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

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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

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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:

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

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

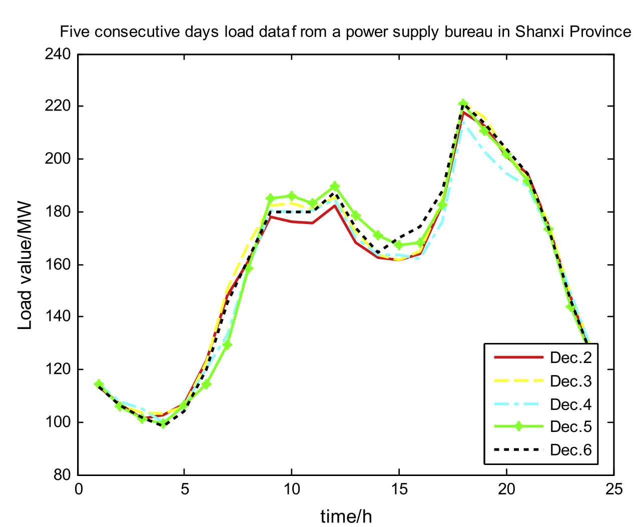

Fig. 1. Five consecutive days load data from a power supply bureau in Shanxi Province.