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Series arc fault detection and line selection based on Non-Intrusive Load Monitoring Method

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***Abstract* – The series arc faults are a common cause of household fires. Low fault current amplitude is the reason for the difficulties in implementing effective arc detection systems. The paper presents a novel arc detection and line selection method. It can be easily used in the low-voltage Alternate Current (AC) network to enhance the functionality of the Non-Intrusive Load Monitoring (NILM) system with arc detection for the whole household. Unlike existing methods, the proposed approach exploits not only current signal but also voltage signal time domain analysis. In the case of arc fault detection, line selection is based on the mean values of changes in the consecutive current signal periods during the arc and comparing them with current waveforms for each appliance in non-arc conditions. Tests have been conducted with up to 6 devices operating simultaneously in the same circuit. Single period arc detection accuracy was 98.47%, with recall at 97.5% and F-score of 0.983. The arc detection accuracy in terms of the IEC 62606:2013 standard was 99.33%, F-score of 99.33. Line selection accuracy was 91.57%.**

Keywords – arc fault detection, line selection, NILM, non-intrusive load monitoring, series arc

I. INTRODUCTION

According to the French ONSE (Observatoire National de la Sécurité Electrique), 25% of the fires in France are caused by electrical sources [1]. One of them is the arc fault, the phenomenon of plasma discharge. The unintentional arcing condition in the electrical circuit may occur for many reasons, such as insulation aging, loose wiring, or external damage when there is discontinuity on the conductors. A series and parallel arc short circuit can be distinguished [2]. During the latter, similar to the short circuit, overcurrent and earth leakage might occur, which can trigger standard protection devices such as fuses and circuit breakers. Unfortunately, the series arc is much more challenging to detect. When such a fault occurs on a single line, the current decreases, and the change amplitude is much smaller than in the case of a parallel arc. The arc and the load are in the series, which results in a reduction in the line current magnitude. Standards were formulated to prevent the consequences of arc faults, such as American UL1699 [3] and European IEC62606 [4]. They recommend the use of Arc Fault Circuit Interrupters (AFCIs) and Arc Fault Detection Devices (AFDD), respectively. The accuracy of these devices is limited in the case of a series arc fault. Some devices generate series arcs during operation (e.g., motors, electronic switching mode power suppliers) [5]. Therefore further research is needed to develop an effective and affordable method for detecting arc-fault in series.

This paper proposes a novel method for arc detection and line selection method. It's based on the NILM method proposed in [6], where the analysis is performed in the time domain. Periodicity of the network voltage signal is exploited, allowing for dividing the signal into separate periods. It was assumed that the beginning of the period is the time instant of the fundamental component of voltage signal zero crossing). From these periods the array-like representation of the current and voltage samples vectors is constructed. It enables easy calculation of proposed arc detection indicators and current signal changes aggregation across consecutive periods during the arc. We observed that the mean values of these changes over 50 periods (1 second) are characteristic for appliances on the fault network branch, despite the discontinuous and aperiodic characteristics of these changes. That allows for identifying the electrical network branch on which arc fault occurs, called line selection. The proposed method can enhance the functionality of the NILM system as in [6] – analyzed signals are collected at a single point of the electrical network.

Unlike most other methods for series arc detection in AC networks, the proposed approach uses a voltage signal the time domain analysis. We observed that the values of the features extracted from the voltage signal are way more resilient for the load-specific changes in non-arc conditions than features extracted from the current signal. It is essential for avoiding false detections.

II. RELATED WORKS IN THE LITERATURE

This paper is focused on the arc faults phenomenon in low-voltage AC networks. It should be noted that there also is a wide research area for DC series arc detection, especially in photovoltaics systems [7–10]. DC signals are not periodic, so arc fault may not be easily detected via recognizable amplitude or frequency signatures for pattern recognition techniques. Arc detection and location systems for DC networks often exploit spectral analysis with Short Term Fourier Transform [7], Wavelet Transform [8], and Discrete Wavelet Transform [9]. Also use of Adaptive Local Mean Decomposition was proposed in [10].

For AC networks, the arc detection and location systems consider three main concepts – mathematical models of the arc, physical characteristics of the arc - exploited in this paper - analysis of characteristics of arc voltage and current signal. Due to the large diversity of the arc fault, the mathematical models need a lot of parameters and can still be imperfect [11]. Analysis of physical arc's characteristics can be based on light, heat, or electromagnetic radiation caused by arc [12–14]. These methods can find application in arc detection in the power distribution lines but are impractical in indoor circuits.

