

# Application of Improved EMD Threshold Algorithm in the Study of the Electric Life State of the AC Contactor

Yiping Bo<sup>1,a</sup>, Liang Zhang<sup>2</sup>, Shuxin Liu<sup>1</sup>, Yanjun Zhang<sup>3</sup>, Yundong Cao<sup>1</sup>

<sup>1</sup>Shenyang University of Technology, 110870, Shenyang, China

<sup>2</sup>State Grid Liaoning Electric Power Co., Ltd. Anshan Power Supply Company, 114001, Anshan, China

<sup>3</sup>Liaoning Provincial Electric Power Co., Ltd. Electric Power Research Institute, 110006, Shenyang, China

**Abstract.** The condition monitoring signal of electrical life of AC contactors has characteristics such as non-linear, non-stationary and strong background noise. The premise and basis for the accurate establishment of the assessment model of the electrical life of AC contactors is how to accurately extract the characteristic parameters of electrical life signals. Therefore, it is of great significance for the study of AC contactors' electrical life to preprocess its characteristic parameters of electrical life signals. Adopting traditional soft and hard methods cannot remove the noise effectively, therefore, a new threshold function can be proposed, and further model the wavelet threshold denoising theory to research the threshold denoising method of empirical mode decomposition (EMD), denoise the main parameters which can influence the state of AC contactors. The experimental results show that adopting the improved EMD threshold algorithm can effectively remove the noise, and it is better than adopting wavelet threshold method or empirical mode decomposition alone

## 1 Introduction

AC contactor is one of the most important and important power equipments in the power system. It is used to open and close huge short-circuit currents to ensure the safe and reliable operation of the power grid. It is an important link in power generation, transmission, distribution and electricity consumption. Its stability and reliability are of great significance to the safety and reliability of power grid<sup>[1-2]</sup>. AC contactors should have a long enough life, with two indicators: one is the mechanical life, the other is the electrical life. Under normal circumstances, the electrical life is far less than the mechanical life, which is an important indicator to evaluate the reliability of AC contactor operation. In order to prolong the service life of electrical equipment effectively and to provide a scientific basis for achieving the best balance between the safe use and economic benefit of electric equipment, the remaining life assessment of electrical equipment is required. Due to the strong background noise characteristic of the AC contactor status data monitoring signal, if the noise is directly processed without analysis, it is very likely that the obtained results will deviate from the real situation and will have an impact on the follow-up work. Therefore, the noise must be filtered out. The important issue is whether the removal of noise is the key to extracting feature parameters. Denoising the feature parameters is the first step in studying the degradation of AC contactors<sup>[3-4]</sup>.

The empirical mode decomposition (EMD) denoising method can adaptively decompose the signal into eigenitems and trend terms one by one according to the local scale characteristics of the signal in the process of stationary signal processing, and select the proper eigenitems to achieve the effect of noise reduction<sup>[5-6]</sup>. Therefore, in this paper, the EMD algorithm is used to decompose the characteristic parameters by EMD, and then the new wavelet threshold function is used to denoise. Therefore, the EMD algorithm is used to decompose the feature parameters by EMD, and then the new wavelet threshold function is used to de-noise, which not only has the advantage of multi-resolution of wavelet transform, but also has good local characteristics. It can effectively ensure that the monitoring signals of AC contactors can be accurately and adaptively partitioned, and the monitored non-stationary characteristic signals can be filtered and de-noised.

## 2 Principle and method of noise elimination

### 2.1. Principle of empirical mode decomposition and denoising method

EMD is to decompose the signal through a process of "sieving". The specific processing<sup>[7]</sup> is as follows:

For a given signal  $X(t)$ , first determine all the extremum points on  $X(t)$ , and the upper envelope line is formed by using the cubic spline interpolation curve to

<sup>a</sup> Corresponding author: YipingBo301@163.com

connect all the maximum points, and the lower envelope line is formed by the same method. The difference between the data  $X(t)$  and the mean value  $m_1$  of the upper and lower envelope lines is denoted as  $h_1$ . Then:

$$h_1 = X(t) - m_1 \quad (1)$$

Take  $h_1$  as a new  $X(t)$ , repeat the above steps until  $h_1$  meets the two conditions of IMF, then it becomes the first order IMF filtered from the original signal, denoted as  $C_1$ . Usually the first order IMF subdivision  $C_1$  contains the highest frequency component of the signal.

