Long Term Power Load Combination Forecasting Based on Chaos-Fractal Theory in Beijing

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***Abstract* — Long term power load has a big impact on the development of industry of power. The forecasting models of linear systems even a single forecasting model of the nonlinear systems can not forecast the long term power load greatly. In the study, the combined forecasting model of nonlinear systems including chaos and fractal was established to improve the accuracy of the forecast. First, the characteristics of chaos and fractal of data were analyzed. Second, the forecasting models based on chaos and fractal were used to forecast the data. Finally, using the combined forecasting model predicted the long term power load and compared the results of combined forecasting model with the results of the single forecasting model. The results show that the combined forecasting model based on chaos-fractal theory has better effect on the forecast of long term power load.**

Keywords - Chaos; Fractal; Combined forecasting Model; Power load forecasting

I. INTRODUCTION

Forecast of power load which can provide a reliable basis for the construction of power plant in some where is an important part of the planning of power system. Therefore, the power load forecasting is very important to the healthy development of the power industry even to the development of the national economy.

Trend extrapolation, regression model and grey system have been widely used in the long term load forecast. However, these methods can not effectively deal with the phenomenon of random and complex. Because the power system is affected by many factors and mutual influence of the factors the nonlinear theory are introduced to analyze the long term power load. Chaos theory plays an important role in nonlinear theory. He Yang, Zou Bo, Li Wenqi used chaos and the local model to forecast the power load of a single day[1]. Zhang Yongqiang used the method of the chaotic local forecasting and largest Lyapunov exponent to forecast the short term power load [2]. Shen Jia used chaotic neural network to forecast the power load of 24 hours[3]. However, there are many defects like the local convergence and the convergence speed in the application of the chaotic neural network. Fractal theory as the perfect describe of the chaotic structure is also applied to the forecast of the power load. Li Xiang, Guan Yong, Guan Xuezhong, Tong Yu all used the method of fractal collage and fractal interpolation to calculate the iterative system of the daily power load and forecast the short term power load [4-6]. Because there are many shortcomings of the single forecasting method the combined forecasting model can improve the accuracy of forecast. Therefore, the combined forecasting model of chaos and fractal is used to forecast the power load in Beijing. At the same time, the previous studies of chaos and fractal are all stuck in short term load forecasting, we will make an empirical analysis to the long term power load system about chaos-fractal characteristics and then forecast.

II. THEORETICAL BASIS

2.1 Chaos Theory

Chaos is a seemingly random phenomenon in a deterministic system. Chaos has a sensitive dependence on initial conditions; in the phase space, the chaotic attractor has a self similar structure which show a fractal structure; chaos is internal randomness, the disorder comes from the internal system rather than outside disturbance; the trajectory of chaotic system is always confined to a certain region; there is a Feigenbaom universal constant in the system; ergodic property makes the chaotic system with different reaction to different initial conditions to convergence to a statistically similar attractor of phase space; the state of the system will suddenly change; the structure of local is similar to whole. The chaotic system is mainly due to the instability of the nonlinear system and the sensitivity to the initial conditions. The analysis of chaotic characteristics mainly uses the maximum Lyapunov exponent and fractal dimension.

2.2 Fractal Theory

Chaos and fractal are closely related and the orbits of the chaotic motion or the strange attractors are fractal. Motion of chaotic system is highly disordered and chaotic and the nature is reflected in the infinite complexity of fractal. Fractal is an appropriate language to describe the phenomenon of chaos. The fractal dimension is a quantitative parameter to study the chaotic phenomenon. Fractal was proposed by the French mathematician Mandelbrot in 1964 in order to represent the complex graphics and complex process to introduce to the field of

Natural Science. The fractal which is produced by iteration is irregular, approximate or statistical self-similar.

2.3 Combination Forecasting

The method of combined-forecasting weights and combines the forecasting results of the single model in order to get a higher precision of the predictive value. The combined forecasting improves the accuracy of forecast by the means of information integration to disperse the uncertainty of the single prediction model [7]. Combination forecasting can be divided into static combination forecasting and dynamic combination forecasting. The weight of the static combined forecasting model remains the same, and the weight of the dynamic forecasting model change with the sample [8].

