Non-invasive electric arc fault detection based on sliding approximate entropy

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Abstract. In recent years, electrical fires have occurred frequently and have become the first cause of various fires. Among them, the electric arc is one of the important causes of electrical fires. In this paper, the research on non-invasive electric arc fault detection is carried out for low-voltage users, which can discover and detect the electric arc only by analysing the aggregated current measurements from outdoors. In order to achieve this goal, firstly, the abrupt change of the current mode is discovered and detected with sliding window from the total load current signal based on the approximate entropy. Then the current signature samples are extracted around the abrupt change. Finally, according to the pre-set electric arc signature classifier, it is judged whether the abrupt change is caused by the electric arc fault. In addition, under laboratory conditions, an electric arc simulation experiment is carried out for common appliances of actual low-voltage users. The results show the effectiveness of the proposed non-invasive electric arc fault detection method based on approximate entropy.

1. Introduction
In recent years, the incidence of electrical fires in China has an increasing trend year by year in the low-voltage system, which have ranked first among all types of fire causes [1]. During the use of appliances, arc faults often occur due to aging of cables, loose electrical connections, or virtual contacts [2]. If effective arc extinguishing measures are not taken in time, the danger of fire or even explosion may occur. Studies have shown that in electrical fires, the accidents caused by arc faults are far more than those caused by metallic short circuits between live conductors. Although the low-voltage power supply system is equipped with many protective devices, such as fuses and residual current operated circuit breakers, these cannot effectively protect against arc faults. When an arc fault occurs, the temperature of the arc may exceed 5500°C. The hot particles emitted by the high-strength thermal arc will accumulate over time and easily ignite the insulating material around the circuit, especially in the complex surrounding environment, which greatly increases the probability of causing electrical fires. Therefore, the research on low-voltage electric arc fault detection is of great significance. Arc faults can be divided into parallel and series arc faults according to their different locations [3]. The current waveform of a parallel arc fault has a strong commonality, which is generally greater than the normal load current. The series arc current is affected by the load type, and the amplitude is generally smaller. Since the traditional low-voltage protection scheme usually operate on the basis of overcurrent, it cannot protect against series arc faults effectively.

At present, the detection methods for series arc faults mainly include the following three aspects: the first is based on arc light, heat, electromagnetic radiation, etc. [4], the second is based on arc mathematical models [5], and the third is based on arc voltage and current waveforms [6]. Among them,
limited by the actual installation scenarios of the power line, the first two kinds of methods are difficult to promote and the research is mainly focused on finding fault detection methods through arc voltage and current waveforms. In addition, due to the complicated indoor circuit topology of low-voltage users, the location of arc occurrence is random and unknown, and arc voltage data is difficult to obtain. So, this paper chooses the arc fault current as the signature. Among the existing researches, the discrete Fourier transform is used to analyse the frequency spectrum of the arc current to detect faults [7]. The phase space reconstruction of the current waveform is carried out in [8], and the information dimension of the current phase plane is calculated based on the fractal theory. The mean value of the information dimension and the zero-break time of the current are taken as the fault features. A novel feature of short-time zero crossing rate of the current signal is introduced by [9]. When the number of d4 component of current wavelet decomposition exceeding the threshold within 0.5s is greater than or equal to 12 times, [10] suggest there is an arc fault. In general, the current arc detection methods are mainly aimed at a single device or a single branch, which is represented as socket protection in the actual scene. The non-invasive arc fault monitoring for low-voltage users has received little research, which can discover and detect the electric arc only by analysing the aggregated current measurements from outdoors. In this paper, based on the approximate entropy theory, current mode abrupt changes are extracted from the total current of users’ load, and whether the abrupt change is caused by arc fault is determined according to the pre-set electric arc signature classifier.

The rest content is organized as follows. In the second section, the general flow chart of the non-invasive arc fault method based on approximate entropy is first proposed and then the implementation details are introduced. In the third section, some experimental results supporting the proposed method are presented. In the fourth section, the paper is summarized and prospected.

2. Non-invasive Arc Fault Detection Method

In this paper the aggregated current data acquired by the entrance smart meter is enough, without the need of adding any indoor auxiliary equipment. The overall flow of the proposed non-invasive electric arc fault detection method is shown in Figure 1. Firstly, the total load current data is obtained. Then, based on the approximate entropy theory, the abrupt changes of the current mode are detected from the total load current signal, and the corresponding current characteristic samples are extracted. Finally, according to the pre-set classifier, whether the abrupt change is caused by the arc fault is determined. The classifier is trained in advance by analysing the common characteristics of fault arc current. When an arc fault is detected, the information is recorded and stored.

