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Power system analysis and control model based on hierarchical model of neural network

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Abstract. In order to further improve the stability of power production process and improve the quality of power production, non-stationary empirical mode decomposition (EMD) method of monitoring production process of power transmission network based on amplitude threshold is proposed. Of which, the production signals of power transmission network collected during the power production process of power plant are analyzed, and then the non-stationary EMD method is introduced into the production process of power transmission network for the design of information monitoring process; the experiment result verifies the effectiveness of the proposed method of monitoring the production process of power transmission network. At last, through the experiment, the effectiveness of the proposed method of monitoring the production process of power transmission network is verified.

Key words. Power transmission network Power system; Process monitoring Empirical mode decomposition (EMD) Power grid technology

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1. Introduction

China is a big country of power production and use, and at the same time, it is a big export country. However, the existing quality defect in power of power plant due to the traditional technology is a problem troubling the actual power production [1-2]. Therefore, researching into a convenient, fast, real-time, objective online quality control technology for power shows an important application value. And the basis of realizing monitoring algorithm is the precision and accuracy [3] of real-time data processing in power production procedure. In this Paper, a non-stationary empirical mode decomposition (EMD) method of monitoring the production process of power transmission network based on amplitude threshold is proposed, in

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which, the production signals of power transmission network collected during the production process of power in power plant are collected and modeled, and then a non-stationary empirical mode decomposition method is introduced to analyze and process signals so as to realize the effective monitoring of production process.

2. Problem description

In the power plant production enterprises, the business process of power production is characterized by: heavy task, tight production time, large quantity of orders, and there is a strong demand for communication between the various links during the production process of power. If a production link has a problem, it will directly affect the next production process, resulting in discontinuous production process of power and affecting the production benefits of enterprises. In the signal acquisition of power transmission network, the production signals of power transmission network are generally stationary characteristic signals, which can be collected and acquired based on A/D conversion control. However, if there are relatively serious strong current interference and other factors on the production site of power, the production signals of power transmission network will be caused to be characterized by complex stochastic process, namely showing the characteristic of non-stationary signal.

In the previous literature, the fitting processing of the production signals of power transmission network during the production process of power is mostly based on the median filtering strategy, the mean filtering strategy and so on. The schematic diagram of production signal denoising of power transmission network is shown in Fig. 1. For the median filtering, the basic filtering principle is to denoise the production signals of power transmission network, that is, to divide the production signals of power transmission network extracted and acquired into 2 categories: interference signal and useful signal. In the whole process of power production, the useful signal has the invariant characteristic in element time and we are allowed to carry out direct conversion operation on production signals to obtain the quality information of the raw cloth material; the interference signal part is the noise part of the data overlapping and generally regarded as white noise data, which is required to be filtered and separated in the actual production monitoring.

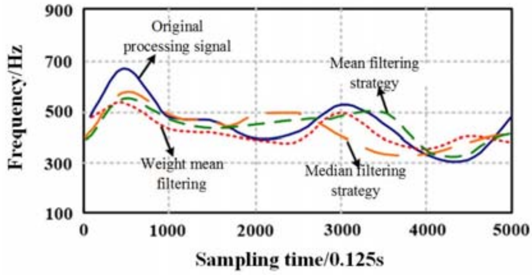

Fig. 1. Effect contrast of denoising production signals of power transmission network

Based on the relevant knowledge of probability theory, the statistical characteristic of white noise is that its mean is zero. Therefore, the production signals of power transmission network extracted can be conducted in model decomposition to obtain the two parts including white noise model and useful signal model. The model form is:

$$z(t) = x(t) + y(t)\,. \tag{1}$$

In the Equation (1), $z(t)$ is the original production data generated by power transmission network, $y(t)$ is the white noise in the mode and $x(t)$ is the useful signal in the model, then the discrete form of signal $z(t)$ can be got as follows:

$$\sum_{l=1}^{N} z_l = \sum_{l=1}^{N} x_l + \sum_{l=1}^{N} y_l\,. \tag{2}$$

Then it can be got that the following relation is established:

$$E[y(t)] = \lim_{T_0 \to \infty} \frac{1}{T_0} \int_0^{T_0} y(t)dt = 0\,. \tag{3}$$

In the Equation (2), T_0 is the sampling time of signal, $y(t)$ is the white noise signal of model, $E[y(t)]$ is the mean of model $y(t)$, and it is satisfied in the following limit theorem $\lim\limits_{N\to\infty} \frac{1}{N} \sum\limits_{t=1}^{N} y_t = 0$.