III. FORECASTING MODEL BASED ON THE THEORY OF CHAOS-FRACTAL

The establishment of the model is divided into four parts including the processing of raw data, identification of the characteristics of chaos-fractal, the establishment of the single forecasting models based on chaos theory and fractal theory, the establishment of the combined forecasting model. The four parts form a reasonable forecasting model.

3.1 The Preprocessing of Original Data

First of all, the original data are processed by the first order difference after taking a log in order to reduce the noise of the original data and improve the accuracy of the load forecasting. Calculated as Eq.1:

$$lx_t = \log x_t - \log x_{t-1} \quad (1)$$

3.2 Recognition of the Characteristics of Chaos-Fractal

Chaos is produced because of the instability of the nonlinear system and the sensitive to initial conditions. The accurate quantitative method is used to calculate the estimated value of the singular attractor to judge the characteristics of chaos. The singular attractor is a phenomenon that is caused by instability of the orbital and shrink of phase space of the dissipative system. Therefore, the maximal Lyapunov exponent is used to describe the diverging rate of the adjacent orbit. The dimension of the attractor is represented by the fractal dimension.

3.2.1 Phase Space Reconstruction

The calculation of the maximal Lyapunov exponent and fractal dimension is based on the technique of the phase space reconstruction. Phase space is the geometric space of the determined state. The electricity consumption of the whole society is one dimensional time series, we get the coordinate of the delay by estimating the delayed parameter and then estimate the embedding dimension to reconstruct the phase space.

The time series of a certain state in a chaotic system is $\{x_t\}(t=1,2, \ldots, N)$, where N is the number of samples. According to the estimated parameters, the delay τ and embedding dimension m, reconstruct phase space Rm, obtain the dynamic characteristics of the original system. The point set in the reconstructed phase space is:

$$y_t^m = \{x(t), x(t+\tau), x(t+2\tau), \cdots x(t+(m-1)\tau)\} \quad (2)$$

The estimation of reasonable parameters is very important to reconstruct the phase space. As for the selection of parameters, the C_C algorithm is easy to operate and the working of calculation is less. The time series is divided into t disjoint sub sequences. Define the S(m,N,r,t) of each sub sequence is:

$$S(m,N,r,t) = \frac{1}{t}\sum_{s=1}^{t}\left[C_S\left(m,\frac{N}{t},r,t\right) - C_s^m\left(1,\frac{N}{t},r,t\right)\right] \quad (3)$$

Order N→∞,

$$S(m,r,t) = \frac{1}{t}\sum_{s=1}^{t}\left[C_s(m,r,t) - C_s^m(1,r,t)\right], m = 2,3,\cdots \quad (4)$$

If each sample data in the time series is independent and identically distributed, for the determined m and t, When N→∞, to all r, all S (m, R, t) is identical to 0. However, in fact the data we have chosen is limited and inevitable correlation. The criterion for determining the interval of local optimal time is S (m, r, t) =0 or S (m, t, r) with minimum deviation for all radius of r.

Select the value of the maximum and minimum of radius r, defined deviation is:

$$\Delta S(m,t) = \max\{S(m,r_j,t)\} - \min\{S(m,r_j,t)\} \quad (5)$$

Then the value of local optimal time T is S (m, r, t) =0 or minimum ΔS(m,t). The delay τ is the first local optimal time t.

Calculate variables:

$$\bar{S}(t) = \frac{1}{N_m * 4}\sum_{m=2}^{M}\sum_{j=1}^{4} S(m,r_j,t) \quad (6)$$

$$\Delta\bar{S}(t) = \frac{1}{N_m}\sum_{m=2}^{M}\Delta S(m,t) \quad (7)$$

$$S_{cor}(t) = \Delta\bar{S}(t) + \left|\bar{S}(t)\right| \quad (8)$$

Where Nm is the number of m, $r_j=i_\sigma/2$,i=1,2,3,4. Find the minimum value of variable Scor (t), obtain the time window t of the first maximum of time series $\{x_t\}$. m is obtained according to the following Eq.9:

$$\tau_w = (m-1)\tau \quad (9)$$

We get the estimation τ of time delay and parameters m of embedding dimension.

