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Research on Intelligent Power Load Forecasting Algorithm Based on Empirical Mode Decomposition

Qinghua Chen

College of Electro-mechanical, Shandong Management University, Jinan 250100, China
QinghuaChen@126.com

The load forecasting of power system is related to the dispatching operation and production planning of power system. Accurate load forecasting can improve the safety and stability of the system and reduce the cost of power generation. The load variation is complicated and influenced by many factors. When the forecasting is carried out separately, the different load components will be separately extracted from the total load, which will help to improve the prediction accuracy. Based on the study of empirical mode decomposition method, this theory is introduced into the field of power load forecasting, we presented a short-term load forecasting method based on Empirical Mode Decomposition (EMD).
Firstly, we introduced the development of EMD and its main application fields, described the basic concepts and decomposition principles of EMD algorithm in detail. According to the power system load composition and characteristics, we proposed a short-term load forecasting model based on Empirical Mode Decomposition (EMD) and used the EMD algorithm to predict the load sequence.

1. Introduction

Load forecasting can make people understand the changing law of load and the trend of the future, so as to provide data for power generation planning, offline network analysis and reasonable scheduling arrangements, but also to ensure the security of power system and economic operation (Liu, et al., 2014); With the deepening of the electric power market reform, the power load forecasting is the necessary tool for accurately grasping the pulse of the market and analyzing the trend of power demand in the electric power market (Sun, et al., 2011). Accurate load forecasting becomes an important way for the power enterprises to formulate purchase and sale plans (Wei, 2016). And ensure the safe and economical operation of the power grid, save energy, reduce equipment loss and waste, and bring huge economic benefits to power generation and power supply enterprises (Ghelardoni et al., 2013).
In power system operation, control and plan management, load forecasting determines the power generation, transmission and distribution of reasonable arrangements, it not only an important part of power system planning, but also one of the important factors to improve the economic efficiency of power enterprises and promote the development of the national economy (Ren et al., 2015).
One of the core problems of load forecasting is forecasting techniques and methods, namely, the mathematical model of prediction, in order to achieve better accuracy requirements (Fan et al., 2016). Empirical Mode Decomposition (EMD) algorithm is widely used in time-frequency analysis of signal and system (An, et al., 2013). According to its basic principles and characteristics, it can be applied to short-term load forecasting of power system, and it has outstanding merits (Qiu et al., 2017).
In this paper, we studied the principle of the algorithm, and combined the method with the short - term load forecasting (Niu et al., 2016). The methods of dealing with the boundary conditions and the degree of decomposition in the EMD decomposition algorithm are discussed emphatically (Haque et al., 2014).
Finally, the calculation and test results are verified by a concrete example, and a useful attempt is made for the application of EMD method in short-term load forecasting.

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2. The basic theory of EMD algorithm

2.1 Introduction of EMD algorithm

In 1998, NASA's NE Huang proposed a new signal processing method called Hilbert-Huang Transform (HHT), which is called EMD-based time-frequency analysis, based on the deep research of the concept of instantaneous frequency method. The method is essentially a signal smoothing process, using the empirical mode decomposition method, the signal of the actual existence of different scales or trends in the gradual decomposition of decomposition, resulting in a series of different characteristics of the scale of the data sequence. After several years of research, EMD time-frequency analysis method has gradually formed an independent theoretical system, as a new time-frequency analysis method, the role and advantages in nonstationary signal analysis have been demonstrated (Tang et al., 2015). This method breaks the traditional definition of frequency and gives an essence description of the signal. It gives a reasonable definition of the instantaneous frequency, physical meaning and solving method, it can be said that it is a significant breakthrough of the whole signal analysis field.

2.2 The basic concepts of empirical mode decomposition

In this section, three basic concepts of EMD algorithm are introduced, and the foundation of EMD modeling is established.
(1) Instantaneous frequency
Instantaneous frequencies are concepts embedded in the most intuitive physical phenomena, such as the fact that we are surrounded by changing light, changing sounds, and many other things that are periodically changing, they all reflect the concept of instantaneous frequency all the time.
(2) Characteristic time scale
Time and frequency are the basic parameters that describe the signal. Frequency defines the number of repeats of the signal per unit time, reflecting the essential characteristics of the signal but not intuitive. However, the feature scale can be obtained by observing the change of the signal directly from the time domain.
(3) Intrinsic mode function
Intrinsic mode function (IMF) is a kind of signal which satisfies the physical interpretation of single component signal. It must satisfy the following two conditions:
1) The number of extreme points and zero-crossing points must be equal or at most one difference over the entire signal length.
2) At any time, the upper envelope defined by the maximum point and the average value of the lower envelope defined by the minimum point are zero, i.e. the upper and lower envelopes of the signal are symmetrical about the time axis.

