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A new method for short-term load forecasting based on fractal interpretation and wavelet analysis

Ming-Yue Zhai

School of Electrical and Electronic Engineering, North China Electric Power University, Beijing 102206, China

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ABSTRACT

Load forecasting based on fractal interpolation is a very important method. However, traditional methods exists several disadvantages such as vertical scale factor difficult to calculate, low-precision, difficult to use. Therefore, a method is proposed combined with self-similarity theory and fractal interpolation theory to solve the above problems. In this paper, the self-similarity of electrical load historical data is analyzed using multi-resolution wavelet firstly, then use the Hurst parameter values to calculate vertical scaling factors in Iterative Function Systems (IFS) based on the values of Hurst parameter. The vertical scaling factors can be used to get the other parameters of IFS affine transformation. Then the electrical load forecasting curve was generated by the iterations system. According to the actual needs of electricity production, this algorithm was used to forecast electrical load from two aspects: fractal interpolation and fractal extrapolation, and the average relative errors are only 2.303% and 2.296%, in the case of only six interpolation points for the entire set of forecast data. The result shows this algorithm has advantages of high-precision, less-sample demands, less-interpolation points and easy to use.

Introduction

Power load forecasting is one of the important works of power dispatching department. Improving the technical level of power load forecasting not only can accurately predict the demand of electricity market and convenient to power companies develop reasonable grid construction planning to improve the economic and social benefits of the system, but also be effective to predict the safety of power system operation and provide a reliable basis for the grid operation, maintenance and repair.

In recent years, with the rapid development of artificial intelligence theory, chaos theory, and vector machine model theory, artificial neural network [1], fuzzy comprehensive evaluation method and support vector machine model method have been widely used in the short-term load forecasting [2,3]. Luis Hernndez presented a very novel solution for short-term load forecasting (STLF) in micro-grids. The proposed system includes pattern recognition, a k-means clustering algorithm, and demand forecasting. The model is validated using micro-grid-sized environment provided by the Spanish company Iberdrola. By computation, the model produces low errors compared to other simple models. At the same times, Luis Hernndez applied STLF in microgrid environments with curves and similar behaviors, using two different data sets: the first one packing electricity consumption information during four years and six months in a microgrid along with calendar data, while the second one will be just four months of the previous parameters along with the solar radiation from the site. The author discussed the first set of data by different STLF models, studying the effect of each variable, in order to identify the best one. The best model was employed with the second set of data, in order to make a comparison with a new model that takes into account the solar radiation, since the photovoltaic installations of the microgrid will cause the power demand to fluctuate depending on the solar radiation.

In view of the power load values are generally subject to the power system operating conditions, the interactive effects of the local electricity consumption levels, market supply and demand, and so on. Combined with the power system nonlinear characteristics, it is feasible to use the nonlinear theory to study the power load forecasting. In recent years, many experts and scholars have introduced the fractal interpolation theory proposed by Barnsley into short term load forecasting. The paper [4] proposed a method to construct an iterated function system, and then directly get the predicted curves. This method has higher accuracy, but the core parameter of the iterated function systems was given based on experience and lack of the accurate quantitative estimation. The paper [5] proposed a method to calculate the vertical scale factor: firstly, block the original data, and then establish an iterated function system to each sub-block. Finally, give the weight of each iterated function system and calculate the mean value of vertical scale

E-mail address: mingyue.zhai@gmail.com

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factor obtained from each sub-block. The method is simple, but lack of data sub-block method and guidelines. Especially in the sub-block endpoints, data mutation will cause the vertical scale factor values deviate from the range of [0, 1]. So far, we have no effective solutions.

In order to solve the above problems, this paper studies the self-similarity of the power load, and proposes a new method to calculate the vertical scale factor, which combine self-similarity theory with fractal interpolation theory. It solves the problem of construction of iterated function system effectively. The computer simulation result shows that the method can be applied to short-term power load forecasting.

Improved fractal interpolation

The theory of fractal interpolation

In 1986, Barnsley proposed the fractal interpolation method based on fractal collage principle. For data sets: $\{(x_n, y_n) : n = 0, 1, \ldots, m\}$ an iterated function system could be constructed. The attractor of this IFS is close to the fractal interpolation function $f(x)$, we need use the affine transformation to achieve an iterated function system [6]:

For data set $\{R^2; w_i, i = 0, 1, \ldots, m\}$, affine transformation w_i is:

$$\begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix} \rightarrow w_i \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a_i b_i \\ c_i d_i \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} e_i \\ f_i \end{bmatrix} \tag{1}$$