3.2.2 Lyapunov Exponent

The sensitivity of the initial condition is expressed by the separation speed of the neighboring two points in the chaotic system. The Lyapunov exponent is the estimate of the diverging rate. Its definition is:

$$\lambda(x_0) = \lim_{N\to\infty}\lim_{\varepsilon\to 0}\frac{1}{N}\log\left|\frac{f^{(N)}(x_0) - f^{(N)}(x_0+\varepsilon)}{\varepsilon}\right| \quad (10)$$

The diverging rate of exponential of adjacent initial trajectories in phase space is determined by calculating the Lyapunov exponent, so as to quantify the degree of chaos.

Using Wolf algorithm to calculate the Lyapunov exponent:

In the reconstructed phase space the initial point $Y(t_0)$ is obtained, setting up the distance from the nearest piont$Y_0(T_0)$ is L_0, with the continuous movement of two points, until time T1, the distance beyond a certain value ε>0, L_0'$|Y(t_1)-Y0(t_1)|>\varepsilon$, retain $Y(t_1)$ and then in the vicinity of $Y(t_1)$ to find another point $Y_1(t_1)$, bring $|Y(t_1)-Y_1(t_1)|<\varepsilon$ and make the angle between the two as small as possible, cycle the above process, until Y (t) runs to the end of the time series N. At this time, the total iterations of the whole process of motion is M', the maximal Lyapunov exponent is:

$$\sigma = \frac{1}{t_{M'} - t_0} \sum_{i=0}^{M'} \ln \frac{L_i'}{L_i} \quad (11)$$

Lyapunov exponent describes the state of two initial close points after a number of iterations, they can be positive, negative or zero. When the exponent is less than zero, the distance between two adjacent points keeps approaching by the rate of exponential quantity, the motion is stability, and the system is not sensitive to the initial condition. When the exponent is equal to zero, there is a stable boundary. When the exponent is greater than zero, the trajectory of the adjacent points is in a state of rapid separating. The trajectory is local instability and forms the chaotic attractor. Therefore, the maximal exponent is greater than zero is the basis for the identification of chaos.

In a multidimensional system, there is a Lyapunov exponent in each direction. All the Lyapunov exponents form the set of Lyapunov exponent. Each of these Lyapunov exponents describes the converging state of the trajectory in a certain direction in the chaotic system. One of the necessary conditions of chaos is the maximum Lyapunov exponent greater than zero.

At the same time, the Lyapunov exponent can be used to estimate the forecasting duration of the system, as Eq.12:

$$t \approx 1/\lambda \quad (12)$$

3.2.3 Fractal Dimension

By calculating the fractal dimension we analyze another important characteristic of the chaotic system. That is the set of all solutions of the trajectory in phase space has fractal characteristics. The fractal dimension is calculated by using the G_P algorithm which is simple and easy. In the reconstructed phase space calculate correlation integral:

$$C_N(r) = \frac{1}{N^2} \sum_{i,j=1, i \neq j}^{N} \theta(r - |X_i - X_j|) \quad (13)$$

Among them, θ(x) is the unit function of Heaviside, when x>0，θ(x)=1, otherwise θ(x)=0. When r→0, there is a relationship between CN(r) and r:

$$\lim C_N(r) \propto r^D \quad (14)$$

Among them, D is the fractal dimension, take a log of the above equation:

$$\log(C_N(r)) = D\log(r) + constant \quad (15)$$

Linear regression of the formula, the estimated value of fractal dimension D is the slope of logCN(r) to logr.