The literature study verified the usefulness of the presented series arc indicators, while modifications were proposed for some of them. Time features exploited in existing methods are Zero Current Period (ZCP) [15–18], the ratio of the current rate of change to the RMS value (CRC) [18], Maximum Split Difference (MSD) [15], and measures related to Euclidean distance (E, MED – Maximum Euclidean Distance) between adjacent cycles[15–17]. Arc detection accuracy of 99.1% and load identification of 99.3% were achieved using PCA and SVM in [15], but it considers only the case of individually operating devices. In [16], where up to 4 appliances operate simultaneously, arc detection accuracy was 94.86%. Load identification and line selection accuracy was 90.91%, with consideration that the harmonic disaggregation results of total current can be obtained by superposition of the harmonic disaggregation results of each appliance current either with or without arc fault. In [18] no accuracy data are provided, the distinguishability of categories in the ZCP-CRC plane is presented. This paper also considers only the case of individual appliance operation. In [17] zero-current time proportional coefficient is combined and compared to the empirical threshold to determine whether there is a series arc. Spectral Dispersion Index analysis with adaptive threshold was exploited in [19]. The arc detection was up to 100%, but with a notable amount of false detections and only one load operating at a time. Gray-Level Co-Occurrence Matrix (GLCM) allows in allows to achieve 99% arc detection accuracy and 98% appliance identification accuracy with 13 appliances in [20], but in all analayzed cases only one appliance was operating. Multi-load scenario was considered in [21], where wavelet transform, variational mode decomposition and Wigner-Ville distribution were exploited. The accuracy of arc fault detection was 99.0%, and line selection was 94.1%.

III. DESCRIPTION OF THE METHOD

A. Experimental setup and dataset

The experimental setup is shown in Fig. 1. The measuring system was adapted from [6]. Only Medium Frequency (MF) Unit with Advantech PCIE 1816 data acquisition card (DAQ) was used. Signals representing values of the total current $i_{total}(t)$ in the main power line $u_0(t)$ and the j-th socket ($j \in (1,7)$) $u_j(t)$ are measured using the current transformers (indicated in Fig. 1 as T_0 and T_j). The transformer T_u allows for acquisition of $u_{total}(t)$ as signal $u_u(t)$.

Experiments were conducted for six typical household appliances of different types. Characteristics of the measured devices are presented in Table 1. A total of 21 sequences of switching on and off devices were recorded. During each registration, the series arc was generated using the arc generator shown in Fig. 2 at a single socket, affecting connected devices. The arc fault generator was built based on the UL1699 standard. According to Table 1, in the case of sockets 1-6, only one appliance was attached. An arc fault scenario on the main power line was simulated by connecting all the appliances to be switched on to a powerstrip connected to socket number 7.

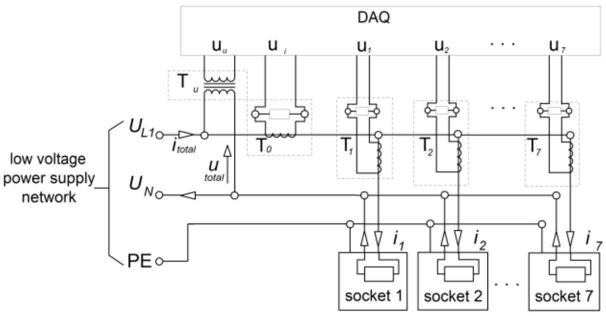

Fig. 1. Experimental setup scheme

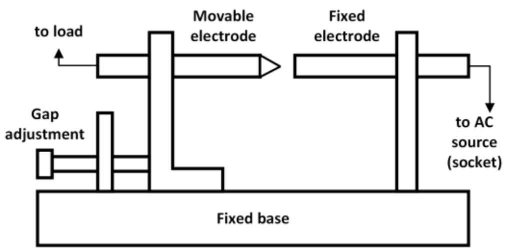

Fig. 2. Schematic setup of series arc fault generator

Samples were collected with the frequency f_s = 250 kHz on 3 channels simultaneously with 16-bit resolution.

In every run, signals u_{total} and i_{total} were registered. At the third channel the signal representing i_j was registered, where j is the number of the socket with arc generator connected. Data from the third channel was used for manual labeling of data and comparison of methods in the single and multi-load conditions. Up to 6 devices operated simultaneously during ten measured sequences, while in the remaining eleven sequences only one device was operating. Collected sequences were split into two subsets: the training (12 sequences) and the testing (9 sequences).

Table 1. Characteristics of the tested electrical appliances

Socket No.	Appliance	Load type	Rated power (W)
1	Computer	SMPS	50
2	Bulb	Resistive	60
3	Furnace	Motor-resistive	1100
4	Hairdryer	Motor-resistive	550
5	Vacuum cleaner	Inductive	450
6	TV	SMPS	40
7	Combinations of 1-6	-	40-2250

B. Data processing and feature extraction

Signals u_{total}, i_{total} and i_j from each registered sequence were transformed, as described in [6] to arrays U I and I_{arc}, respectively. Each column in the array represents samples from the single 50 Hz period $k = 1, \dots, K$. One such period I_k can be defined as

$$I_k = [i_{1,k}, \dots, i_{m,k}, \dots, i_{M,k}], \qquad (1)$$

and for f_s = 250 kHz, it contains M=5000 samples, identified by the index m.