For Eq. (1), let $b_i = 0, a_i, d_i, c_i, e_i, f_i$ meet the following four linear equations:

$$\begin{aligned} & a_i x_0 + e_i = x_{i-1} \\ & a_i x_N + e_i = x_i \\ & c_i x_0 + d_i y_0 + f_i = y_{i-1} \\ & c_i x_N + d_i y_N + f_i = y_i \end{aligned} \tag{2}$$

The d_i is a free variable, $d_i \in [0, 1)$ otherwise, the iterated function system does not converge. The other five constants of w_i can be expressed as:

$$\begin{aligned} a_i &= \frac{x_i - x_{i-1}}{x_N - x_0} \\ c_i &= \frac{y_i - y_{i-1}}{x_N - x_0} - d_i \frac{y_N - y_0}{x_N - x_0} \\ e_i &= \frac{x_N x_{i-1} - x_0 x_i}{x_N - x_0} \\ f_i &= \frac{x_N y_{i-1} - x_0 y_i}{x_N - x_0} - d_i \frac{x_N y_0 - y_N x_0}{x_N - x_0} \end{aligned} \tag{3}$$

From Eq. (3), the selection of has a greater influence on the calculation of the other four parameters affine transformation. Therefore, an accurate estimate of is particularly important for predicting results.

Improved fractal interpolation algorithm

According to fractal theory, G is the attractor of the iterated function system, if $\sum_{n=1}^{N} |d_n| > 1$, and the interpolation points are not collinear. Then fractal dimension of the fractal interpolation function attractor satisfies the equation:

$$\sum_{n=1}^{N} |d_n| a_n^{D-1} = 1 \tag{4}$$

For Eq. (4), if we can verify the self-similarity is one of the characteristics of the power load, then we use the fractal box dimension D to calculate d_n. Here, the fractal box dimension D and the Hurst value H has the following relationship [7,8]:

$$D = 2 - H. \tag{5}$$

Therefore, use an accurate estimate of value H to calculate d_n is a reasonably simple method, meanwhile, also combine self-similarity theory and fractal interpolation theory closely.

Here, we make a reasonable assumption: assuming that each vertical scaling factor value d_n equal to the size, is equal to $|d|$, then:

$$|d| = \frac{1}{\sum_{n=1}^{N} a_i^{1-H}}. \tag{6}$$

According to Eq. (6), after estimate the parameters Hurst, we will get the value of d. Then calculate the other iterative parameters by Eq. (3), the complete iterated function systems will be constructed.

Here, define the average standard error between prediction curve and original historical curve is:

$$e = \sqrt{\frac{1}{n} \sum_{i=1}^{i=n} (\hat{y}_i - y_i)^2}. \tag{7}$$

where y is predictive value, y_i is the original historical data. is the number of forecast points. If the average standard error is small, we would consider the prediction is accurate.

Self-similarity of the power load

From the above we can calculate the D value from the point of view of the fractal dimension of fractal interpolation curve. But we must make sure that the load data set has the characteristics of self-similarity. Therefore, we need to studied the self-similarity of the power load firstly, and the purpose of this work is to draw two important conclusions: (1) Prove that the power load data has the characteristics of self-similarity. (2) Use a high-precision parameter estimation method to estimate the Hurst value. We carry out specific studies for these two aspects.

The study of self-similarity of the power load

Power load series is a discrete sequence which time is independent variable. If we observe in a fixed period, we will find the overall curve showing an obvious regularity. This regularity is called the geometric self-similarity (as shown in Fig. 1) [9]. Especially for long-term load data, this self-similarity is more apparent. This paper selects a set of five consecutive days load data from a power

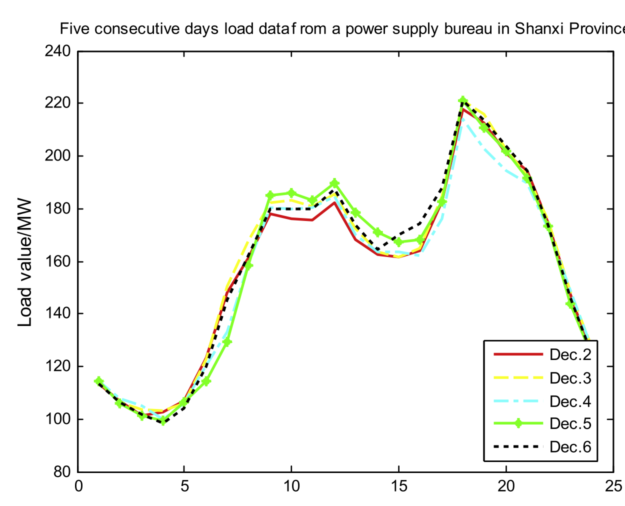

Fig. 1. Five consecutive days load data from a power supply bureau in Shanxi Province.

supply bureau in Shanxi Province as the sample. Now we analyze the self-similarity of the electric load data with the method of wavelet analysis [10,11].