3.3 The Establishment of the Combination Forecasting Model of Chaos-Fractal

3.3.1 Neural Network Forecasting Model Based on Chaos Theory

The forecast of chaotic time series based on neural network is by using the ability of the nonlinear approximation of neural network in the phase space reconstruction to find the similar evolution law.

The transfer function of each hidden layer of neuronal of the network constitutes a base function of the fitting plane[9]. Generally use Gaussian function, which was expressed as Eq.2:

$$R_i(x) = \exp\left(-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right), i = 1, 2, \ldots, m \quad (16)$$

Where: x is n-dimensional entered vector; c_i is the center of i-th basis function;σ_i is the planning factor of the i-th base function; m is the number of hidden nodes. $\|x - c_i\|$ is the norm of the vector x-c_i, it usually represents the distance between x and c_i; there is a unique maximum of $R_i(x)$ at c_i , with the increasing of $\|x - c_i\|$, Rix decay to zero rapidly. For a given input,only a small portion near the center of x is activated. Set input layer entered as $X=(x_1, x_2,\ldots,x_j,\ldots, x_n)$, the actual output is $Y=(y_1, y_2,\ldots, y_k,\ldots, y_p)$.The input layer achieves a linear mapping from $X \rightarrow R_i(x)$, the output layer achieves a nonlinear mapping from R (X) → y_k, k-th neuronal network output in the output layer is Eq3:

$$y_k = \sum_{i=1}^{m} w_{ik} R_i(x), k = 1, 2, \ldots, p. \quad (17)$$

Where: n is the input layer nodes; m is the hidden nodes; p is the output layer nodes; w_{ik} is the connection weights of the i-th neuron of hidden layer and the k-th neuron of output layer; $R_i(x)$ is the action function of i-th neuron of the hidden layer.

3.3.2 Fractal Interpolation Forecasting Model Based on Fractal Theory

Given a data set{（x_i,y_i):i=0,1,2,....N)}, the following constructs a IFS, its attractor G is the image of a continuous function f：$[x_0,x_N]\rightarrow R$ of interpolation data. Consider IFS{R2；w_n，n=1,2,...N}, Among them W_N is a simulation transformation with the following form.

$$w_n \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a_n & 0 \\ c_n & d_n \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} e_n \\ f_n \end{bmatrix} \quad (18)$$

And

$$w_n \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} x_{n-1} \\ y_{n-1} \end{bmatrix} w_n \begin{bmatrix} x_N \\ y_N \end{bmatrix} = \begin{bmatrix} x_n \\ y_n \end{bmatrix} \quad (19)$$

Where b_n=0 is to make sure that the function of inter cell does not overlap. Specifically written as:

$$\begin{cases} a_n x_0 + e_n = x_{n-1}, \\ a_n x_N + e_n = x_n, \\ c_n x_0 + d_n y_0 + f_n = y_{n-1}, \\ c_n x_N + d_n y_N + f_n = y_n. \end{cases} \quad (20)$$

There are five parameters in the four equations. So there is one free parameter. In the fact the transformations of matrix in the definition is elongation transformation. The line segment which is parallel to the Y axis is mapped to the other line segment of the Y axis and the ratio of the length of the two segments is |dn|. dn is also known as the vertical scaling factor of the transformation of the WN.Obviously we can choose dn as the free parameter. Order |dn|<1(otherwise IFS does not converge), solve equation group, and order $L=x_N-x_0$,

$$\begin{cases} a_n = L^{-1}\left(x_n - x_{n-1}\right), \\ e_n = L^{-1}\left(x_N x_{n-1} - x_0 x_n\right), \\ c_n = L^{-1}\left[y_n - y_{n-1} - d_n\left(y_N - y_0\right)\right], \\ f_n = L^{-1}\left[x_N y_{n-1} - x_0 y_n - d_n\left(x_N y_0 - x_0 y_N\right)\right]. \end{cases} \quad (21)$$

3.3.3 Combination Forecasting Model

we choose four indicators to evaluate the effect of forecasting including the mean absolute error, the mean percentage absolute error, the root mean square errors, the root mean percentage square errors. Then we will make a comparative analysis of the dynamic combined forecasting model with the forecasting results of two separate forecasting models.

