Detection of DC Series Arc Fault Based on VMD and ELM

Tao Ma¹, Ersheng Tian², Zhenxing Liu³, Shuxin Liu³*, Tianhong Guo¹, Taowei Wang², Long Fu¹

¹State Grid Xiong' an New Area Electric Power Supply Company, Baoding, Hebei, 71600, China
²Xuji Group Corporation, Xuchang, Henan, 461000, China
³Institute of Electrical Apparatus New Technology and Application, Shenyang University of Technology, Shenyang, Liaoning, 110870, China

*Corresponding author’s e-mail: liushuxin@sut.edu.cn

Abstract. With the increase of domestic electrical equipment, the incidence of electrical fires has also increased, and research on fault arc detection has become a hot topic today. In this paper, a method combining variational mode decomposition (VMD) and extreme learning machine (ELM) is proposed to detect arc faults accurately. The characteristic signals of the resistance, capacitance and inductive load under normal conditions and arc fault conditions were collected by experiments. Then, the current data was processed by variational mode decomposition (VMD). Due to the different spectral characteristics of normal mode, arc fault mode and switching transient mode, the intrinsic mode function (IMF) under arc fault mode can be selected. Finally, according to the characteristic of determined IMF components, a new arc fault criterion was proposed for general DC arc detection. The experimental results verified that the proposed method can detect arc faults accurately.

1. Introduction
In the transmission or distribution line, the fault arc is a common failure phenomenon, which often occurs in insulation-damaged or damaged circuits and equipment, or in the case of loose conductor connections. Failure to take effective protective measures in a timely manner may cause accidents such as fires. Therefore, for the analysis and research of the fault arc characteristics, the arc fault is detected quickly and timely, so as to cut off the faulty line, which has strong engineering practical value [1-2].

There are many physical quantities that can describe fault arcs, such as temperature, arc sound, arc light, arc voltage, and so on [3]. However, the detection of the above physical parameters is more difficult in practical applications, and is more suitable for occasions where the arc combustion is severe, and the sensor for measuring these physical parameters must be installed near the point of occurrence of the fault arc, and in the actual line or equipment, the fault arc The location is uncertain and the line conditions are complex, which makes the detection of the above parameters very difficult. To this end, the author proposes the current of the protected line as the physical parameter of fault arc detection and analyses the characteristics by using appropriate analysis methods to extract the feature quantity that can be used to quickly and effectively diagnose the fault arc.
In order to obtain better fault arc detection effect, a fault arc recognition method based on variational mode decomposition (VMD) combined with extreme learning machine (ELM) is proposed.

2. Variational mode decompositionalgorithm

The general definition of the intrinsic mode is:

The number of local extreme zero crossings must be equal, or at most equal to one.

At any point in time, the local mean of the signal is zero.

On this basis, VMD introduces the more stringent requirement of limited bandwidth, transforming the traditional recursive mode into the variational framework, avoiding problems such as modal aliasing. VMD is mainly to solve the following problem:

$$\min_{\{u_k\};\{\omega_k\}} \left\{ \sum_k \left( \int \left( \delta(t) + \frac{j \omega}{\pi t} \right) u_k(t) e^{-j \omega \tau} dt \right)^2 \right\}$$

s.t. $\sum_k u_k = f$

(1)

Where $\{u_k\} = \{u_1, \ldots, u_k]\}$ is the resolved K modes, $\{\omega_k\} = \{\omega_1, \ldots, \omega_k\}$ is the center frequency of the K modes. Introducing the quadratic multiplication factor $\alpha$ and the Lagrangian multiplication operator $\lambda(t)$ to ensure the reconstruction accuracy under Gaussian noise and the strictness of the constraint. Equation (1) can be extended as follows:

$$L(\{u_k\}, \{\omega_k\}, \lambda) := \alpha \sum_k \left[ \int \left( \delta(t) + \frac{j \omega}{\pi t} \right) u_k(t) e^{-j \omega \tau} dt \right]^2 + \left\| f(t) - \sum_k u_k(t) \right\|^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle$$

(2)