For the mean filtering, during the data sampling time T_0 of the whole production process of power transmission network, select N groups of sampling points and carry out statistics on the mean of them to realize data approximation. Through the data smoothing operation, the useful part $x(t)$ of production signals of power transmission network is constant in the N times' measurement processes, and noise model $y(t)$ shows the characteristic of random variation. After the mean extraction operation, the $y(t)$ values are partially offset by the random complementary characteristic existing between the errors, thus reducing the random noise's impact on the signal. In addition, with the increase of N value, the mean of production data of power transmission network will be close to 0.

For weight mean filtering, the strategy adopts the minimum mean square error manner based on smoothing data to approach the original production information and realize the solving of weight coefficient based on LMS strategy. Within the range of sampling time T_0, conduct weight distribution on the sampling points of the section and set the centrifugal principle, that is, the farther the distance is, the smaller the distributed weight will become. Move the positions of sampling points until the smoothing filtering operation of all signals has been completed. According to Fig. 1, it can be got that above 3 different kinds of filtering manners all achieve relatively good smoothing effect after the respective fitting of production signals of original power transmission network; however, within the range of sampling time T_0, they have not realized the complete white noise removal on the original production signals, especially in the wave crest and other positions where obvious white noise disturbance still exists. Such disturbance phenomenon will result in the abnormal quality of power production process, which requires pre-event forecast and timely processing. Otherwise, the finished product quality of power obtained based on above filtering strategy will neither meet the consumers' demands nor meet the enterprises' production and management requirements. Therefore, the effective filtering processing of information data of power transmission network is of great significance to production stage.

3. No-stationary empirical mode decomposition of signal

3.1. signal decomposition steps

For the production signals of power transmission network with non-stationary characteristic, an improved empirical mode decomposition strategy proposed is adopted here, and the strategy design is assumed as follows:

Assumption 1: The production signals of power transmission network contain at least two groups of signal extreme values: maximum value and minimum value;

Assumption 2: The oscillation natural mode time-scale can be defined based on the time distance between the two adjacent sampling points of maximum value and minimum value.

Then under above two assumed conditions, the production signal $x(t)$ of power transmission network can be conducted in EMD decomposition with steps as follows:

Step 1: collect and determine all the extreme points of production signal sequence $x(t)$ of original power transmission network and fit the data signals based on cubic spline to obtain the sequence envelope and its mean m_1; after that, solve the difference value h_1 between $x(t)$ and m_1: $x(t) - m_1$ and judge whether the difference value h_1 meets the following IMF conditions:

Condition 1: The number of sequence extreme points of the whole process production signals of power transmission network is the same as that of data points passing through the zero position, or differs in one data point;

Condition 2: For any data point in the signal sequence, the mean of the envelope obtained using the maximum value and that obtained using the minimum value is 0, namely the signal meets the symmetrical characteristic on the time axis.

If above two IMF conditions are met, the first IMF component imf_1 of $x(t)$ can be obtained, and $imf_1 = h_1$. And then solve the differential value r_1 between the original process signal original $x(t)$ and IMF signal obtained by using the calculation form of $r_1 = x(t) - imf_1$.

Step 2: If h_1 does not meet the two conditions listed by IMF, then regard the production signal sequence as a new sequence, and return to step 1 to re-calculate the mean m_{11}, and then solve the difference value h_{11} between the signal h_1 and m_{11}, and $h_{11} = h_1 - m_{11}$. Repeat above steps on h_{11} for k times until h_{1k} meets the IMF condition limit, and $h_{1k} = h_{1(k-1)} - m_{1k}$, then regard it as the first IMF composition imf_1 of $x(t)$, and $imf_1 = h_{1k}$. After that, solve the difference value r_1 between the original production signal and above obtained IMF by using the calculation form of $r_1 = x(t) - imf_1$.

Step 3: regard $r_1(t)$ as a new "original" sequence and update it, and repeat above steps. Gradually get IMF composition component $imf_2, imf_3, \cdots, imf_n$, $r_2 = r_1 - imf_2, \ldots, r_n = r_{n-1} - imf_n$ of the 2nd group, 3rd group, ..., until nth group, then r_n will become a single sequence form which will not contain any forms of information, that is, the remainder term of production data of original power transmission network might be called as trend term.