The mean absolute error is the mean of the absolute value of the difference between forecasting result and the actual value, as Eq.18:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\left(\hat{y}_t - y_t\right)\right| \quad (22)$$

The mean percentage absolute error is the mean absolute value of the ratio of the difference between the forecasting result and the actual value and the actual value, as Eq.20:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\left(\hat{y}_t - y_t\right)/y_t\right| \quad (23)$$

The root mean square errors are the mean square value of the difference between forecasting result and the actual value, as Eq.19:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{y}_t - y_t\right)^2} \quad (24)$$

The root mean percentage square errors is the extraction of a root of the ratio of the square of the difference between the forecasting result and the actual value and the square of he actual value, as Eq.21:

$$RMPSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\frac{\left(\hat{y}_t - y_t\right)^2}{\left(y_t\right)^2}} \quad (25)$$

Among them, n is the number of the forecasting period, $\hat{y}_t$ is the forecasting result of y_t.

According to the principle of the error minimization of combination forecasting the weight functions of the combined forecasting model are built on the basis of using the forecasting model of chaos and fractal.

The average forecasting error produced by the individual forecasting model is ERR:

$$ERR = \frac{1}{4}\left(MEA + MAPE + RMSE + RMPSE\right) \quad (26)$$

Then, ERR_1 and ERR_2 correspond to the average forecasting error of the forecasting model of chaos and fractal.

The sum of the average error function is denoted as SUM_{ERR}:

$$SUM_{ERR} = ERR_1 + ERR_2 \quad (27)$$

Then the weight functions are built according to the principle that the error of combination forecasting is minimized.

$$W_1 = \frac{\frac{1}{ERR_1/SUM_{ERR}}}{\frac{1}{ERR_1/SUM_{ERR}} + \frac{1}{ERR_2/SUM_{ERR}}} \quad (28)$$

$$W_2 = \frac{\frac{1}{ERR_2/SUM_{ERR}}}{\frac{1}{ERR_1/SUM_{ERR}} + \frac{1}{ERR_2/SUM_{ERR}}} \quad (29)$$

The purpose is to make the single model of the maximum error to occupy the smallest proportion in the combined forecasting model. Furthermore, the setting of weight function can guarantee that the weight coefficients of the combined forecasting model are driven by the data and avoid the subjective determination of the coefficient of the forecasting model[10]. Finally, according to the selected sample set and the above weight functions the weighted average of 2 separate models is calculated and then the predictive value is got based on dynamic combination forecasting model.

IV. LONG TERM POWER LOAD FORECASTING BASED ON CHAOS-FRACTAL THEORY IN BEIJING

We select the electricity consumption of Beijing from 1979 to 2015 from Beijing Electric Power Corporation as the original data. In order to reduce the noise of the original data and improve the accuracy of prediction, use the formula of 2.1 (1) to process the data, as shown in Table I.

After the pretreatment of the data, using the method of 2.2 calculate the maximal Lyapunov exponent and the fractal dimension of the system.

4.1 Empirical Analysis of The Characteristics of Chaos-Fractal

The method of numerical analysis is used to demonstrate the chaos-fractal characteristics of the data of the long term power load. The parameters of the phase space reconstruction are obtained by the C_C algorithm. The phase space is reconstructed according to the parameters and then the maximal Lyapunov exponent and fractal dimension are obtained by using the Wolf algorithm and the G_P algorithm. The MATLAB software is used to estimate the parameters, reconstruct the phase space and obtain the relevant values.