The occurrence of a series arc in the appliance branch causes changes in the current and voltage signal. Examples of changes in the current signal are shown in Fig. 3. Similar current signal changes were observed in [17].

Using an array notation of signals, a method of calculating the following signal features for every signal period was prepared. The feature E (2) is the sum of differences between adjacent periods from the array I [16].

$$E_I(k) = \left| \sum_{m=1}^{M} (I_{k+1}(m) - I_k(m)) \right| \qquad (2)$$

Calculation of $E_{I_{arc}}$ and E_U (and other array-based features) is done analogically by using the arrays I_{arc} and U respectively. The second feature is the modification of the Maximum Euclidean Distance (MED) proposed in [15]. Instead of calculating Euclidean distance between the whole adjacent cycles, the Maximum Single Sample Distance (MSSD) is used:

$$MSSD_I(k) = \max(|I_{k+1}(m) - I_k(m)|), m \in <1, 2, .., M>. \qquad (3)$$

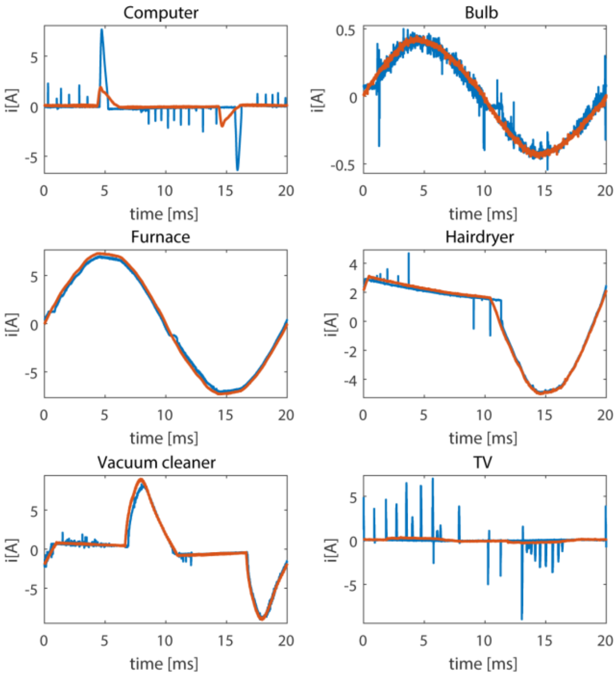

Fig. 3. Current waveform with (blue line) and without (orange line) series arc fault for tested appliances

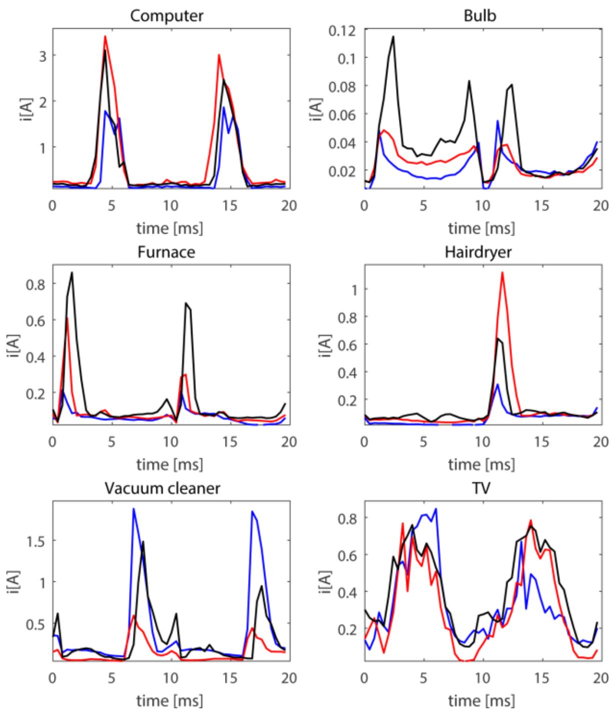

Fig. 4. Examples of $MVC_{50-mean}$ vectors for the occurrence of series arc on line with particular tested appliances for different number of devices operating simultaneously(blue line–one device, red line – two devices, black line – three devices)

The third feature is the modified CRC feature proposed in [18]. It is the ratio of change between two consecutive samples to the RMS value from the previous cycle. As a result of our analysis, we observed that more efficient is the maximum change in a cycle (MCC), without calculation of ratio to RMS value:

$$MCC_I(k) = \max(|I_k(m+1) - I_k(m)|), m \in <1,2,..,M) . \quad (4)$$

The feature used for line selection after the arc fault is detected is the vector of mean values of changes in the current signal across 50 consecutive periods (MVC_{50}):

$$MVC_{50}(k) = (\sum_{i=1}^{50} |I_{k+i} - I_{k+i-1}|) / 50 . \quad (5)$$

Values of MVC_{50} may vary depending, for example, on the size of the gap, but the general characteristic of these changes is repeatable for devices on the fault line. The mean was calculated for every 100 values, what allows for reducing the number of attributes from 5000 to 50 in $MVC_{50-mean}$. Examples of $MVC_{50-mean}$ vectors are shown in Fig. 4.

