAB, we referred to the energy planning in the 13th Five-Year Plan of Huainan City in Anhui Province[1], we simulated the middle-long-term electric load forecasting model of Huainan City and set the Elman neural network and the GM (1,1) model in grey theory which both based on MATLAB as control group for comparative simulation experiments. We put forward that We put forward that the grey Elman network has higher precision than the control group, and the grey Elman network has better training effect than Elman network[2].

Keywords: The electric Load Forecasting; The Grey Theory; The Elman Neural Network; The Grey Elman Neural Network

1. INTRODUCTION

Today, Chinese economy is developing rapidly and the social demand for electricity is growing rapidly. Many cities put the energy construction planning in an important position, which shows the importance of electricity to all walks of life. In the energy construction plan, being able to accurately predict the power load in the area is the first step in planning the construction of various power plants or adjusting the power generation ratio of generator sets, and it is a crucial step. Many regions are planning to build power plants to fill the gap in regional power supply, and it will take more than 30 months to build a thermal power plant with a capacity of 2000MW. It can be seen that the construction period of the power plant is relatively long. And it is necessary to make accurate power load forecasting in the power supply area to ensure that the power plant can meet the long-term power supply demand after it is completed. Load forecasting plays an extremely important role in the power system dispatch and is an important module of the energy management system. Load forecasting refers to determining the load data at a specific time in the future based on many existing conditions of the system and meeting certain accuracy requirements. The accuracy of load forecasting is related to the reasonable arrangement of the start and stop of generators in the power grid. Accurate load forecasting can maintain the stability of grid operation, while effectively reducing power generation costs and improving economic and social benefits. However, the existing load forecasting algorithms are more general, and it is difficult to fit the true value of the forecast in a specific area even far away. Therefore, there is a great need for a load forecasting algorithm with a higher degree of fit and suitable for local characteristics. This paper takes the "13th Five-Year Plan" energy plan in Huainan City, Anhui Province as an example, establishes a gray Elman power grid load forecasting model based on MATLAB, and proposes to establish a target power load forecasting model for Huainan City.

2. BRIEF INTRODUCTION OF LOAD FORECASTING AND METHODS

Load forecasting is an important part of the energy management system (EMS) and a significant content of economic dispatch of power grid system. The accurate load forecasting can reduce the unnecessary hot standby motor, arrange the maintenance plan of electrical equipment reasonably. While ensuring the stable operation of the power grid system, it can ensure the normal production and life of people, and bring higher economic benefits and social effects to the society[3].

2.1 Trend extrapolation

Trend extrapolation method, also known as trend extension method, was first proposed by R.lane. It is a prediction method that summarizes the law of change with time and extrapolates the predicted value in the future according to the historical data known by observation. This method is often used when the development trend of observation object is continuous, progressive and functional. However, if the development law of the observed objects is abrupt or jump, it is not suitable for this kind of method. Generally, linear model and exponential model are widely used.

The exponential curve method is a very important trend extrapolation method. When the known development law of the observation object presents the exponential curve law or approximate exponential curve law, the past, present and future development law of the observation object in the prediction period follow the exponential law, and the future development law of the observation object is inferred from the outside.

The reason why the exponential curve method is a very important trend extrapolation method is that in real life, the development law of many things is similar to the exponential curve law. We divide the long-term power load growth into three stages: beginning, development and maturity. In the development stage, it will show a trend of rapid growth with the economic and social development, which is an obvious exponential growth law of the first curve, so the first-order exponential curve method is often used in load forecasting.

The exponential curve method includes the following steps:

1) Identify the target of the prediction.
2) Collect data and summarize the rules.
3) Fit the exponential curve.
4) Trend extrapolation.
5) Summarize and organize forecast data.

Because the exponential curve method is very suitable for load forecasting, and many classical load forecasting methods have the idea of trend extrapolation. For example, time series method is often combined with trend extrapolation method for load forecasting and the typical exponential curve law in GM (1,1) of grey theory.