By separating  $C_1$  from  $X(t)$ , an interpolation signal  $r_1$  which removes the high frequency component is obtained, ie

$$r_1 = X(t) - C_1 \quad (2)$$

Take  $r_1$  as a "new" signal and repeat the step1 until the residual signal of order  $n$  becomes a monotone function, and the IMF component can no longer be screened out.

$$r_n = r_{n-1} - C_n \quad (3)$$

In mathematics,  $X(t)$  can be expressed as the sum of  $n$  IMF components and a residual term, ie

$$X(t) = \sum_{j=1}^n C_j(t) + r_n(t) \quad (4)$$

In the formula:  $r_n(t)$  is the residual quantity, which represents the average trend in the signal; each IMF component  $C_j(t)$  represents the component of the signal from different high to low frequency bands. Each frequency segment contains different frequency components. In the same IMF component, the instantaneous frequency at different time points is also different. The local time distribution of such different frequency components changes with the signal itself. Most EMD noise reduction applications remove the high-frequency components of the signal decomposition directly as noise. In many cases, it is possible to remove useful signal components.

## 2.2 Wavelet Threshold Denoising Theory and Denoising Method

Assume that there is an observation signal:

$$f(k) = s(k) + n(k) \quad (5)$$

In the formula,  $f(k)$  is a noisy signal;  $s(k)$  is the original signal;  $n(k)$  is Gaussian white noise and obeys the  $N(0, \sigma^2)$  distribution.

Since the wavelet is a linear transformation, after discrete wavelet transform is performed on the signal

$f(k) = s(k) + n(k)$  containing noise, the wavelet coefficient  $W_{j,k}$  still consists of two parts, one part is the wavelet coefficient corresponding to the real signal  $s(k)$ , which is denoted as  $U_{j,k}$ , and the other part is the noise signal  $n(k)$  correspondence. The wavelet coefficient, denoted as  $V_{j,k}$ .

Donoho<sup>[8]</sup> proposes that the wavelet transform, especially the orthogonal wavelet transform, has strong data correlation ability. It can make the energy of the signal concentrated in some large wavelet coefficients in the wavelet domain. The large amplitude wavelet coefficients are generally mainly signals, and the wavelet coefficients with smaller amplitude are largely noise. At this time, a suitable  $\lambda$  value can be found as the threshold (i.e. threshold). When  $W_{j,k} < \lambda$ ,  $W_{j,k}$  is mainly caused by noise, and when  $W_{j,k} > \lambda$ ,  $W_{j,k}$  is mainly caused by signal. Thus, the threshold denoising method can keep the signal coefficients and reduce most of the noise coefficients to zero.

When dealing with wavelet coefficients above the threshold, a new threshold function is proposed, which combines the hard threshold method with the improved soft threshold method:

$$\hat{W}_{j,k} = \begin{cases} W_{j,k} - \alpha\lambda + \frac{\alpha\lambda}{1 + \exp(\frac{-W_{j,k} + \alpha}{\lambda})} & |W_{j,k}| \geq a \\ 0 & |W_{j,k}| < b_L \\ \frac{a}{a - b_L}(W_{j,k} - b_L) & others \end{cases} \quad (6)$$

Take  $a = b = \lambda$ , discuss the change of  $\alpha$ : (1) when  $\alpha = 0$ , that is equivalent to hard threshold denoising method. (2) when  $\alpha = 1$ , that is to say, it degenerates to soft threshold denoising method. (3) when  $0 < \alpha < 1$ ,  $W_{j,k} \rightarrow +\infty$ , there is  $\hat{W}_{j,k} - W_{j,k} \rightarrow a\lambda$ . So this function can reduce the constant deviation produced in the soft threshold method, improve the reconstruction accuracy, and improve the denoising effect. It can be seen that the new threshold function is a better and more flexible choice than the soft and hard threshold function. As long as  $\lambda$  is adjusted appropriately between zero and one, a better denoising effect can be obtained.

## 2.3 Improved Emd Threshold Denoising Method

In view of the shortcomings of EMD and the advantages of the new wavelet threshold, a noise elimination method combining the EMD with the new wavelet threshold is proposed, that is, the improved EMD threshold algorithm, and the more accurate feature parameters are extracted. The steps of the denoising method are as follows:

a. EMD decomposition of a signal containing noise.

The EMD method is an effective tool for nonlinear and non-stationary signal analysis, which has the

advantages of self-adaptability, completeness and approximate orthogonality. However, the EMD denoising method also has some defects, such as boundary effect, excessive decomposition, interpolation error and so on. Due to these defects, pseudo-components<sup>[1]</sup>, also called "false components", are often found in the decomposition process of EMD, so this paper uses the correlation number to remove the false components. Then wavelet threshold is used to reduce noise.

After the original signal is decomposed by EMD, the pseudo-components can be removed according to each IMF component of the signal and the correlation coefficient of the original signal. Suppose two time Series  $x_n, y_n$ . The correlation coefficient  $r_{xy}$  is defined as follows:

$$r_{xy} = \frac{Cov(x_n, y_n)}{\sqrt{Varx_n \bullet Vary_n}} \quad (7)$$

$n$  is the number of sampling points, and the number of correlations between the IMF and the original signal is calculated, and the threshold is set to one-tenth of the maximum value in the correlation coefficient sequence, and components smaller than the threshold are removed. b. The high frequency component IMF1 is regarded as the highest frequency noise, and the new wavelet threshold denoising is performed.