2.3 The principle of EMD algorithm

(1) The basic idea of EMD algorithm
Empirical Mode Decomposition (EMD) is the decomposition of the signal into a series of time-scale IMF components, so that the IMF component is a narrow-band signal, the IMF component must meet the following two conditions: Over the entire signal length, the number of extreme points and zero crossings must be equal or at most only one difference. At any moment, the upper envelope defined by the maximum point and the mean value of the lower envelope defined by the minimum point are zero, that is, the upper and lower envelopes of the signal are symmetric about the time axis. EMD decomposition algorithm is also known as the screening process, the screening process has two functions: the removal of double wave and to make data more symmetrical waveform.
(2) The specific steps of EMD algorithm
EMD algorithm specific steps are as follows:
1) Find all the maximum points of the original signal s (t), and use the cubic spline function to fit the upper envelope of the original signal. Similarly, find all the minimum points of the signal and fit the lower envelope.
2) Calculate the mean of the upper and lower envelopes, denoted by m1 (t); then the first IMF of the original signal is calculated by:

$$s(t) - m_1(t) = h_1(t) \tag{1}$$

3) This process is repeated *k* times for $h_1(t)$, until $h_1(t)$ complies with the definition of IMF, and the resulting mean tends to zero. Thus, the first IMF component C1 (*t*) is obtained, which represents the signal *s*(*t*) of the highest frequency components:

$$h_{1(k-1)}t - m_{1k}(t) = h_{1k}(t) \tag{2}$$

$$C_1(t) = h_{1k}(t) \tag{3}$$

4) C_1 (t) is separated from $s(t)$, that is to get a high-frequency component to remove the difference signal $r_1(t)$, that is:

$$r_1(t) = s(t) - C_1(t) \tag{4}$$

The $r_1(t)$ is used as the original signal, and repeated steps (1), (2) and (3), obtained the IMF component $C_2(t)$, repeat n times, get n IMF component. Then there is:

$$r_1(t) - C_2(t) = r_1(t) \cdots \tag{5}$$

$$r_{n-1}(t) - C_n(t) = r_n(t) \tag{6}$$

When $C_n(t)$ or $r_n(t)$ satisfies the given termination condition (usually, $r_n(t)$ becomes a monotone function), we conclude by:

$$s(t) = \sum_{j=1}^{n} C_j(t) + r_n(t) \tag{7}$$

Where $r_n(t)$ is the residual function and represents the average trend of the signal. Each IMF component $C_1(t)$, $C_2(t) \ldots C_n(t)$respectively contains the components of the signal at different time scales, and the scales are in order from small to large. According to the mathematical model description of the algorithm described above, the flow chart of the EMD algorithm can be drawn, as shown in Figure 1.