2.2 The significance of load forecasting

1) Provide reference for the reasonable electricity price: At present, the development level of science and technology is not enough to store a large amount of electric energy, so the electric energy is still generated and used immediately, resulting in certain fluctuations in the price of electricity. Accurate load forecasting can accurately predict the supply and demand of electric energy, and provide reference for relevant practitioners. It can not only meet the needs of power enterprises' own interests, but also make consumers satisfied with the price, so as to achieve a win-win situation of mutual benefit[4].
2) Coordinate synchronous generation and load: Because the electric energy itself is not easy to store, and the load changes from time to time. Practitioners can specify corresponding generation plan according to the change of electric energy to improve the fitting degree with load. It can not only improve the economic effect of power generation, but also can consume power in time to improve the stability of the system[5].
3) Guide consumers to use electricity rationally: Due to the change of load time, the cost of power generation is different in peak period and low period. Especially in the peak of power consumption, the working load of power generation, transmission and distribution equipment is at the peak and the power flow is blocked, which not only increases the cost of power generation, but also increases the pressure of each link in the power grid system. According to the combination of load forecasting, practitioners can adjust pricing reasonably and in real time to guide consumers to use electricity reasonably. Thus "peak load shifting" links the power grid pressure. "Gradient electricity price" mode can guide consumers to use electricity reasonably[6].

4) Improve the economic efficiency of power network enterprise transport business: The transport business in power grid enterprises is an important business, which requires accurate load forecasting model to provide technical support. The higher the load forecasting accuracy is, the higher the economic benefits will be brought to the power enterprises, and the better the coordination among the three parties of power generation, transmission and distribution can be achieved[7].
5) Reasonable distribution of outgoing lines: According to the load forecasting results, the power plant can adjust the different flow reasonably and in real time. Improve the generation plan of power intensive lines.

2.3 Methods of load forecasting

The typical medium and long term load forecasting methods are divided into extrapolation method and correlation analysis method. The extrapolation method is based on historical load data, and the researchers analyze the law of its variation and extrapolate the law of future load development. Both the elastic coefficient method and the grey system are typical extrapolation methods. The law of correlation analysis will consider the influence of social correlation factors on load and establish the relationship model between load and influence factors to predict the future development law of load. Regression analysis is a typical correlation analysis method. With the gradual maturity of artificial intelligence technology, technologies such as neural networks and support vector machines are also used by researchers in load forecasting.

Common load forecasting methods are as follows:

1) Trend extrapolation method: It is widely used in medium and long term load, fitting the corresponding function curve according to the existing historical data, and predicting the future load through the development law of the function curve. The advantage of this method is that it needs less data and less calculation. However, when the load change is complex and there are many inflection points, the fitting effect is general. In bibliography [8], the trend extrapolation method, linear regression method and envelope model are used to fit the historical load data of Lianjiang county and extrapolate to forecast the future load. The extrapolation results and rules of different prediction models are different, and the optimal model is selected by comparison[8].
2) Grey system prediction method: In gray theory, known events are white and unknown events are black. Gray, which is between white and black, indicates that the information is somewhere in between. The power load is a typical grey system, and the future load development law can be predicted by the curve fitting of cumulative sequence. The grey theory requires few historical samples, and the technology is mature and widely used. In bibliography [9], the accuracy of medium and long-term load forecasting is improved by improving the grey system prediction method. The load data from 2015 to 2017 are accurately predicted by analyzing the power load data of Xinjiang over the years, with the relative error less than 5%[11].
3) Regression analysis: Statistical analysis of the observed data of the selected dependent variables and independent variables and the relationship between them is carried out, and the mathematical model is deduced to predict the future load development law. Regression analysis method can reflect the influence of economic, population change, environment and other factors on load, but it needs to analyze a large number of data and establish corresponding mathematical model. Linear regression model and nonlinear regression model belong to regression analysis method, and the accuracy of different models is different.
4) Artificial neural network method: By establishing some neurons to learn and process information, it can approach any function in theory. Three-layer feedforward neural network is widely used in short-term load forecasting, and Elman neural network is often used in long-term load forecasting in combination with other algorithms. The neural network has the characteristics of self-adaptive training and can approximate any function, which makes the prediction effect better, and can solve

the uncertainty of load change. But the training time is often long and the operation may fall into local minimum. In bibliography [10], the application of ant colony recurrent artificial neural network can effectively improve the accuracy of short-term load forecasting. It has good stability and adaptability for working days and rest days, and improves the problem of local minimum [9].

5) Combination prediction method: Due to the complexity and randomness of load changes, a single algorithm is not easy to fit the actual load changes, and it is difficult to accurately predict the load. Therefore, by studying the advantages and disadvantages of different algorithms, several algorithms are combined reasonably to complement each other to improve the accuracy of load forecasting. There must be errors in the results of load forecasting. We should not only pay attention to the forecasting results, but also analyze the causes and the range of error fluctuation. The prediction model is improved step by step, and the error is corrected until it meets the target requirements [9].