![Figure 1. Non-invasive arc fault detection method flow](image)

2.1. Abrupt change detection of current mode

The abrupt change of the total load current mode may be caused by the arc fault, or by the appliance state switches and background noise, etc., which is reflected in the measured data as the abrupt change of the current time series. The approximate entropy is a nonlinear dynamical index, which can be used to measure the complexity of time series. For different time series belonging to the same dynamic
structure, their approximate entropy is more consistent, otherwise there are obvious different. Compared with the common power index and current effective value, approximate entropy has many incomparable advantages. Therefore, the approximate entropy method is adopted to detect the abrupt change of current mode according to the complexity differences before and after the change of current time series.

2.1.1. Fundamental principles of approximate entropy. The calculation process of approximate entropy method is as follows:

The time series \( \{x(t), t = 1, 2, \ldots, n\} \) of length \( n \) is reconstructed in the phase space:

\[
X(i) = \{x(t_i), x(t_i + \tau) \cdots x(t_i + (m-1)\tau)\}
\]

Where: \( \tau \) is the time delay (\( \tau = \alpha \cdot \Delta t \)) and \( m \) is the embedding dimension. Perform the above operation for each point in the time series to obtain a \((n - \alpha(m-1))\)-dimensional vector matrix:

\[
M = \{X(i), i = 1, 2, \ldots, n - \alpha(m-1)\}
\]

In this paper, \( \alpha \) is taken as 1, and the distance \( d[X(i), X(j)] \) between vector \( X(i) \) and \( X(j) \) is defined as the one with the largest difference between the corresponding elements, i.e.,

\[
d[X(i), X(j)] = \max [|x(i+k) - x(j+k)|], k = 0, 1, 2, \ldots, m-1.
\]

For each \( i(1 \leq i \leq n-m+1) \), we can calculate:

\[
C_i^m(r) = \frac{P}{n-m+1}
\]

Where, \( C_i^m(r) \) represents the probability that the distance between vector \( X(i) \) and \( X(j) \) is less than \( r \) when the dimension is \( m \) and the allowable deviation is \( r \) with \( X(i) \) as the centre, thus represents the degree of mutual approximation between all \( X(i) \) and \( X(j) \), namely the degree of correlation. The parameter \( P \) is the number of \( d[X(i), X(j)] \leq r \).

Take the logarithm of \( C_i^m(r) \), and then solve the average value of all \( i \) cases, namely \( \phi^m(r) \), i.e.

\[
\phi^m(r) = \frac{1}{n-m+1} \sum_{i=1}^{n-m+1} \ln C_i^m(r)
\]

Add the dimension \( m \) by 1 and repeat the above steps to get \( C_i^{m+1}(r) \) and \( \phi_i^{m+1}(r) \). Theoretically, the approximate entropy of this sequence is:

\[
ApEn(m,r) = \lim_{n \to \infty} [\phi^n(r) - \phi^{n+1}(r)]
\]

In general, this limit exists with probability 1. But in reality, the length of the time series \( n \) can't be \( \infty \). When \( n \) is a finite value, the approximate entropy calculation formula can be obtained as follows:

\[
ApEn(m,r) = \phi^n(r) - \phi^{n+1}(r)
\]

2.1.2. Abrupt change detection of current mode based on sliding approximate entropy. When the arc fault occurs, it will cause the distortion of the current waveform, but it has no significant effect on the basic current amplitude and other extended indexes. For this reason, this paper integrates sliding approximate entropy algorithm and t-test index to detect the abrupt change of current mode. The specific steps are as follows:

**Step 1** Select the length \( L \) of the sliding data window based on the total load current time series with the time length of \( n \) obtained.
Step 2 Select $L$ data continuously from the $j$th ($j = 1, 2, ..., n - L + 1$) data of the current sequence to be studied, and calculate the approximate entropy value of the current sequence within the window.

Step 3 Slide the data window Step by Step with Step size $L$, and repeat Step 2, Step 3 until the end of the original current sequence.

Step 4 Through Step 1 to Step 4, a time series of current approximate entropy can be obtained.

Step 5 Analyse the sliding approximate entropy sequence obtained in Step 4. When the sequence starts to change at a certain point, it can be considered that this point is the turning point of the trend change of the current sequence. Here, the sliding t-test method is used (according to formula (7)) to find the change point to avoid the setting of the rigid threshold. Furthermore, the abrupt area of the original current sequence is determined.

$$t = \frac{ApEn_1 - ApEn_2}{\sqrt{(\sigma_1^2 + \sigma_2^2)/k}}$$

(7)

Where: $ApEn_1$, $ApEn_2$, $\sigma_1$, and $\sigma_2$ are the mean value and standard deviation of the data in the two windows before and after the window length $k$ in the approximate entropy sequence.