First, after decomposing the IMF1 signal, the large-scale, low-resolution coefficients all remain, and for other scales, the wavelet coefficients. Then, a threshold can be set, and below this value, the wavelet coefficient is set to zero above the threshold. The wavelet coefficients or complete reservation. Finally, using the new wavelet threshold function method to denoise the IMF1 component and other components plus the residual amount to form a new signal. In order to get a better denoising effect, this paper chooses a new wavelet threshold function.

New wavelet threshold decomposition steps:

Step1. Decomposition of IMF1 component of EMD decomposition: Select appropriate wavelet basis functions and perform  $j$ -layer decomposition of IMF1.

Step2. Wavelet decomposition Threshold compression of high-frequency coefficients: Select a suitable threshold, use a new threshold function to perform threshold compression on the high-frequency coefficients from layer 1 to layer  $j$ , and remove the noise part.

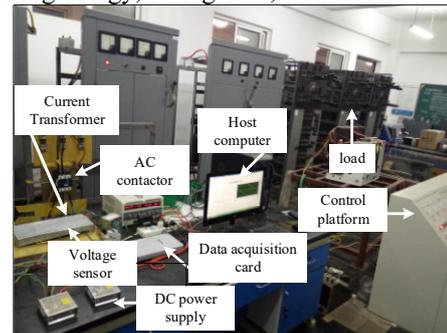
Step3. Signal reconstruction: the low frequency coefficients of the  $j$  layer and the processed high frequency coefficients of the first to the  $j$  layers are used to reconstruct the signal, and the IMF1 signal after noise reduction is obtained.

c. Finally, a new signal is formed by adding the residue to the IMF1 component and other components after wavelet threshold denoising.

d. Calculate the characteristics of the AC contactor life monitoring signal characteristics evaluation indicators, analysis of the denoising effect.

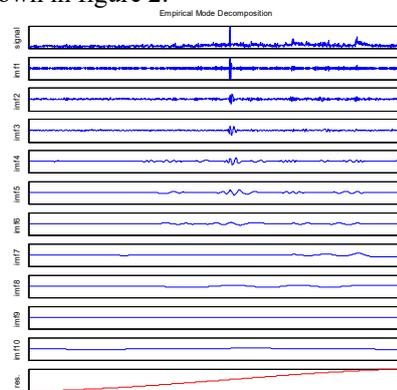
### 3 Example calculation

The test platform is shown in Figure 1. The CJX 2-8011 AC contactor is used as the research object. Under AC-4 conditions, AC 50Hz, coil voltage AC 220V, load voltage 400 (380) V, load current 240A, load type It is resistive, room temperature, operating frequency 300 times / h, sampling frequency 1M / S, monitoring the life of the AC contactor. Nearly 48,000 sets of raw data were collected, and then the characteristic parameters affecting the electrical life state of the AC contactor were calculated: contact resistance, pull-in time, bounce time, arcing energy, arcing time, and the like.



**Figure 1.** AC contactor electrical life test platform

Taking the A phase contact resistance data as an example, the effectiveness of the denoising method is verified. First, the data of phase A contact resistance are decomposed by EMD, and 10 IMF components and 1 residual component are obtained. The decomposition result is shown in figure 2.



**Figure 2.** A-phase contact resistance EMD decomposition diagram

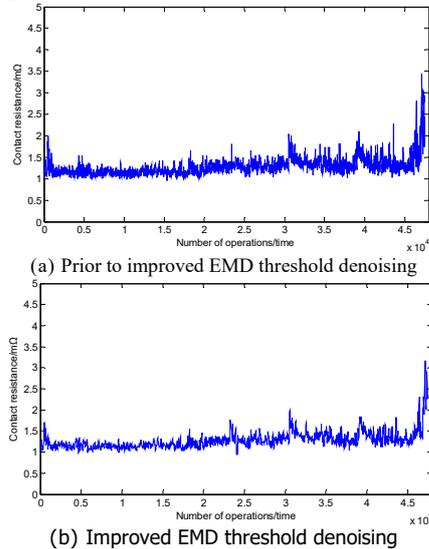
Using the method proposed in this paper to denoise, according to formula (7) to calculate the number of each IMF and the original signal, as shown in Table 1.