3. ANALYSIS OF ORIGINAL DATA IN HUAINAN CITY

By consulting the geographical location, climate characteristics and city yearbook information of Huainan City, it can be known that Huainan City is located in the Yangtze River Delta, with flat terrain, rich natural resources and developed waterway traffic. In 2017, Huainan's regional production value was 110 billion yuan, making it one of the major industrial cities in Anhui Province.

Table 1 Average annual temperature of Huainan City in recent years

Year	Annual average temperature (unit/degree Celsius)
2007	17.4
2008	16.8
2009	16.9
2010	16.8
2011	16.4
2012	16.6
2013	17.3
2014	16.8
2015	16.7
2016	17.1

As shown in Table 1, the average annual temperature in Huainan City is stable, and stable climatic conditions can prevent sudden changes in climate from affecting the accuracy of power load results.

Table 2 Statistics of electricity consumption in the whole society in Huainan City over the years

Year	Total electricity consumption in society (100 million kWh)
2006	42.20
2007	47.10
2008	51.10
2009	56.11
2010	59.79
2011	65.69
2012	72.88
2013	77.75
2014	75.09
2015	73.78
2016	83.11
2017	84.73

As shown in Table 2, Huainan City has a large power load base and a steady growth overall, which is in line with the characteristics of an industrial city.

4. LOADF ORCASTING METHODS

4.1 Load forecasting steps

1) Improve the mathematical theory of medium and long-term load forecasting for Huainan City.
2) Build a grey Elman network load forecasting simulation model based on mathematical theory, and perform error verification [12].
3) Set the related Elman artificial network algorithm and the traditional gray system GM (1,1) model as the reference group, and conduct comparative simulation experiments.
4) Analyze the obtained experimental data, and modify the gray Elman network load forecasting model until it meets the accuracy requirements.

4.2 Load forecasting theory

4.2.1 Medium and long term load forecasting

Load forecasting models are generally divided into short-term load forecasting, medium-term load forecasting, and long-term load forecasting. Short-term load forecasting is generally based on days as the statistical unit, medium-term load forecasting is generally based on months, and long-term load forecasting is based on years. Among them, the general forecast time limit of medium-term load forecasting is several months in the future, while long-term forecasting is often several years or even longer.

Due to the rapid development of technology and the optimization of related algorithms, ultra-short-term load forecasting and medium- and long-term load forecasting have been derived, and ultra-short-term load forecasting is generally based on hours. The time limit of mid- and long-term load forecasting is between mid-term load forecasting and long-term load forecasting.

Among various load forecasting models, it is obvious that ultra-short-term load forecasting and short-term load forecasting are not applicable to this article. This paper needs to predict the power load of Huainan City in the next 1-2 years by processing the original electricity data of Huainan City in the past few years.

At the same time, considering the characteristics of gray theory and neural network involved in this article, the traditional gray theory model can handle small sample data better and conforms to the regional power development law due to its index characteristics. Combining it with neural network can optimize the input the underlying laws of the original data in the matrix and can reduce the amount of original data.

Finally, after comparing mid-term load forecasting, mid-long-term load forecasting and long-term load forecasting models, this article will select the mid- and long-term load forecasting model as the simulation model of the case. On this basis, appropriate methods such as time series method and virtual forecasting method will be introduced to test and improve the accuracy of the algorithm.

4.2.2 Time series method

Since the general yearbook information statistics power load information is discrete and each year is the data value of a time node, this paper will use the time series method to predict the power load[13].

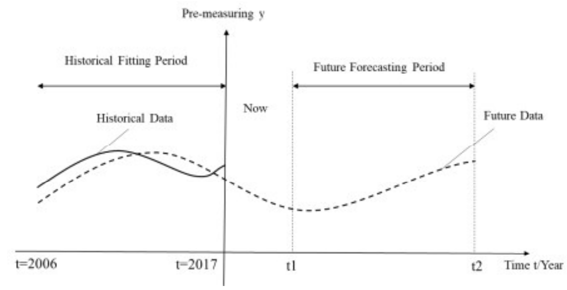

Figure 1 Schematic diagram of time series method

As shown in Figure 1, the time series method takes time t as the axis, and this paper uses one year as a time node t for load forecasting. The interval $t \in [2006,2017]$ is the known historical area power load data, which is called the historical fitting period. The interval $t \in [t1, t2]$ is the predicted power load forecast y, which is called the future forecast period. Due to the delay in the statistics and publication of regional yearbook data, there is a blank period in the interval $t \in [2017, t1]$.