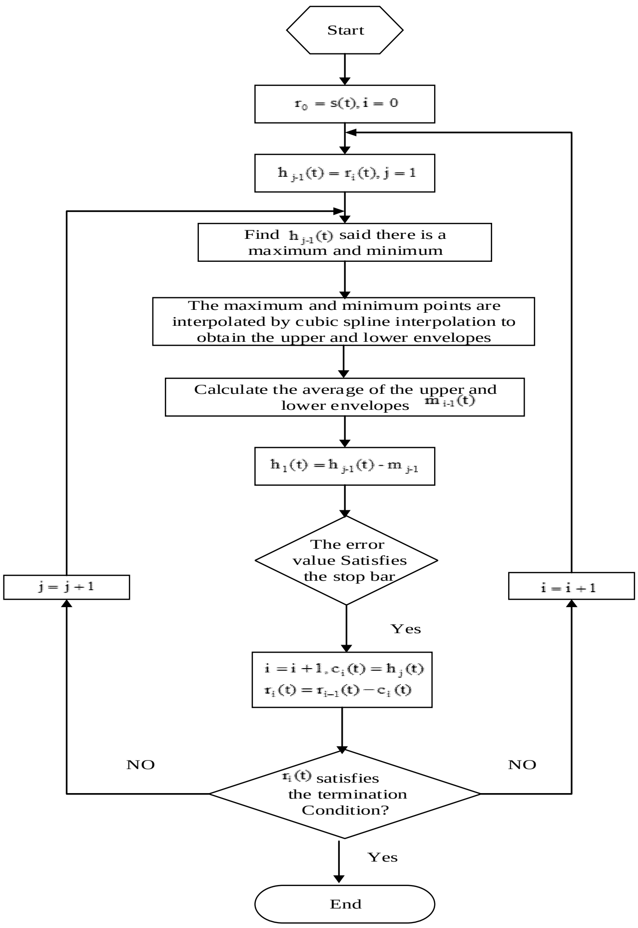

Figure 1: EMD flow chart

3. Research on intelligent power load forecasting model based on empirical mode decomposition

As mentioned above, the power system load can be decomposed into several components from the theoretical analysis.If we can decompose it into several components with different meanings according to the input load sequence and further realize the modeling prediction, it will be very beneficial to improve the accuracy of load forecasting. EMD decomposition method can be used as a useful attempt to achieve the above program.

3.1 Model design

As mentioned above, the power system load can be decomposed into four types of components, the four types of components received different factors, with different changes at the same time. Therefore, this paper adopts the method of forecasting each component after load decomposition to improve the accuracy of load forecasting. For the data processing of the historical load sequence, instead of directly forecasting the original load sequence, we separately forecast the several components contained in the load separately. After the prediction results of the components are obtained, the resulting components are summed together to obtain the final prediction load sequence.

If the power load curves as a signal, then from the perspective of the wave, the load curve is actually a non-stationary non-linear signal. Therefore, the analysis of the load curve from the perspective of the wave, the final analysis can be more accurate load forecasting model to improve forecast accuracy. Combined with the characteristics of power system load, it can be decomposed and predicted by empirical mode decomposition theory.

The main factors affecting the load variation in the load change model are load composition, load variation with time, the influence of meteorological changes and stochastic load fluctuation. According to the system load structure can be divided into: urban civil load, commercial load, industrial load, agricultural load and other types of load. Different types of load have a different variation. All kinds of electricity load time variation is different, the total load of the system, of course, have different changes.

For the factors that affect the system load, the total load forecast model of the power system at a certain time can be described by four component models as follows:

$$L(t) = B(t) + W(t) + S(t) + V(t) \tag{8}$$

In the formula, L (t) is the total system load at time t;
B (t) is the basic normal load component at time t;
W (t) is the weather-sensitive load component at time t;
S (t) is the special event load component at time t;
V (t) is the random load component at time t.

For short-term load forecasting, the basic normal load component B (t) is generally periodic, and can be described by a linear change model or a periodic variation model, or by a combination of the two.

3.2 Realization and simple analysis of EMD decomposition of power

According to the above formula (3-1), the load sequence can be decomposed into four components. The four components in different forecasting cycles showed different trends. Empirical mode decomposition theory can decompose a non-stationary non-linear signal into the form of multiple components, and these components are superimposed on the original signal curve. Therefore, EMD can be applied to analyze the composition of the load sequence using empirical mode decomposition (EMD) theory.

Figure 2 is the result of the original load data sequence and its empirical mode decomposition in the power supply area of a city grid in China for the past two weeks, in which (a) is the original load sequence; (b) to (i) is the IMF component, and (j) is the margin. As can be seen from the figure (b), (c), (d) shown in the IMF component is no significant change in the law of high-frequency components, it is the random component of the load sequence. The IMF components shown in (e) and (f) have a significant periodicity and are the periodic components of the original load sequence. The IMF shown in (g), (h), (i) and (j) are obviously trend-changing, and these components can be regarded as the trend component of the original load sequence.

From the point of view of load characteristics, the load at any time can be composed of random component, meteorological sensitive load and normal component, a load sequence is decomposed by empirical mode to obtain periodic and random sub-sequences, in a sense just corresponding to the characteristics of the load division. For example, the original load sequence decomposition of Figure 2 (b) of the components obtained as a random component, (c) and (d) are meteorological sensitive components, and (e) to (f) are normal components. After separating the periodic, random and trend components of different frequency bands, we use the extrapolative prediction method to predict and forecast the components, and then superimpose the results of each component forecast. The obtained prediction accuracy can obviously be improved greatly.