Hurst parameter estimation based on wavelet method

For a wide-sense stationary random process $\{X_n\}_{n=0,1,2,\ldots}$, if $X(\upsilon)$ is the power spectrum of $\{X_n\}_n$ satisfy:

$$\{X_n\}_{n=0,1,2,\ldots} C_f|\upsilon|^{1-2H}. \tag{8}$$

Then the process $\{X_n\}_n$ is called the progressive self-similar process [16]. For the random process $\{X_n\}_{n=0,1,2,\ldots}$, its wavelet decomposition can be obtained wavelet scaling function $\Phi_{J,K}(t)$ and the wavelet function $\Psi_{J,k}(t)$. Here we should be noticed that the $\Phi_{J,K}(t)$ and $\Psi_{J,k}(t)$ will be changed if we chose different types of wavelet [10].

$$\begin{aligned} a_x(J,k) &= < X, \Phi_{J,k}(t) > \\ d_x(J,k) &= < X, \Psi_{J,k}(t) > \end{aligned} \tag{9}$$

where $d_x(j,k)$ is the wavelet transform coefficient of $X_n, n = 1, 2, \cdots$, then a following relationship was established:

$$\begin{aligned} \log_2(\hat{\Gamma}_x(2^{-j}\upsilon_0)) &= \log_2\left(\frac{1}{n_j}\sum_k |d_x(J,k)|^2\right) \\ &= (2\hat{H}-1)j + \log_2 \hat{C}_f \end{aligned} \tag{10}$$

where n_j is the number of wavelet coefficients under current decomposition levels, according to the above equation, different decomposition levels will lead to different values of $\widehat{H}$. Then we use the Matlab software to simulate above process. The result could be observed form Fig. 2, which j is the decomposition level and the abscissa axis, $\log_2(\frac{1}{n_j}\sum_k |d_x(J,k)|^2)$ is the vertical axis, by the least squares straight line fitting, the slope is $(2\widehat{H}-1)$, then Hurst value can be obtained.

With the above analysis methods to analyze the electric load data, we get the Hurst value is 0.9010. Obviously, $0.5 < H < 1$, so we prove that this data set has the self-similar characteristic. The value of H is more closer to 1, the self-similar degree is more apparent [12]. In fact, the re-scaled range analysis, time-variance method, the period-gram method, and other Hurst parameter estimation will get similar result.

An improved method for short-term load forecasting based on fractal interpretation

Two aspects of problems are often encountered in the practice of power load forecasting:

(1) For the existing historical data (Working day), due to the influences come from system failure, outside interference, human error and other factors, system had only measure load value at part time points, but several other moments of load value is not measured. So we need a reliable prediction of these moments to complement the historical data.
(2) For the future data (have not happened yet), we need accord the laws of historical data trend to forecast data value. If predicted values deviate from the actual value is too large, may be a sign of system failure and other emergencies.

The two problems correspond to the fractal interpolation and fractal extrapolation respectively.

Fractal interpolation

This paper selects three consecutive load data as the objects for the study, the main prediction steps are as follows:

(1) Sample selection: we chose December 6 as the starting day, the day before that day (December 5) is the base day, and December 4 and December 3 are the similar days.
(2) Determine the interpolation point sets: we select the main feature points of December 3, 4, 5, usually these points concentrate in the starting point, end point, peak point and valley point. In this paper we choose 1:00, 4:00, 9:00, 12:00, 18:00, 24:00 six time point as the set of interpolation points, then 18 values were divided into five segments to predict.
(3) Construct the iterated function system: we use the self-similarity analysis methods to analyze the load date selected from December 3, 4, 5, and then calculate the vertical scale factor by the Hurst value. According to step (2) to establish the IFS, we can get the following four parameters: a_i, c_i, e_i, f_i. Then give a certain weight for each parameter and calculate the mean value, a statistical IFS will be established successfully.
(4) Get the predicted curve based on fractal interpolation: we select the load value of December 6 at 1 am to start the iteration function system, the resulting attractor is the