4.2.3 Virtual prediction

The introduction of virtual forecasting method based on time series method can test the accuracy of power load forecasting algorithm. This article will focus on using the virtual prediction method to calculate the error between the virtual prediction value and the real value of the three algorithms to determine the accuracy of the algorithm.

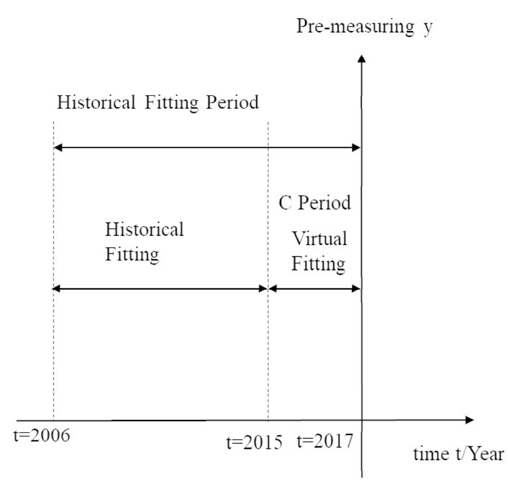

Figure 2 Schematic diagram of virtual prediction method

As shown in Figure 2, a virtual prediction period C is introduced in the interval , and the history fitting period is divided into history fitting and virtual fitting. The data prediction interval t of the known interval is called the virtual prediction value, and it is compared with the actual value of the interval to obtain the target error.

4.3 Artificial neural network method

Artificial neural network method is often used in power load forecasting, which has the characteristics of nonlinear mapping, high fault tolerance, autonomous learning, and the algorithm is easy to implement. Theoretically, the artificial neural network can approximate any regular nonlinear continuous function in three steps [14].

4.3.1 Artificial neural network theory

Artificial neural algorithms can be compared to biological neurons. Each input is a kind of stimulus, and each neuron is like an excitation function. The response of the nerve is the output, and there is a weight relationship between them. Different connection methods and different weight relationships will lead to different output results, which may also result in different results for each training. Mathematical model of artificial neural network[15]:

$$\mathrm{T} = \mathrm{F}（\vec{W}\vec{P} + \mathrm{b}）\quad \text{Formula (1)}$$

Where T is the operation output matrix, $\vec{W}$ is the weight vector, $\vec{P}$ is the operation input matrix, b is the threshold, and $F()$ is the transfer function of the entire operation.

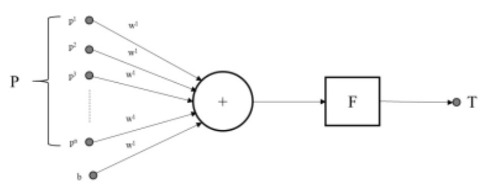

Figure 3 Schematic diagram of the mathematical structure of artificial neural network

4.3.2 Elman network

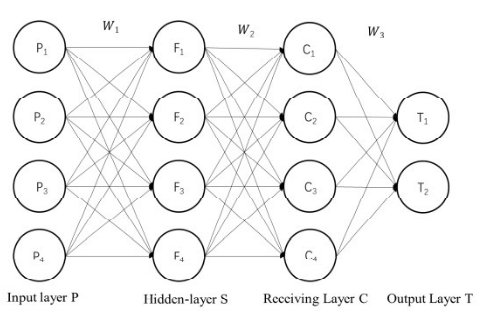

Figure 4 Schematic diagram of Elman network structure

The Elman network is an improved algorithm based on the BP network. The structural feature of the Elman network is to add a layer C after the hidden layer. The structure of the Elman network becomes four layers: input layer P, hidden layer S, receiving layer C, and output layer T [16]. The role of the Elman network receiving layer C is to record the data output by the hidden layer S at the previous moment to form a delayed delay operator. This enables the Elman network to perform internal feedback learning before outputting. The characteristics of memory also make the Elman network more sensitive to historical data than the BP network. The use of recursion makes the Elman network more powerful than the BP network, which can reduce the frequency of training and time of training

4.4 GM (1,1) in gray theory

If the certain data information is defined as a white event, and the unknown data information is defined as a black event. A system that includes both white and black events is called a gray system. Grey theory is a classic algorithm often used in power load forecasting. Its advantage is the analysis of small sample data. The grey theory model is generally expressed as GM(n,n). This article will use the GM (1,1) model in grey theory[17].