Using the alternate direction method of multipliers (ADMM) calculation, continuously updating $\mu_k^{k+1}, \omega_k^{k+1}, \lambda^{k+1}$, and finding the saddle point of equation (2), the solution of the intrinsic mode can be obtained:

$$\hat{\mu}_k^{k+1}(\omega) = \frac{\hat{f}(\omega) - \sum_i \hat{\mu}_i(\omega) + \hat{\lambda}(\omega)}{1 + 2 \alpha (\omega - \omega_k)^2}$$

(3)

The solution of the center frequency:

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{\mu}_k(\omega)| d\omega}{\int_0^\infty |\hat{\mu}_k(\omega)| d\omega}$$

(4)

$\hat{\mu}_k^{n+1}(\omega)$ is the Wiener filter of $\hat{f}(\omega) - \sum_i \hat{\mu}_i(\omega)$; $\omega_k^{n+1}$ is the center frequency of the corresponding modal power spectrum; $\{\hat{\mu}_k^{n+1}(\omega)\}$ is inverse Fourier transform, and the real part is $\{\hat{\mu}_k^{n+1}(t)\}$, which is the modal time domain component.

3. Theory of extreme learning machine

For any N samples $(x_i, t_i)$, where $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in \mathbb{R}^n$ is the input vector, $t_i = [t_{i1}, t_{i2}, \ldots, t_{in}]^T \in \mathbb{R}^n$ is the network output, and the mathematical model of the standard single hidden layer forward network for the $\hat{N}$ hidden layer nodes is:
\[
\sum_{i=1}^{\hat{N}} \beta_i g_i (x_i) = \sum_{i=1}^{\hat{N}} \beta_i g_i \left( \omega_i \cdot x_i + b_i \right) = o_j \quad (j = 1, \ldots, N)
\]

In the formula: \( \omega_i = \left[ \omega_{i1}, \omega_{i2}, \ldots, \omega_{in} \right]^T \) is the input weight connecting the input node to the \( i \)-th hidden layer node; \( \beta_i = \left[ \beta_{i1}, \beta_{i2}, \ldots, \beta_{in} \right]^T \) is the output weight connecting the \( i \)-th hidden layer node to the output node; \( b_i \) is the threshold of the \( i \)-th hidden layer node; \( \omega_i \cdot x_i \) is the \( \omega_i \) and \( x_i \) inner product. The standard single hidden layer feedforward network with \( \hat{N} \) hidden layer nodes can approximate these \( \hat{N} \) examples with zero error, that is, \( \sum_{i=1}^{\hat{N}} \| o_i - t_i \| = 0 \) has \( \beta_i, \omega_i \) and \( b_i \) can satisfy
\[
\sum_{i=1}^{\hat{N}} \beta_i g_i \left( \omega_i \cdot x_i + b_i \right) = t_i, \quad \text{N formulas written as matrix operators:}
\]
\[
H \beta = T
\]

among them:
\[
H \left( \omega_1, \ldots, \omega_{\hat{N}}, b_1, \ldots, b_{\hat{N}}, x_1, \ldots, x_{\hat{N}} \right) =
\begin{bmatrix}
  g \left( \omega_1 \cdot x_1 + b_1 \right) & \cdots & \cdots & \cdots \\
  \vdots & \ddots & \vdots & \vdots \\
  \vdots & \vdots & \ddots & \vdots \\
  g \left( \omega_{\hat{N}} \cdot x_{\hat{N}} + b_{\hat{N}} \right) & \cdots & \cdots & \cdots \\
\end{bmatrix}_{N \times \hat{N}}
\]

\[
\beta =
\begin{bmatrix}
  \beta_1^T \\
  \vdots \\
  \vdots \\
  \beta_{\hat{N}}^T \\
\end{bmatrix}_{N \times \hat{N}}
\]

\[
T =
\begin{bmatrix}
  t_1^T \\
  \vdots \\
  \vdots \\
  t_{\hat{N}}^T \\
\end{bmatrix}_{N \times \hat{N}}
\]

4. Diagnostic case analysis

4.1 Feature quantity extraction and analysis

According to the UL1699 standard, the self-developed arc generator is used to simulate various typical load arc faults. Each load is connected in parallel to the 220 V power supply through a switch, and a voltage sensor of the type HP16-400/5V is set at the load end to detect the measured signal is sent to the Advantech PCI1711L data acquisition card, which has a 12-bit A/D converter with a sampling rate of 50 kHz, as shown in Figure 1. In the experiment, five typical loads (26.5, 26.5+34.4mH, hand drill, computer and induction cooker) were selected as research objects, of which 26.5, 26.5+34.4mH were linear loads, and the hand drill, computer and induction cooker were non-linear loads, and 220V was selected 50Hz single-phase alternating current is used as the experimental power source. There is a large randomness and instability in the arc combustion process, which will cause strong distortion and distortion of the collected signals. In order to improve the accuracy of signal data acquisition, 10 groups
of normal and fault signals are collected for each load, and the distortion is severely eliminated. Signal data to eliminate the effects. Figure 2 shows an arc generator prototype.