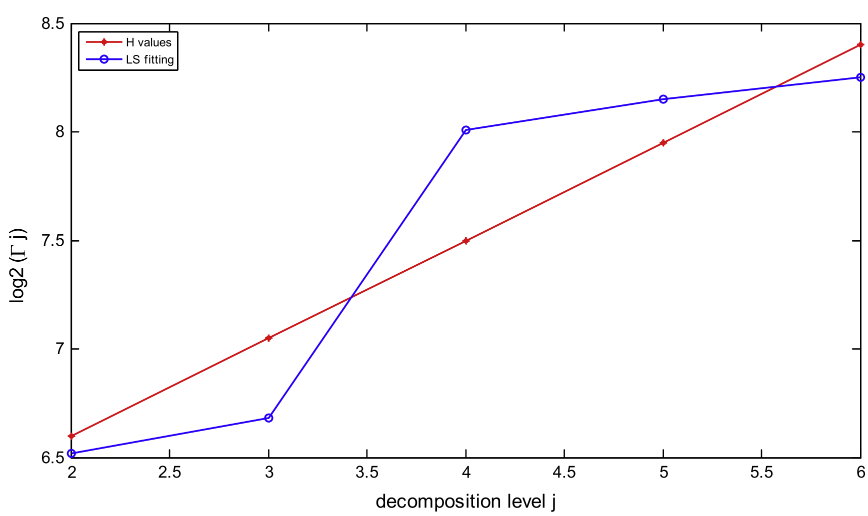

Fig. 2. Hurst parameter estimation based on wavelet method.

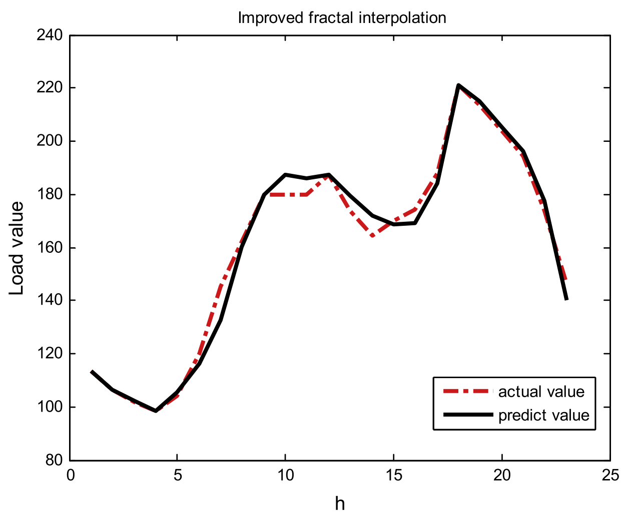

Fig. 3. The prediction results by the proposed and compared methods.

corresponding load predict curve (shown in Fig. 3 and the prediction error shown in Table 1).

We also performed comparison between the proposed fractal interpolation method and the method presented in [13]. The comparison is shown in Fig. 3. We can see that the prediction errors for these two methods are at the same level, therefore, we can believe that the proposed method can get as good prediction as other methods, but with less computation.

Fractal extrapolation

From the view of fractal self-similarity and scale invariance, it can be concluded that when the epitaxial initial interpolation points on the extension of the attractor, this extension of interpolation point will have the same fractal characteristics to the interval point. Moreover, if the extended point closer to the interval range, more fractal characteristics will be reserved. Based on this method, just make sure the historical data with self-similarity, we can choose a future point as a starting point into Eq. (1), generate a new prediction curve. If the average standard error between prediction curve and original historical curve not exceed a fixed error range, we will believe that the forecast result is accurate. The main prediction steps of fractal extrapolation are as follows:

(1) Sample selection:we selected December 5 as the base day, December 4 and December 3 as the similar days.
(2) Determine the interpolation point sets: according to the characteristics of the historical data set, we selected the starting point, end point, peak and valley point of December 3, 4, 5 as the main feature points. This paper selects 1:00, 4:00, 9:00, 12:00, 18:00, 24:00 as the feature points. Select the 1:00 on December 6th point as the initial iteration point, make up the interpolation set together with the interpolation point of history data.
(3) Construct the iterated function system: we used the self-similarity analysis methods to analyze the load date selected from December 3, 4, 5, and then calculate the vertical scale factor by the Hurst value. According to step (2) to establish the IFS, we can get this following four parameter: a_i, c_i, e_i, f_i. Then give a certain weight for each parameter and calculate the mean value, a statistical IFS will be get successfully.
(4) Get the curve based on fractal interpolation: according to Eq. (1), the predicted curve is generated. According to the need of practical requirement, we calculated the average relative error between the forecasted value and the original historical value. If such relative error does not meet the given error, fractal extrapolation will be continued to refine until it is satisfied.

The prediction result shown in Fig. 3. The prediction error shown in Table 2. It can be found that the relative error is small, so this method used to short-term load forecasting has high precision and is feasible.