If the GM (1,1) model is used for regional load forecasting, only a set of original power information sequence $x^{(0)}$ needs to be constructed, and is:

$$x^{(0)} = [x_1^{(0)}, x_2^{(0)}, x_3^{(0)}, \cdots, x_n^{(0)}] \quad \text{Formula (2)}$$

After accumulating $x^{(0)}$ to get the new sequence $x^{(1)}$, then is:

$$x^{(1)} = \left[x_1^{(1)}, x_2^{(1)}, x_3^{(1)}, \cdots, x_n^{(1)}\right] \quad \text{Formula (3)}$$

$$x_k^{(1)} = \sum_{i=1}^{k} x_i^{(0)} \ (k = 1,2,3 \cdots n) \quad \text{Formula (4)}$$

Since the new sequence $x_k^{(1)}$ conforms to the linear differential equation[18]:

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

The mean expression of $x_k^{(1)}$:

$$x_k^{(1)} = \frac{1}{2}[x_k^{(1)} + x_{k+1}^{(1)}] \qquad \text{Formula (6)}$$

$$\frac{dx^{(1)}}{dt} = x^{(0)}(k+1) \qquad \text{Formula (7)}$$

Converted to matrix form:

$$\begin{bmatrix} x_2^{(0)} \\ x_3^{(0)} \\ x_4^{(0)} \\ \vdots \\ x_n^{(0)} \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\left[x_1^{(1)} + x_2^{(1)}\right] & 1 \\ -\frac{1}{2}\left[x_2^{(1)} + x_3^{(1)}\right] & 1 \\ -\frac{1}{2}\left[x_3^{(1)} + x_4^{(1)}\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x_{n-1}^{(1)} + x_n^{(1)}\right] & 1 \end{bmatrix} \begin{pmatrix} a \\ u \end{pmatrix}$$

Formula (8)

Simplified to:

$$y_n = BA \qquad \text{Formula (9)}$$

$$y_n = \begin{bmatrix} x_2^{(0)} \\ x_3^{(0)} \\ x_4^{(0)} \\ \vdots \\ x_n^{(0)} \end{bmatrix}、B = \begin{bmatrix} -\frac{1}{2}\left[x_1^{(1)} + x_2^{(1)}\right] & 1 \\ -\frac{1}{2}\left[x_2^{(1)} + x_3^{(1)}\right] & 1 \\ -\frac{1}{2}\left[x_3^{(1)} + x_4^{(1)}\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x_{n-1}^{(1)} + x_n^{(1)}\right] & 1 \end{bmatrix}、A =$$

$\begin{pmatrix} a \\ u \end{pmatrix}$, In this paper, the least square method is used to solve the parameters u and a to get [19]:

$$\hat{A} = (B^T B)^{-1} B^T y_n = \begin{pmatrix} \hat{a} \\ \hat{u} \end{pmatrix} \qquad \text{Formula (10)}$$

Bring $\hat{a}$ and $\hat{u}$ into $\frac{dx^{(1)}}{dt} + ax^{(1)} = u$ to get: $\hat{x}^{(1)}(k+1) = \left[x_1^{(0)} - \frac{\hat{u}}{\hat{a}}\right] e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}} \quad (k = 0,1,2,3,\cdots)$

Formula (11)

Finally, the above formula is reduced and reduced to get:

$$\begin{cases} \hat{x}_1^{(1)} = \hat{x}_1^{(0)} = x_1^{(0)} \\ \hat{x}_{k+1}^{(0)} = \hat{x}_{k+1}^{(1)} - \hat{x}_k^{(1)} = (1 - e^{\hat{a}})\left(x_1^{(0)} - \frac{\hat{u}}{\hat{a}}\right) e^{-\hat{a}k} (k = 1,2,3,\cdots \end{cases}$$

Formula (12)

The final power load forecast result is obtained through the calculate from Formula 2 to Formula 12.