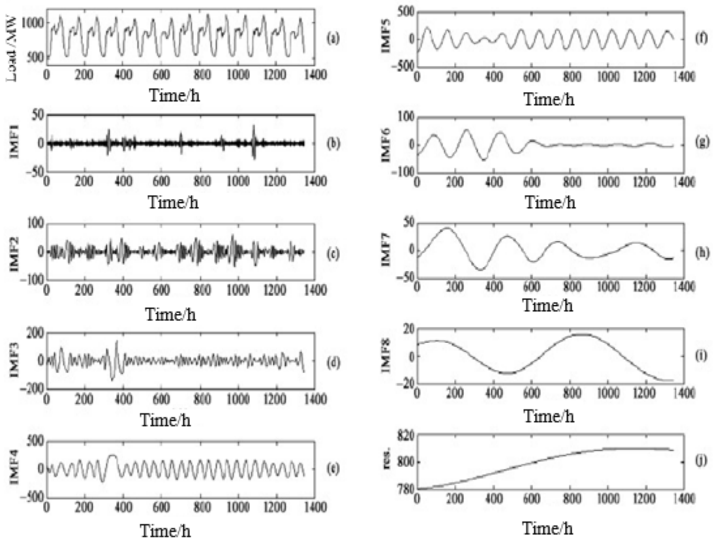

Figure 2: Empirical Mode Decomposition Results of Load Sequence

3.3 Power load forecasting model based on EMD algorithm

The random components of the load sequence often have a greater impact on the load forecasting accuracy. Therefore, this paper uses empirical mode decomposition to extract the high frequency random components in the original load sequence, and then make modeling predictions according to their characteristics. After the original load sequence is decomposed to obtain the periodic, random and trend components, we use the fitting prediction model to predict, and then add the predicted results to obtain the final prediction result. The prediction model is shown in Figure 3.

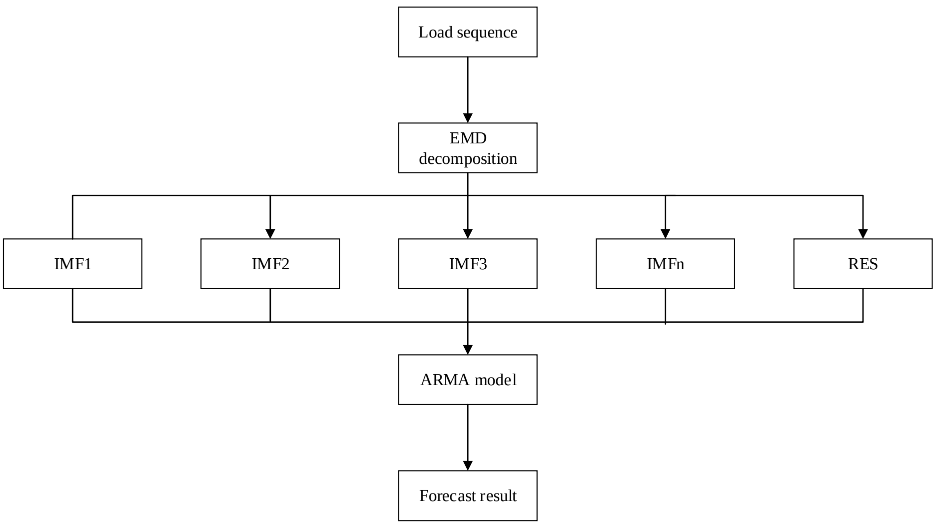

Figure 3: Intelligent Power Load Forecasting Model Based on Empirical Mode Decomposition

Based on the EMD algorithm of intelligent power load forecasting model, it is shown that the EMF-based intelligent power load forecasting model proposed in this study does not eliminate the influence of climate factors on load forecasting, In order to further improve the accuracy of prediction, this paper will introduce an intervention analysis model to analyze the impact of climate factors on load forecasting (Yang et al, 2016).

4. Conclusion

Short-term load forecasting has always been the concern of the power industry workers, improving the prediction accuracy of intelligent power load forecasting is especially important in the changing environment of power system nowadays, many researchers have done a lot of work in the research and application of short-term load forecasting methods, and have made the development of this field. EMD time-frequency analysis method of signal decomposition is based on the time scale characteristics of the signal itself. The results show that the EMD algorithm is applied to the short-term load forecasting, the prediction result can obtain high precision.

In this paper, we introduced the basic theory of EMD method in detail, and give the concepts of instantaneous frequency, intrinsic mode function and so on. The principle of the EMD analysis method, implementation of the specific steps and algorithm flow chart are analyzed in detail from the characteristic time scale of the signal itself. The short-term load structure and characteristics of the power system were discussed, and then the idea of applying EMD algorithm to the intelligent power load forecasting was put forward according to its characteristics. Analysis and discussion of the experimental results show that this method is feasible, and gives a reasonable complete model ideas and processes.

EMD method can improve the accuracy of intelligent power load forecasting, it has obvious superiority. However, there are still many imperfections in the process of using this method to solve the problem, it needs further study.

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