Conclusion

Through the analysis of the self-similarity of actual power load data, it shows that the electric load data are with obvious self-similarity; By the help of the Hurst parameter, which is combined with self-similarity and fractal interpolation closely, systematic analyses of the fractal interpolation and fractal extrapolation are applied to the power load forecasting to meet the actual operational needs. The proposed scheme for forecasting short-term load is commercialized and becomes a module of the commercial software called "SmartSignalProcessing". From the results of experiments the following significant conclusions can be obtained:

(1) By observing the data from Tables 1 and 2, under the condition which only select six interpolation points, the average relative error of fractal interpolation and fractal extrapolation were only 2.303% and 2.296%. It can be proved that using the Hurst parameter to estimate the vertical scale factor is feasible.
(2) The study of self-similarity is not only laid a solid foundation for theoretical basis, but also has very important significance for accurate prediction. Meanwhile, this approach provides a quantitative method to calculate the vertical scale factor, and solve the partition problem in the conventional problem.

Table 1
The prediction error between actual load and predict load based on fractal interpolation [MW].

Time	2	5	7	10	13	15	17	20	21	22	23
Actual load	106.3	104.0	145.2	179.9	173.7	169.9	187.8	203.9	194.2	173.6	146.4
Predicted load	106.4	105.4	132.3	187.5	179.5	168.7	184.2	205.3	196.1	177.7	140.0
Relative error	0.103	1.329	8.77	4.231	1.236	0.729	1.937	0.007	0.992	2.372	4.372

Table 2
The prediction error between actual load and predict load based on fractal extrapolation [MW].

Time	2	3	6	7	13	15	18	19	21	22	23
Actual load	106.3	101.6	120.1	145.2	173.7	169.9	221.2	213.4	194.2	173.6	146.4
Predicted load	106.4	102.0	116.4	132.4	179.8	168.7	223.1	215.0	196.2	177.7	149.0
Relative error	0.103	0.416	3.046	8.771	3.483	0.729	0.852	0.762	0.994	2.372	1.801

(3) Experiment shows that the fractal interpolation and fractal extrapolation have advantages of high-precision, less-sample demands, less-interpolation points and easy to use. However, some moments, such as 7:00, the average relative error is slightly larger, which proves the load value of this moment have greater volatility in daily life and the process of production, and provide a certain reference for power dispatching department and maintenance department.

References

[1] Luis H, Carlos B, Belen AJMC, Jaime S-EAJL, Joaquim M. A survey on electric power demand forecasting: future trends in smart grids, microgrids and smart buildings. IEEE Commun Surveys Tutorials 2014;16(3):1460–95.
[2] Hernndez L, Baladrn C, Aguiar J, Calavia L, Carro B, Sanchez-Esguevillas A, et al. Artificial neural network for short-term load forecasting in distribution systems. Energies 2014;7(3):1576–98.
[3] Hernndez L, Baladrn C, Aguiar J, Carro B, Sanchez-Esguevillas A, Lloret J. Artificial neural networks for short-term load forecasting in microgrids environment. Energy 2014;75:252–64.
[4] Yan G, Xue-shan H, Li H. Short-term load forecasting based on least squares support vector machines. Power Syst Technol 2008;31:72–6.
[5] Xiang L, Yong G, Yan-fen Q. Fractal theory based durability analysis and forecasting of power load. Power Syst Technol 2006;30:84–8.
[6] ZHAI M-Y, Kuzma H, Rector JW. A new fractal interpolation algorithm for seismic data based on the iteration function systems. Europhys Lett 2010;92(4). 49001p1-p6.
[7] lei XUE W, Ji-lai Y. Application of fractal extrapolation algorithm in load forecasting. Power Syst Technol 2006;30:49–54.
[8] Hong. Fracatal geometry and fractal interpolation. Science Publishing House; 2011.
[9] ZHAI M-Y, Rector JW, Kuzma H. A new fractal algorithm to model discrete sequences. Chin Phys B 2010;19(9):91–5.
[10] ZHAI M-Y, Fernndez-Martnez JL, Rector JW. A new fractal interpolation algorithm and its applications to self-affine signal reconstruction. Fractals-Complex Geomet Patterns Scaling Nat Soc 2011;19(3):355–65.
[11] yi REN X, Ru-chuan W, Hai-yan W. Wavelet analysis method for detection of DDoS attack based on self-similar. J Commun 2006;27(5):6–11.
[12] ZHAI M-Y. Signal recovery in power line communications systems based on the fractals. IEEE Trans Power Delivery 2011;26(3):1864–72.
[13] Daneshi H, Shahidehpour M, Choobbari AL. Long-term load forecasting in electricity market. In: The proceedings of the 2008 IEEE international conference on electro/information technology; 2008. p. 395–400.