4.5 Grey-Elman network model

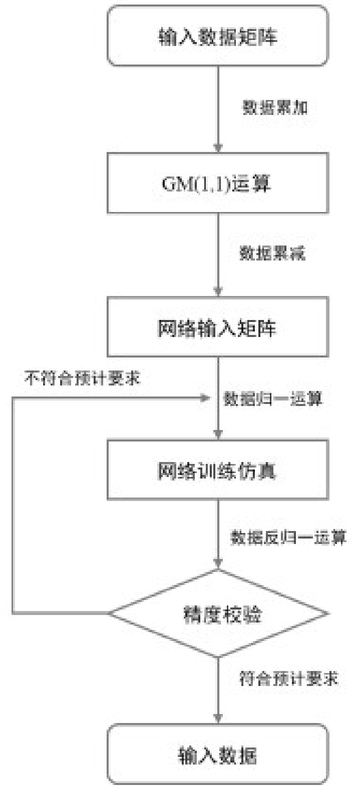

Figure 6 Schematic diagram of gray Elman network structure

The Elman neural network [20] is introduced into the GM (1,1) model in gray theory, and the original information of regional power and data of some related factors are input into the network. After the GM (1.1) model in gray theory outputs the data, after training and correcting with Elman network, the power load forecast results are output, and the GM (1,1) model in gray theory and Elman neural network are connected in series to form a gray Elman network.

5. SIMULATION

5.1 The code of Gray Elman network in MATLAB

5.1.1 Input data

```
y= [42.20;47.10;51.10;56.11;59.79;
  65.69;72.88;77.75;75.09;73.87];
```

Matrix y is the historical power load data of Huainan City from 2006 to 2015 shown in Table 2.

5.1.2 Accumulation and reduction of partial data in gray theory

1) Data accumulation

```
n=length(y);
yy=ones(n,1);
yy(1) =y(1);
for i=2: n
yy(i)=yy(i-1) +y(i)
end
```

2) Data reduction

```
yys(1) =y(1);
for j=n+t_test: -1:2
ys(j)=yys(j)-yys(j-1);
end
```

5.1.3 Least square method calculation parameters a (development coefficient), u (ash effect)

```
A=inv (BT*B) *BT*YN;
a=A (1);
u=A (2);
```

Using the above code can simplify the implementation of least squares statement.

5.1.4 Network data processing

The data is fed into the network through reduction, and then the premnmx() function and postmnmx() function are used to normalize the data respectively. This can enhance the underlying laws of the data and reverse normalization

1) Normalization processing

```
[pn,minp,maxp,tn,mint,maxt]=premnmx(P,T);
```

2) Reverse normalization processing

```
TestResult= postmnmx(PN,mint,maxt);
```

5.1.5 Network construction

Use the newelm() function and other related codes to build a network with Elman network characteristics, set the first layer transfer function tansig, the second layer set the linear function purelin, and the improved momentum gradient descent training model raningdm [21].

Set the network learning rate to 0.1, the additional momentum factor of 0.9, the maximum network training value to 500, and the target error to 5%, and initialize the network.

```
net=newelm(minmax(pn),[10,1],{‘tansig’,’purelin’},’traingdm’);
net.trainParam.lr =0.1;
net.trainParam.mc =0.9;
net.trainParam.epochs =500;
net.trainParam.goal=0.05;
net=init(net);
```

After the network is trained, the corrected value is output, and then compared with the real data to calculate the error. Repeat 50 times to simulate more accurate values.

5.2 Analysis of simulation results

This paper takes the “13th Five-Year Plan” energy plan in Huainan City, Anhui Province as an example, and uses MATLAB tools to design a power load forecasting experiment with a reference team, and predicts the data for 2016 and 2017 through virtual forecasting methods. Due to the randomness of the simulation results of Elman network and gray Elman network, 50 simulation experiments will be carried out, and various data will be summarized at the end. The calculation result of the GM (1,1) model is only once.

Table 3 Comparison table of virtual prediction results

Unit:/100 million kWh

year	GM (1,1) model	Elman network (mean value)	Gray Elman network (mean value)	True value
2016	85.43	82.31	83.05	83.11
2017	90.59	84.09	84.99	84.75

Through the numerical calculation shown in Table 3, the annual difference of the power load forecast of the three algorithms is compared in the following table:

Table 4 Comparison table of virtual prediction error

year	GM (1,1) model	Elman network	Gray Elman network
2016	2.79%	2.02%	1.56%
2017	6.89%	2.32%	1.94%
Average error	4.48%	2.17%	1.75%

The annual difference between the virtual predicted value and the real value by calculating the three algorithms is shown in Table 4.