**Table 1.** Correlation coefficient between each IMF component and original signal.

Parameter	IMF1	IMF2	IMF3	IMF4	IMF5
Correlation coefficient	0.1946	0.1084	0.0763	0.0684	0.0320
Parameter	IMF6	IMF7	IMF8	IMF9	IMF10
Correlation coefficient	0.0589	0.0396	0.0723	0.0216	0.0034

According to the threshold of one-tenth of the maximum value of the correlation, the threshold is 0.0195, and the correlation coefficient of the component

IMF10 is less than the threshold and is regarded as a spurious component. After removing the IMF10, an improved EMD threshold denoising algorithm is selected to denoise the high-frequency component IMF1 of the contact resistance signal. Finally, a new signal is formed by adding the residual quantity to the IMF1 component and other components after denoising the new wavelet threshold. The comparison chart before and after denoising is shown in Figure 3.



**Figure 3.** A-phase contact resistance before and after noise comparison chart

Compare the results of wavelet soft threshold function, hard threshold function, EMD, and improved EMD threshold denoising method, and use signal-to-noise ratio (SNR), deviation (BIAS) and smoothness ( $r$ ) before and after signal denoising to remove noise evaluation indicators. To measure the signal denoising effect, the larger the signal-to-noise ratio, the better. The closer the deviation is to zero, the better the denoising effect, and the smaller the smoothness index value, the smoother the signal<sup>[9]</sup>. The characteristic index analysis of the contact resistance signal of phase A is shown in Table 2.

**Table 2.** Correlation coefficient between each IMF component and original signal.

Denoising method	Characteristic index		
	SNR	BIAS	$r$
hard threshold method	26.0165893	0.0456419	0.0135034
Soft threshold method	26.0862202	0.0453509	0.0138673
EMD denoising method	28.9475021	0.0438955	0.0327874
Improved EMD denoising method	29.3940285	0.0425840	0.0102833

From Table 2, it can be seen that the improved EMD combined with the new wavelet threshold denoising method is better than using EMD alone and wavelet threshold alone in the three indicators of signal-to-noise ratio, deviation, and smoothness. Overall, the improved The EMD threshold denoising method is better, illustrating the effectiveness of the improved EMD threshold denoising method.

## 4 Conclusion

By studying the electrical life status parameters of AC contactors and taking the contact resistance as an example, the EMD threshold denoising process was conducted, and the following conclusions were drawn:

1) The characteristic parameters that characterize the law of degradation have the characteristics of nonlinearity, non-stationary and strong noise. In view of these characteristics, the problem of false components and excessive denoising is easy to be produced by using EMD method alone. The improved EMD threshold denoising method can solve these problems well.

2) The experimental results show that the improved EMD denoising method is better than using the wavelet threshold alone and EMD denoising alone. Denoising the feature parameters with the improved EMD threshold algorithm can provide true and clean data for the extraction of the following AC contactor degradation law features, and thus help to improve the accuracy of the electrical life status assessment.

## References

- Zheng Shumei, Li Kui, Liu Zhengjun, et al. Research on Distributional Characteristic of Electrical Endurance of AC Contactor Based on Arc Erosion[J]. Proceedings of the CSEE, 2017, 37(22): 6730-6739.
- LI Kui, Duan Yu, Huang Shao Po, et al. Residual Electrical Life Prediction of AC Contactor Based on the Wiener Process[J]. Proceedings of the CSEE: 2018, 38(13): 3978-3986+4039.
- Hou C, Yu X, Cao Y, et al. Prediction of synchronous closing time of permanent magnetic actuator for AC contactor based on PSO-BP[J]. IEEE Transactions on Dielectrics & Electrical Insulation, 2018, 24(6):3321-3326.
- Cao Yundong, Gao Xiaoting, Liu Shuxin, et al. Feature Information Extraction Based on Life-cycle Condition Monitoring Data of Switchgear[J]. High Voltage Engineering, 2016, 42(09): 2980-2987.
- Liu Yang, Cao Yundong, Hou Chunguang. The Cable Two-terminal Fault Location Algorithm Based on EMD and WVD[J]. Proceedings of the CSEE: 2015, 35(16): 4086-4093.
- Li Xiaoyu, Jin Jing, Shen Yi, et al. Noise level estimation method with application to EMD-based signal denoising[J]. Journal of Systems Engineering and Electronics, 2016,27(04): 763-771.
- Yin Hongyan, Cao Yundong. Application of Improved EMD Denoising Method in the Study of Degradation Law of AC Contactor[J]. Electrical & Energy Management Technology, 2016(15):28-31.
- Donoho D L, Johnstone L. Adapting to unknown smoothness via wavelet shrinkage[J]. Journal of American Statistical Association, 1995, 13(90): 1201-122510].

9. Tu Binbin, Gu Lihua, Xu Hui. Quality evaluation method for wavelet de-noising in gait recognition[J]. Journal of Shenyang University of Technology, 2017, 39(01): 61-66.