After completing the EMD decomposition process, the original production signal sequence $x(t)$ will become a sum of IMFs and certain remainder term in the form as follows:

$$x(t) = \sum_{i=1}^{n} imf_i + r_n \,. \tag{4}$$

According to the instantaneous frequency, decompose all IMFs in the high-low order. The frequency component of each IMF composition component is not only related to the sampling frequency, but also related to the frequency of the signal itself. Therefore, the EMD strategy is used to deal with production signals for self-adaptive processing, which has a good effect on the complex signal sequence with non-stationary and non-linear characteristics and can obtain relatively high signal-to-noise ratio.

3.2. Amplitude threshold mode model

The traditional EMD strategy believes that the composition component of the signal consists of two parts: the IMFs symmetry envelope and the remainder term. IMF is the oscillation component of the signals with inherent characteristic and is the most common form of oscillatory motion. A complete oscillation group consists of three parts: trough, crest and zero-crossing point. There is a signal trough or crest between any two adjacent zero-crossing points and it is the IMF's most basic constituent element, indicating that the data signal has complete element in local oscillatory motion. Here the most basic oscillatory motion element form of IMF is called as modal element, on which any hard threshold or soft threshold filtering operation will damage the inherent integrity of local oscillation.

The modal amplitude can be defined as the maximum amplitude presented by the modal element and denoted as a_m. The modal type can be discriminated based on the size of the modal amplitude to determine the modal element retention and obtain the filtering effect of modal element. In this Section, we mainly discuss the problem of modal element type discrimination and construct the amplitude threshold filtering model of modal element. Record modal element k in the component imf_i as m_i^k, then imf_i can be expressed as $imf_i = \{m_i^k, k = 1, 2, \cdots, K\}$, where, $i = 1, 2, \cdots, n$. $a_i^k$is the modal amplitude of m_i^k, tha_i is the amplitude threshold mode of component imf_i , and $\chi(tha_i)$ is the data processing coefficient of modal element m_i^k at the threshold of tha_i; the use of amplitude threshold on the modal element m_i^k can be processed using the following mathematical model:

$$m_i^k(tha_i) = \chi(tha_i) m_i^k \,. \tag{5}$$

In Equation (5), the calculation form of parameter $\chi(tha_i)$ is as follows:

$$\chi(tha_i) = \begin{cases} 1, \ a_i^k \geq tha_i \, . \\ 0, \ a_i^k < tha_i \, . \end{cases} \tag{6}$$

Denote the imf_i obtained through processing the amplitude threshold as $thaimf_i$ and the calculation form is as follows:

$$thaimf_i = \{m_i^k(tha_i), k = 1, 2, \cdots, K\} \, . \tag{7}$$

At last, use the obtained $thaimf_i$ component to deal with the production signals of original power transmission network for reconstruction operation, and the mathematic model is as follows:

$$\tilde{x}(t) = \sum_{i=1}^{i_e} thaimf_i + \sum_{i=i_e+1}^{n} imf_i + r_n(t) \, . \tag{8}$$

In Equation (8), i_e is the number of modal filtering required, and the selection of whose value is affected by noise and signal type. According to the results of a large number of experiments, it can be got that the first 8 groups of modal components contain the majority of the energy values of Gaussian noise after processing the Gaussian noise by EMD decomposition. Therefore, in Equation (8), we set $i_e = \min(8, n)$, that is, we only select the first 8 groups of modal components to execute filtering operation during the reconstruction process of production signals of power transmission network, and the subsequent IMFs components are operated in a simple superposition manner. From this, the amplitude threshold mode shown in Eqs. (5) to (8) is a key part of the modal element filtering process. In this paper, the EMD decomposition method using amplitude threshold mode is called as element modal filtering strategy.

3.3. Calculation on amplitude threshold value mode

Amplitude threshold value mode model is a method to determine type of mode unit through amplitude size. If noise component imf_i of EMD decomposition course has special evolution correlation with the maximum value $\max a_i$ of mode amplitude, and mode unit amplitude is relatively great, then $\max a_i$ evolution correlation will be damaged. It is generally set that when $a_i^k > \max a_i$ is met, mode unit will be subject to signal component, and otherwise it will be subject to noise component. Therefore, researching $\max a_i$ evolution correlation possessed by different noises is of great significance to tha_i parameter determination.