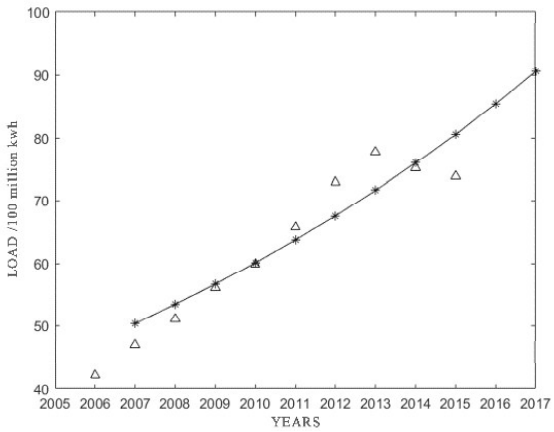

Figure 7 GM (1,1) model prediction fitting

The triangle in Figure 7 represents the historical power data values of Huainan City from 2006 to 2015, and the asterisks in the line represent the various power data processed by the GM (1,1) model. It can be seen from the figure that GM (1,1) The predicted value of the model has obvious exponential law. The large errors caused in 2012, 2013, and 2015 are due to the use of mid and long term load forecasting. Compared with short-term forecasting, the simulation has not yet introduced environmental and social influence factors to ensure the popularity of forecasting methods.

As shown in Table 4, the error of the predicted value of the GM (1,1) model increases year by year. It is believed that this is due to the exponential characteristic of the output value of the GM (1,1) model. The prediction error of Elman network and gray Elman network with neural network characteristics is smaller than that of GM (1,1) model, and the prediction error of gray Elman network is smaller than that of Elman network.

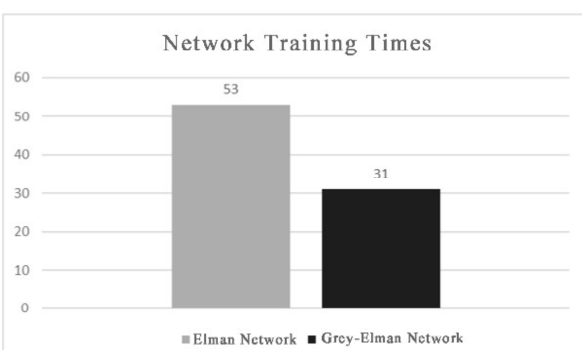

Figure 8 Comparison of two kinds of network simulation training result data

Figure 8 shows the average training times of 50 simulations of Elman network and gray Elman network. The average training times of the gray Elman network is significantly lower than that of the Elman network, that is, the Elman network needs an average of 50 training times to obtain the prediction result, and the gray Elman network is only used 31 times. This paper believes that this is because the original data of the gray Elman network is processed by the GM (1,1) model to obtain a set of network input matrices that are closer to the true value, which can shorten the number of network training.

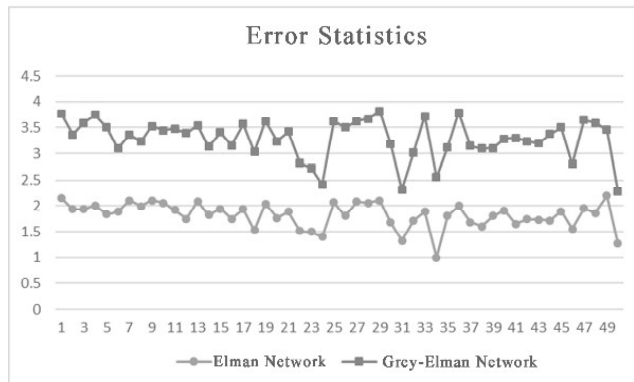

Figure 9 Two network simulation training error line graphs

Analyze the Elman network and the gray Elman network 50 simulation results, and then use the annual difference of the results as the point data and connect the points with a line to obtain a line chart as shown in Figure 9. The gray Elman network has a smaller annual error than the Elman network in fifty simulations.

In the 25 to 35 simulations, the fluctuation of the line graph of the Elman network training results increased, that is, the network training results differed greatly and the output value was unstable, while the gray Elman network improved significantly. Moreover, the fluctuation of the error line of the overall gray Elman network is obviously smaller than that of the Elman network, and the broken line is smoother. This shows that the output value of each training of the gray Elman network is closer to the true value.

CONCLUSION

Through simulation, the gray Elman network has less fluctuations in the virtual prediction error, average number of training times, and the error line of the calculation. It is believed that the calculation accuracy and training effect of the gray Elman network are better than the GM (1,1) model and the Elman network. Gray Elman network load forecasting can avoid situations such as GM (1,1) model outputting ideal index characteristics and Elman network falling into local minimum. In addition, the gray Elman network load forecasting model can achieve higher accuracy than the direct use of a single gray theory GM (1,1) model. It has fewer training times and higher accuracy than the direct single Elman network.