Compare the obtained t-test value with the critical value obtained by looking up the table under a certain confidence level, and take the data point corresponding to the maximum value of the continuous t-test value greater than the critical value as the change point in the approximate entropy sequence, and then lock the region of abrupt change in the original current sequence.

2.2. Arc fault identification method

2.2.1. Arc fault feature analysis. In this research, the operation current waveforms without and with arc faults of various appliances are collected each includes 100 samples in normal operation and 100 samples with arc fault operation. Examples of the electric kettle and air conditioner are shown in Fig 2. The data sampling frequency is 25kHz.

The ratio of the arc current change rate to its effective value (DIV), that is, the difference between two adjacent sampling points divided by the sampling interval between the two points, and then the current effective value, as shown in formula (8). Regardless of linear or non-linear load, the proportion of high frequency component of the current during normal operation is much smaller than that of the
fundamental wave component. When an arc fault occurs in the line, there are many "high frequency burrs" in the arc current waveform. At this time, the variation range of DIV will far exceed the maximum value during normal operation, as shown in Figure 3. It can be seen that using the DIV as the time-domain characteristic quantity of the high-frequency component of the arc current and setting an appropriate comparison threshold can realize the effective identification of arc faults.

\[
\text{DIV} = \frac{\frac{d(i(t))}{dt}}{I_{\text{rms}}} \tag{8}
\]

Where: \(I_{\text{rms}}\) is the effective value of the previous current cycle.

Figure 3. Values of DIV under normal and arc fault conditions of different load appliances

The wavelet transform can decompose the signal into multi-band signals. Each frequency band signal contains both the time domain and frequency domain characteristics of the signal, and the irregularity of the signal will be reflected in both the time domain and the frequency domain. In this paper, the db4 wavelet analysis is performed on the simulation signal, and the current waveform obtained by the abrupt change detection is decomposed in four layers. Take the arc fault of an electric kettle as an example, and its decomposition waveform is shown in the figure 4. The db3 and db4 components of normal condition and arc fault are quite different. The absolute value of db4 is almost higher than 1 in the arc period, and almost zero in the normal period.

Figure 4. Wavelet decomposition diagram of electric kettle current
2.2.2. Arc classification and recognition. Based on the DIV (numerical), db4 component (nominal), and the arc zero-break feature (numerical), that is, the duration when the absolute value of sampling point in each current cycle is less than 5% of the maximum value, this paper calculates the detected abrupt current signatures, and comprehensively considers the above three features to determine whether the abrupt change of current mode is caused by the normal appliance state switches or arc faults. Here, the decision tree (DT) is selected for arc classification and recognition since it can handle numerical and nominal features at the same time and it is easy to understand, explain and implement.

3. Experiment

3.1 Experimental design

In order to obtain the series arc fault characteristics under various typical load operation conditions and build the signature library of common load appliances, an arc fault generator is built in this paper. Figure 5 is a self-made arc fault generator according to UL1699 standard. The arc generator consists of a movable electrode (copper rod) and a fixed electrode (carbon rod). The diameter of the carbon rod is 6.4mm. The contact point of the copper rod is sharp and a is in the range of (17.8 ± 7.6) mm. The arc waveform is generated by connecting different loads and controlling the air gap.

3.2 Results and analysis

For the experimental test of abrupt change detection of current mode, the approximate entropy are related to the values of \( m \) and \( r \). Reference [11] suggested that the values of parameters should be \( m = 2, r = 0.1\sigma - 0.2\sigma \) respectively (\( \sigma \) is the standard deviation of the original data). On this basis, according to the actual test results, the parameters are \( m = 2, r = 0.2\sigma \). In addition, the effect of abrupt change detection greatly depends on the size of the sliding window used to calculate the approximate entropy. At the sampling frequency of 25kHz, we take \( L=1000 \), that is, the current data window containing two cycles. Three typical cases in the experimental test results are shown in Figure 7.

Through the analysis of the experimental results, it can be seen that the current mode abrupt change may occur in the occurrence of arc fault or the appliance state switching. The corresponding approximate entropy sequence can show obvious abrupt change, and its position can be accurately determined by sliding t-test algorithm. In Figure 7(c), only the resistive electric kettle is working. When the arc fault occurs, the current amplitude has almost no change, but presents "zero-current" feature. The occurrence
of abrupt change can be determined by detecting the approximate entropy sequence. This shows that the fusion method of sliding approximate entropy and t-test is effective.