When Gaussian noise fractal is made, under value of special Hurst exponent H, difference of iterations will affect $\max a_i$ value greatly. When amplitude threshold value mode model is adopted, $\max a_i$ value shall be utilized to estimate tha_i, and therefore the maximum value rate of mode amplitude is defined as $r \max a_i = \max a_i / \max a_1$, and its evolution rule is researched. It is found that value of $1og_2 r \max a_i$ will present linear variation with change of i. For H value given,

$1og_2 r \max a_i$ variation tendency can be calculated as follows:

Step 1: 1000 groups of Gaussian noise data will be obtained based on wfbm function, its sequence length is L=1024, and EMD decomposition will be respectively implemented to 1000 groups of noise group, to obtain 8 groups of mode component imf_i respectively, and $i = 1, 2, \cdots, 8$, and then $r \max a_i$ of each component imf_i will be calculated respectively, and logarithm value will be obtained, denoted as $1og_2 r \max a_i$.

Step 2: obtain average value of 1000 groups of $1og_2 r \max a_i$ generated above, to obtain $E(1og_2 r \max a_i)$ value, and average value $E(1og_2 r \max a_i)$ will be taken as value standard to obtain value interval of error between average value and true value.

Step 3: based on above steps, 3 kinds of value mode, i.e. $H = 0.2$, $H = 0.5$ and $H = 0.8$ shall be set respectively to obtain error interval of $E(1og_2 r \max a_i)$ and true value.

$E(1og_2 r \max a_i)$ obtained from different value of exponent H will present straight evolution tendency with value of i, and affect rate of decay possessed by noise $\max a_i$ in different way. The larger the value of H is, the quicker the rate of decay of signal will be. Computational formula of $E(\max a_i)$ can be fitted as follows:

$$E(\max a_i) = \max a_1 \times 2^{(-0.53(0.5-H)-0.4)(i-1)}. \tag{9}$$

Experiment shows that value scope of $r \max a_i$ is relatively great. At the same time, the closer the distance between threshold value of tha_i and upper limit $\max a_i$ is, the better the noise removal effect will be. tha_i estimation formula adopted is:

$$tha_i = \max a_1 \times 2^{(-0.8(0.5-H)-0.4)(i-2)}. \tag{10}$$

Core of above EMD decomposition model is how to realize accurate estimation to $\max a_1$. $\max a_1$ estimation method adopted is:

$$\max a_1 = \frac{\lambda}{L} \sum_{t=1}^{L} |imf_1(t)|. \tag{11}$$

In formula (11), λ is proportionality coefficient chosen, $\lambda = 2.6$ can be obtained through statistics and L is sequence length of production signal of power transmission network.

3.4. Monitoring algorithm flow

EMD decomposition course is to make adaptive decomposition to multivariate data acquisition signal according to difference of vibration mode to obtain IMF component with different vibration mode, of which IMF high-frequency component part includes numerous fault information, but includes numerous noise interference information simultaneously, and if IMF high-frequency component is reconstructed directly, and spectral analysis process is realized, it will be difficult to obtain accurate fault data feature. Therefore, in the process of choosing IMF component

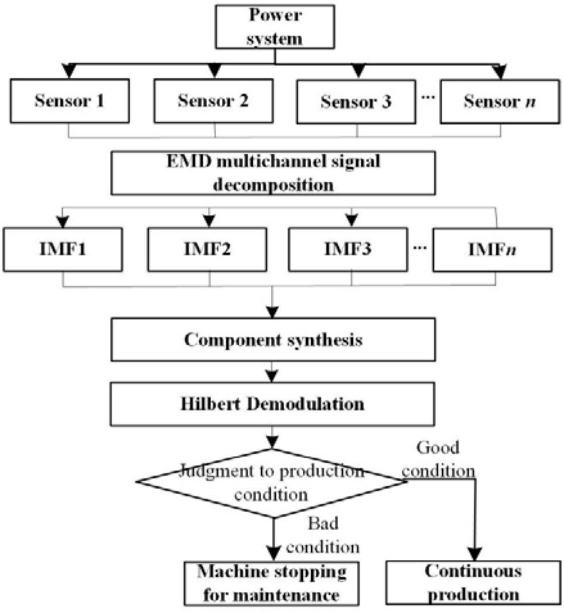

Fig. 2. Monitoring algorithm flow

and implementing filtering operation, effective extraction of fault feature is the key problem to improve algorithm performance. See Fig.2 for diagnostic analysis flow of production signal of power transmission network based on EMD decomposition.