TABLE I DATA AFTER PRETREATMENT

YEAR	LOGXN-LOGXN-1	YEAR	LOGXN-LOGXN-1	YEAR	LOGXN-LOGXN-1	YEAR	LOGXN-LOGXN-1
1980	-0.0381	1990	-0.0134	2000	-0.0319	2010	-0.0301
1981	-0.0274	1991	-0.0246	2001	-0.1117	2011	-0.0397
1982	-0.0063	1992	-0.0304	2002	-0.0172	2012	-0.0063
1983	-0.0284	1993	-0.0375	2003	-0.0414	2013	-0.0269
1984	-0.0141	1994	-0.0390	2004	-0.0265	2014	-0.0189
1985	-0.0320	1995	-0.0283	2005	-0.0404	2015	-0.0112
1986	-0.0313	1996	-0.0348	2006	-0.0460		
1987	-0.0285	1997	-0.0405	2007	-0.0302		
1988	-0.0366	1998	-0.0329	2008	-0.0377		
1989	-0.0305	1999	-0.0203	2009	-0.0145		

TABLE II PARAMETERS OF PHASE SPACE RECONSTRUCTION

τ	m	tw	N
3	5	1	36

τ=3 and m=5 are got through the C_C algorithm. The maximal Lyapunov exponent of the total electricity consumption in Beijing from 1979 to 2015 is 0.0867. The maximal Lyapunov exponent is greater than zero.It indicates that the trajectory of the adjacent points is quickly separated. The orbit is local instability and the system is sensitive to initial conditions, which is satisfied the necessary condition of chaotic characteristics. According to the Lyapunov exponent it can be estimated that the predicted period of system is 11.5.

At the same time the calculating formula of G_P algorithm is ran. The fractal dimension of total electricity consumption in Beijing from 1979 to 2015 is -0.0317, as shown in Table1

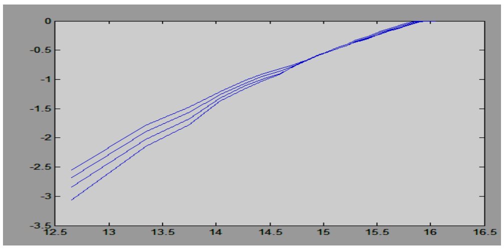

Figure.1 Graph of fractal

The maximal Lyapunov exponent is positive and the fractal dimension is non integer, which proves that the system of long term power load has characteristics of chaos and fractal. Then the models of the chaotic neural network and the fractal interpolation can be used to forecast.

4.2 Long Term Power Load Forecasting Based on Chaos Theory

Before the prediction, the data have to be normalized. The data from 1979 to 1996 are selected as training data, and the data from 1997 to 2015 are selected as test data. The date is preprocessed by the phase space reconstruction and the power load is forecasted by the intelligent algorithm of neural network. Then we choose four indicators to evaluate the effect of forecasting, such as the mean absolute error, the mean percentage absolute error, the root mean square errors and the root mean percentage square errors. Error evaluation indicators are shown in Table 3.

TABLE III. PREDICTION RESULTS

	MAE	MAPE	RMSE	RMPSE
Error of chaotic forecast	0.0044	0.0000218	0.49	0.557

As can be seen from the above table, the mean absolute error and the mean percentage absolute error of the chaotic forecasting model are relatively small. The former is less than 5/1000, and the latter is only 2/100000. The root mean square errors and the root mean percentage square errors are relatively large, and the error almost reaches 50%. So, chaos forecasting model has both advantages and disadvantages. The best results can not be obtained only by the chaos forecasting model.

4.3 Long Term Power Load Forecasting Based on Fractal Interpolation

The original data is plotted according to the electric consumption in Beijing from 1979 to 2015, as shown in Fig.2. Before constructing the fractal interpolation model, the point set of the fractal interpolation needs to be selected firstly. Beijing power grid will be divided into 13 sub ranges from 1979 to 2015 and the length of each interval is 2. The longitudinal compression ratio is set to be 0.03, and the iteration number is 4. The Matlab programs are written to construct a deterministic iterative function system with affine transformation based on the existing interpolation points and the longitudinal compression ratio. The fractal interpolation curve is shown in Fig.3.