Reference

[1] Suggestions of Huainan Municipal Committee of the Communist Party of China on the formulation of the 13th five-year plan for the national economic and social development of Huainan City [N]. Huainan daily,2015-12-30(001).

[2] Jun SONG, Ling YANG, Qiang JIN. Soft sensor modeling method based on modified Elman neural network. Computer Engineering and Applications, 2008, 44(16): 233- 235.

[3] Yuancheng LI, Tingjian FANG, Erkeng YU. Study of support vector machines for short-term load forecasting[J]. Proceedings of the CSEE, 2003(06):55-59.

[4] Mengqiu LI, Ling FAN, Xiuyong REN, Ping LIU, Wenhao YUAN. Torque Ripple Control of Switched Reluctance Motor Based on RBF Neural Network[J]. Proceedings of the CSU-EPSA, 2017,29(12):28-34.

[5] Lei DONG, Mengxia LIU, Naishi CHEN, Shixiong FAN, Tianjiao PU. Coordinated Optimal Control of Distributed Energy Based on Stochastic Model Predictive Control [J]. Power System Technology,2018,42(10):3219-3227.

[6] Taonian LIANGÿ Yong L Iÿ Jilin DUÿ Chonghui ZHAO. Review of Control Strategies for Switched Reluctance Motor [J]. Small & Special Electrical Machines,2014,42(12):77-81.

[7] Dong WANG. The Summary of Power System Load Forecasting [J]. Electric Switchgear,2020,58(01):6-8+20.

[8] Huihuang XIE, Rongjin ZHENG, Xiaosheng HUANG. Application of trend extrapolation method in load forecasting of Lianjiang county [J]. Electric Age,2017(06):78-80.

[9] Wanzhen MA, Bin du. Research on medium and long term load forecasting method based on Improved Grey Theory [J]. Intelligent City,2019,5(23):20-21.

[10] Zhengda ZOU, Yaming SUNÿZhisheng ZHANG. Short-term load forecasting based on recurrent neural network using ant colony optimization algorithm [J]. Power System Technology,2005(03):59-63.

[11] Chao PAN, Baochun LU, Liying SUN, Weiguo GUAN.Review of Load Forecasting Methods in Power System [J]. Journal of Liaoning University of Technology(Natural Science Edition), 2016,36(05):296-299.

[12] Deqiang SUN. Analysis of Medium and Long-term Load Forecasting Technology in Power Network Planning [J]. Telecom Power Technology, 2019,36(12):154-155.

[13] Li QIN.The application of GM(1,1) model in the medium and long tern load forecasting in power system [J]. Hunan Agricultural Machinery,2013,40(05):104-105.

[14] Zhiyuan RUI, Lina REN, Ruicheng FENG. Load Forecasting Model for Gansu Electric Power Network Based on Elman Neural Network [J]. Modern Electric Power,2007(02):26-29.

[15] Ning LUO, Hua GAO, Molin HE. Research on power load forecasting method based on neural network [J]. Automation & Instrumentation, 2020(01):157-160.

[16] Buxiang ZHOU, Yanping LUO, Baifu ZHANG. Medium and long term load forecasting based on number orders grey Elman combination mode [J]. Water Resources and Power, 2019,37(02):192-195.

[17] Meijuan ZHAO, Zhongyan WANG. Improvement and application of GM (1,1) modeling method [J]. Mathematics in Practice and Theory,2006(11):110-116.

[18] Yafei ZHOU. Realization and application of GM (1,1) by MATLAB [J]. Journal of Changchun Normal University(Natural Science),2010,29(02):32-35.

[19] Yu LIUÿ Lin GUOÿ Feng YANGÿ Dengli JIANG, Ling RENÿJun LI. Medium and Long Term Load Forecasting Based on Improved Gray Theory [J]. Power System and Clean Energy, 2016,32(08):51-56+61.

[20] Hui WU, Dongpo XU, Zhengxue LI. Convergence of gradient learning method for Elman network [J]. Applied Mathematics and Mechanics, 2008(09):1117-1123.

[21] Yan WANG, Yuping QIN, ZhiQiang ZHANG, Zheng TANG, WeiJiang LIU. A kind of improved Elman neural network algorithm [J]. Journal of Bohai University(Natural Science Edition), 2007(04):377-380.