After data acquisition by sensor used in Fig.2, ZigBee transceiver can be used for signal transmission.

4. Experiment and analysis

Experiment condition: sampling time is set as $T_0 = 5000ms$; 500Hz is chosen as frequency. For hardware environment, 2 sets of Inspur + WIN2013 servers with the same machine type under the same temperature and humidity environment shall be chosen, memory capacity is 16 GB, and hard drive capacity is 500 GB, communication bandwidth is 1 Gb/s, and centralized data signal on-line monitoring mode shall be chosen. Test network system established is as shown in Fig.3, and the system includes 4 distribution powers and 6 uncertain loads, of which power, position and deviation of distribution powers are as shown in Table 1 and relevant data information of uncertain loads is as shown in Table 2. Nominal voltage value of the system is 4.17Kv, and real-time voltage measurement positions are at 21, 36, 43 and 52 nodes positions. Its voltage simulation value is obtained by adding Gaussian normal deviation based on tidal value calculated and Gaussian distribution is $\mathcal{N}\left(0, 0.0001^2\right)$. Points 21, 17, 3, 42, 54 and 28 in test network shown in Fig.3 are chosen as test points for data acquisition and analysis.

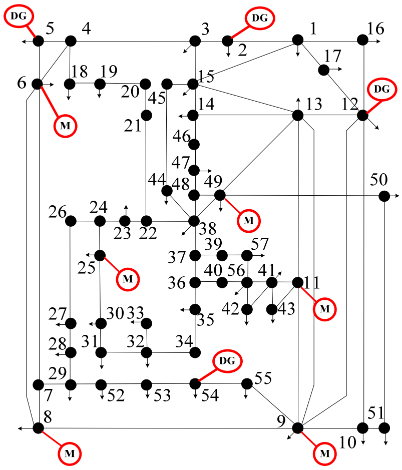

Fig. 3. IEEE 57-bus network test system model

Table 1. Distribution power information of IEEE 57-bus system

Node	Type	Voltage deviation/%	Active power/kW	Active deviation/%	Power factor
2	Photovoltaic	1.2	[100,0,0]	15	0.95
5	Wind power	1.3	[0,100,0]	15	0.95
12	Photovoltaic	1.2	[150,150,150]	15	0.95
54	Wind power	1.3	[150,150,150]	15	0.95

Table 2. Information of uncertain load

Node	Voltage deviation /%	Active power /kW	Active deviation /%	Power factor
7	1.1	[0,0,20]	15	[∼,∼,0.87]
9	1.1	[40,0,0]	20	[0.87,∼,∼]
12	1.1	[0,20,0]	25	[0.81,0.81,0.81]
19	1.1	[35,35,35]	30	[0.81,0.81,0.81]
24	1.1	[35,35,70]	25	[∼,0.87,∼]
48	1.1	[105,70,70]	20	[0.87,∼,∼]

Make noise reduction processing to high-frequency signal existing in production signal of power transmission network, transform form $z(t)$ of production signal of power transmission network into $\tilde{z}(t)$, and set sampling time of data point as $t = 0.125s$ to obtain all local extreme points of production signal of power transmission network, and judge whether $e_i'(t)$ meets 2 conditions of IMF set under $i = 8\,(i = 1, 2, \cdots, 8)$. If above 2 conditions set are met, based on formula

$s_i(t) = \tilde{z}(t) = d_i(t)$, result of δ_d is 0.263 through calculation, and if the value calculated is within confidence interval $[0.2, 0.3]$, flicker value processing shall be made through EMD decomposition to obtain smooth and steady feature state of production signal of power transmission network at wave crest. Combined with decomposition result of Fig.4, it can be seen that after production signal of power transmission network is smoothened based on EMD decomposition, slight fluctuation still exists in its signal, which reflects true condition of production signal of power transmission network, and it is real state reflection of power transmission network.

To make straight comparison between method proposed and traditional methods (median filtering method, arithmetic mean filtering method and weight mean filtering method etc.), under the same experiment settings, the same Inspur server shall be used to make fitting to production signal of power transmission network and the comparison results are as shown in Fig.5.