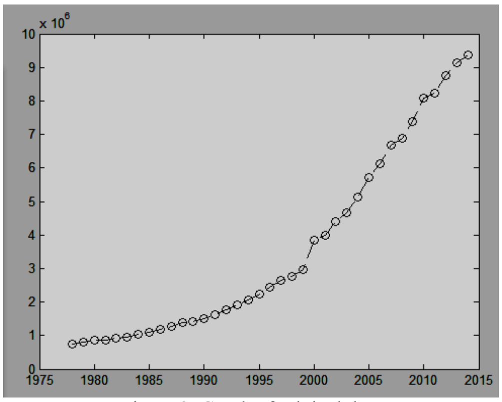

Figure.2. Graph of original data

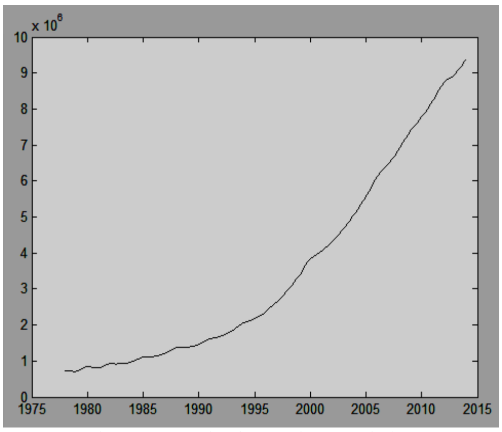

Figure 3. Graph of Fractal Interpolation

Comparing the original data graph with the graph plotted by fractal interpolation, we can see that there are subtle differences between the two maps. The error between the actual value and the fitted value is shown in Table IV.

TABLE IV. HE ERROR OF FRACTAL INTERPOLATION

	MAE	MAPE	RMSE	RMPSE
The error of fractal interpolation	0.0076	0.00016	0.064	0.16

As can be seen from the above table the mean percentage absolute error is 1/10000. The root mean percentage square errors is larger but it is only 16%. While the mean absolute error is less than 1%, the root mean square errors are less than 7%. The result shows that the model of the fractal interpolation can predict the future value of the power load accurately. However, the individual indicator of error is still larger than that of the chaotic forecasting model.

4.3 Combination Forecasting for Long Term Power Load

In order to avoid the defects and inaccuracy of the single forecasting model, the combined forecasting model is put into use to calculate the error on the basis of the above two forecasting models. Then, this section makes a comparative analysis with the single forecasting model.

TABLE V THE ERROR COMPARISON OF SINGLE MODEL AND COMBINED MODEL

	MAE	MAPE	RMSE	RMPSE
Chaos	0.0044	0.0000218	0.49	0.557
Fractal	0.0076	0.00016	0.064	0.16
Combination	0.0070	0.000135	0.141	0.232

The error of two single forecasting models is relatively small and both of them are less than 1% in the first two evaluation indexes. The error of the chaotic forecasting model is smaller and only reaches 2/100000. In the last two evaluation indicators, the error of the chaotic forecasting model is significantly larger than that of the fractal model, and the advantages of fractal forecasting model are shown. However, the error of the combined forecasting model is controlled within a small range in all the evaluation indexes. Using the combined model, the advantages of the two single forecasting models can be combined and the disadvantages can be reduced.

In the combined forecasting model the forecasting model with larger error accounts for a smaller proportion and the smaller one accounts for a larger proportion by setting the dynamic weight, so as to improve the accuracy and stability of forecasting.

V. CONCLUSION

Because of the randomness and instability of long term power load, this paper selects the typical nonlinear analysis methods such as chaos and fractal for combined forecasting to improve the accuracy of forecasting. We make an empirical analysis of the long term power load by using phase space reconstruction technique, C-C algorithm and G-P algorithm, and found that the time series has characteristics of chaos and fractal. Then, the chaos prediction model and the fractal interpolation method are used to predict the data. On the basis of data prediction by the neural network forecasting model based on Chaos theory and forecasting model of fractal interpolation, this paper makes the dynamic combination forecasting. It is found that the prediction error is significantly reduced after combined forecasting and the effect of combined forecasting is better than that of any single prediction model.

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