Figure 7. (a) (c) (e) is the original current waveform data of the total load before and after the occurrence of two arc faults and a state switching (the kettle has been running and then the air conditioner is on), in which the orange area is the detected abrupt change area; (b) (d) (f) is the corresponding sliding approximate entropy sequence.

According to the detected abrupt points, the current characteristics after abrupt are calculated, that is, the DIV, the db4 component and the zero-break features. The arc fault classification and recognition is realized by using the pre-trained decision tree to distinguish the abrupt changes of the current mode caused by the state switching and the arc fault. For the three cases built above, the experiments have been conducted for each case 50 times, and the results are shown in Table 1. When only one appliance is in operation, the detection accuracy is higher. When the fault occurs on the main power supply branch, with the increase of appliances in operation, the comprehensive load situation is more complex, resulting in a slight decrease in the detection accuracy, but the overall detection effect is competitive.

Table 1. Test results of non-invasive fault arc classification.

| Case | Operating appliance                | Arc fault branch | Accuracy |
|------|-----------------------------------|-----------------|----------|
| 1    | Electric kettle                   | ①               | 97%      |
| 2    | Electric kettle, Air conditioner  | ②               | 91%      |
| 3    | Electric kettle, Air conditioner, Heater | ③               | 85%      |
4. Conclusion
Accurate detection of arc fault can provide important reference basis for timely troubleshooting and clearing of electricity hidden danger. The non-invasive detection scheme only needs the aggregated load electricity consumption data, which provides the possibility for the large-scale popularization and application of arc fault detection. In this paper, a non-invasive arc fault detection scheme based on approximate entropy is proposed, and its general algorithm flow is given, especially the realization method of key technical links and experimental results are provided.

The occurrence of arc faults will inevitably cause the changes of current mode. Since the system dynamics structure before and after the changes is different, and the complexity of the current time series is also different, a current mode abrupt detection method combining the sliding approximate entropy and t-test algorithm is proposed. The empirical calculation shows that this method has a high recognition accuracy, and can detect correctly when the arc fault induced current pattern abrupt is small in a single resistive electric appliance scene.

The arc fault current characteristics of various appliances are analyzed. The ratio of current change rate to its effective value (DIV), db4 component obtained by wavelet transform and zero-break feature are selected as signatures of current mode abrupt. The experimental results show that the proposed DT-based arc classification method has a high accuracy in different scenes. Furthermore, it is worth noting that when multiple appliances are running, they are coupled with each other, and the influence of background noise is intensified, which reduces the detection accuracy. Therefore, further optimization and improvement are needed.

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References
[1] Shixiong Li. (2009) China Fire Statistical Yearbook. China Personnel Press, Beijing.
[2] Xiaorong Chen, Xiaowen Li. (2011) Data statistical analysis and application of the characteristics of electrical fire law in China. Science and Technology Information, 22: 381-382.
[3] Guangeng Liu, Songhuai Du, Juan Su, Xianhui Han. (2017) Research and development trend of low voltage arc fault protection technology. Power Grid Technology, 01: 321-329.
[4] KIM C J. (2009) Electromagnetic radiation behaviour of low voltage arcing fault. IEEE Transactions on Power Delivery, 24(1): 416-423.
[5] Lei Wang, Lesheng Chen. (2013) Research progress on mathematical model of switching arc simulation. Electrical Materials, 3: 32-40.
[6] Yao Wang, Ming Tian, Feng Niu, Zhizhou Bao, Kui Li. (2018) Review of Research on Low Voltage AC Arc Fault Detection Method. Electrical Appliances and Energy Efficiency Management Technology, 10: 8-13+44.
[7] Yao Wang, Yang Li, Leijiao Ge, et al. (2017) Fault Identification of Series DC Arc Based on Sliding Discrete Fourier Transform. J. Transactions of China Electrotechnical Society, 32 (19): 118-124.
[8] Shaohua Ma, Jieqiu Bao, Zhiyuan Cai, et al. (2016) Arc Fault Identification Method Based on Information Dimension and Zero Break Time. J. Proceedings of the CSEE, 36 (9): 2572-2579.
[9] Xiaoming Liu, Yefei Xu, Ting Liu, et al. (2015) Arc Fault Detection Based on Short-time Zero-Crossing Rate of Current Signal. J. Transactions of China Electrotechnical Society, 30 (13): 125-133.
[10] Zhengxin Wang, Zhihong Xu. (2014) Research on General Diagnosis Method of Low Voltage Series Arc Fault. J. Journal of Electronic Measurement and Instrumentation, 9: 991-997.
[11] Pincus S. (1991) Approximate entropy as a measure of system complexity. Proceedings of the National Academy of Sciences, 88(6): 2297-2301.