![Arc generator prototype](image)

**Figure 1.** Arc voltage detection in the load side of series arc fault.

**Figure 2.** The controllable arc generator.

4.1.1 Resistive load test. The experiment selects 26.5Ω pure resistance as the load, and the current waveform under normal conditions and fault conditions is shown in Figure 3. It can be seen from the figure that the current waveform of the pure resistive load line under normal working conditions is regular and has a small amount of noise interference, which is close to the standard sine wave. When the series arc fault occurs, the current waveform is obviously distorted, and there is a flat shoulder phenomenon, which contains a lot of high-frequency noise interference. The arc "zero rest" phenomenon causes the signal to appear "flat shoulder" phenomenon.

![Current waveform of resistive load](image)

**Figure 3.** The current waveform of the 26.5Ω resistance under the normal and fault condition.

![IMF components](image)

**Figure 4.** The set of IMF components obtained by the EMD decomposition of the resistive load voltage signal when the series arc fault occurs.
4.1.2 Nonlinear load series arc fault test. In this paper, three kinds of nonlinear loads are selected for simulation experiments, namely, hand drill, computer and induction cooker. The normal and fault current signal waveforms collected by the experiment are shown in Figure 6.

4.2 ELM-based fault diagnosis
The normal and simulated arc fault states of five typical loads (26.5, 26.5 + 34.4mH, hand drill, computer and induction cooker) were sampled in the experiment, among which 130 groups of normal state and fault state training samples, 5 eigenvectors per group. After network training, 100 fault test samples (20 for each load) after analysis and analysis were selected for network diagnostic performance test. The test results are shown in Table 1.

| working condition       | Number of test samples | Identify the number of samples | Correct rate |
|-------------------------|------------------------|--------------------------------|--------------|
| Resistive fault         | 20                     | 19                             | 95%          |
| Resistance failure      | 20                     | 18                             | 90%          |
| Hand drill failure      | 20                     | 19                             | 95%          |
| Computer malfunction    | 20                     | 20                             | 100%         |
| Electric kettle failure | 20                     | 19                             | 95%          |
5. Conclusion
The load-end fault arc voltage signal of the low-voltage distribution line has obvious nonlinearity and non-stationarity. The IMF component obtained by VMD decomposition can effectively reflect the characteristics of the fault arc and can be used for the feature quantity extraction of the fault arc. This paper addresses these deficiencies by taking advantage of VMD of the good noise robustness and separation of harmonic components with similar frequencies. Finally, the use of ELM to diagnose and identify fault arcs has the characteristics of high recognition efficiency and good real-time performance. The experimental results verified that the proposed method can detect arc faults accurately.

Acknowledgement
Funded by science and technology project of State Grid Corporation of China(5204XQ) (190003)

References
[1] Zheng, H. (2008) Overview of arc fault protection technology application prospect in domestic electrical safety. ChinaOccupational Safety and Health Association Academic Annual Meeting. Beijing, 71-73.
[2] KANG, C.S. (2007) The design of arc fault current interruption in arc current. Proceedings of the 7th WSEAS/ASME International Conference on Electric Power Systems, High Voltages, Electric Machines, 21-23.
[3] Luebke, C, Pier, T., Pahl, B.et al. (2011) Field test results of DC arc fault detection on residential and utility scale PV arrays. IEEE Photovoltaic Specialists Conference. Seattle: IEEE, 001832-001836.
[4] HUANG, G.B., HU, Q.Y., SIEW, C.K.(2006) Extreme learning machine: Theory and applications. Neurocomputing, (70): 489-501.
[5] WANG, S.X,WANG, Y., LIU, Y.et al. (2014) Hourly solar radiation forecasting based on EMD and ELM neural network. Electric Power Automation Equipment, 34(8): 7-12.