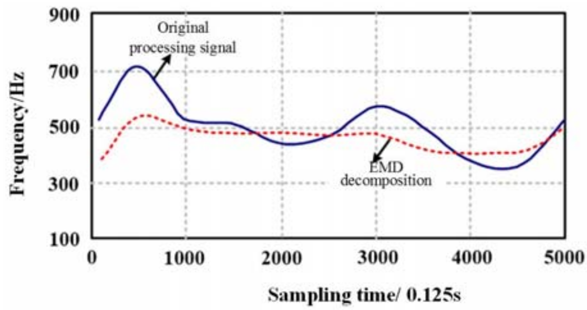

Fig. 4. Empirical mode decomposition of power generation process

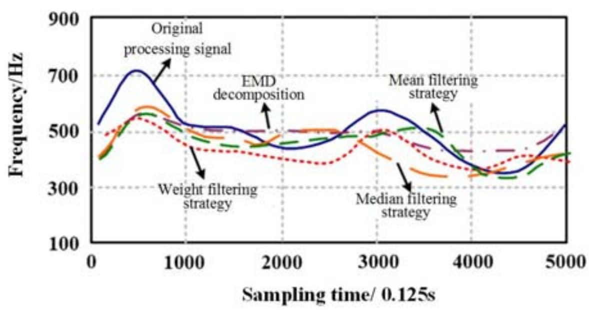

Fig. 5. Comparison on filtering of power transmission network

From processing result of Fig.5, although signal obtained through EMD decomposition fluctuates in a certain way, the fluctuation is slight and real condition of power transmission network is reflected. At the same time, data signals obtained through 3 traditional filtering methods chosen are different at wave crest, and processing data obtained through 3 filtering methods has relative approach variation tendency, which shows that filtering effect of 3 algorithms is similar. Above result shows that through flicker value processing to production signal of power transmission network by EMD decomposition course, “abnormal signal” can be processed effectively, to make movement direction of production signal of power transmission network smoother at wave crest. Real-time processing of production signal of power transmission network based on EMD decomposition can obtain production signal curve with smaller fluctuation range, and especially when production signal of power transmission network is within pulse period, amplitude of curve obtained through method proposed in this paper is more stable than that of fitting method.

In addition, to compare EMD decomposition result advantage further, error value is calculated by combining with tested signal for production of power plant, and comparative computation is as shown in Fig.6.

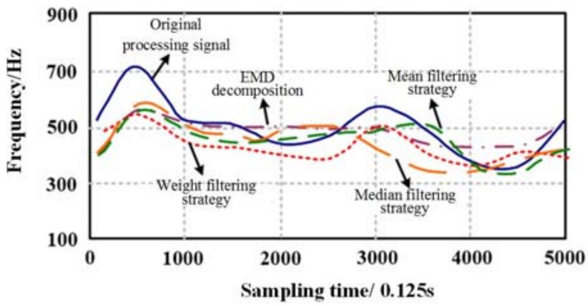

Fig. 6. Comparison on error of power generation process

Seen from computation of Fig.6, after high-frequency noise reduction is made to production signal of power transmission network based on EMD method, operation efficiency error of power transmission network obtained is smaller, and with advancing of power generation time, calculated value of the error will be more stable. The value is lower than 2%, but permissible error of general power plant enterprise is 3%. Although operation efficiency errors of power transmission network calculated by median filtering method, mean filtering method and weight filtering method are lower than permissible error value 3%, compared with EMD decomposition strategy, their fluctuations are greater, and especially in handover or starting process of power generation time, fluctuating error is greater than 5%, which will cause overgreat power generation system error and affect quality of finished product of power. Therefore, EMD decomposition can make stabilizing processing of non smooth and steady feature to production signal of power transmission network in more effective mode, which is beneficial to improve power yield and quality, and it is relatively ideal processing method for production data of power plant.

5. Conclusion

This paper proposes monitoring method for production process of power transmission network based on non smooth and steady empirical mode decomposition (EMD) of amplitude threshold value. Firstly, production signal of power transmission network collected in power production process of power plant shall be collected, mechanism analysis shall be made to signal to obtain useful signal and noise generation signal and model construction shall be made to them; secondly, aimed at production signal model of power transmission network proposed, non smooth and steady empirical mode decomposition method shall be introduced, type of mode unit shall be determined through amplitude scale of mode, and threshold value mode of amplitude shall be determined through Hurst exponent, and improved EMD method shall be utilized to make information monitoring flow design to production process of power transmission network. Above algorithm is verified under laboratory environment. How to construct monitoring system under actual production environment is the emphasis of research in next step and how to adjust production strategy of power plant effectively and improve quality control effect through monitoring data analysis result is also main direction of research in next step.

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