IV. RESULTS AND DISCUSSIONS

To evaluate the accuracy of the proposed arc detection method, a measure based on mean absolute error (MAE), used in the most recent publications, was adopted [16]:

$$Accuracy = 1 - MAE \times 100\% = 1 - \sum_{k=1}^{K} |\hat{x}_k - x_k| \times 100\% , \quad (6)$$

where $\widehat{x_k}$ is the test result and x_k is the ground truth for the k-th period out of the total K identified ones. The accuracy was calculated for the single cycle analysis and also in terms of IEC 62606:2013. The arc fault status is activated only when at least 7 cycles are identified as an anomaly within 1 second. A random forest classifier was used for decision making, which is the typical choice when the approach is supposed to be operating in the measurement uncertainty conditions. Attributes used for classification were $E_I, MSSD_I, MSSD_U, MCC_I,$ MCC_U. The obtained results are shown in Table 2. Row #A summarizes results for single cycle analysis. The total accuracy was 98.47% on the sample of around 100000 detected cycles. Despite the overall good results, it should be noted that there are over 3 times more missed detections (False Negative - FN) than detections (False Positive - FP). Results for standard IEC 62606:2013, shown in row #B are even better. As presumed, the application of this standard made it possible to reduce the number of errors. Accuracy was 99.33%. It should be noted these results were obtained for data collected at a high sampling rate (f_s=250 kHz). Thus, the results were also calculated for a signal downsampled to 6.25 kHz, 12.5 kHz and 25 kHz, and the arc detection accuracy obtained was 95.11%, 96.55% and 98.48% respectively, in terms of IEC 62606:2013 standard.

Table 2. Results of series arc fault detection

#	TP	TN	FP	FN	Recall	Precision	F-Score
A	51717	59866	384	1350	0.9745	0.9926	0.9835
B	56375	56188	368	386	0.9931	0.9935	0.9934

For the identification circuit branch on which arc fault occurred (line selection) the k-nearest neighbor algorithm was used, with k=6. The test set was divided into 996 disjoint 1-second fragments during which an arc fault should be detected.

Attributes used for classification were based on $MVC_{50-mean}$ vectors' values. Additional two attributes were the mean and maximum value of $MVC_{50-mean}$. The confusion matrix for line selection classification is shown in Fig. 5.

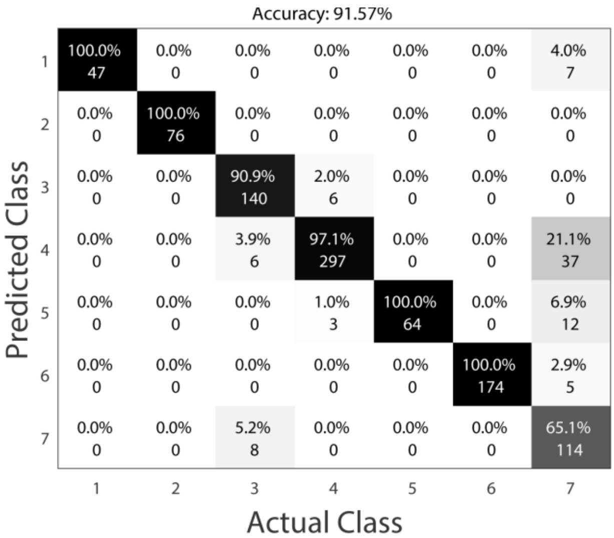

Fig. 5. Results of line selection identification

The overall accuracy of 91.57% was achieved. The method is vulnerable to the occurrence of an arc fault on the main power line, resulting in more than one device being powered through the arc. Some misclassifications occurred between classes 3 (furnace) and 4 (hairdryer). Both of them are of motor-resistive type. Although it should be noted the high accuracy of line selection was achieved for the occurrence of arc fault for a single device, even though in a considerable part of identified cases, multiple devices were operating simultaneously.

V. CONCLUSIONS AND OUTLOOK

The application of the proposed features of the current and voltage signal made it possible to achieve high detection accuracy of series arc faults with a low false detection ratio. Especially the use of features extracted from the voltage signal allows for a false detection ratio decrease. High accuracy was also persisted for the signal of sampling rate affordable for real-world application in NILM system. Further research will focus on the adaptive determination of decision thresholds for proposed signal features. That will allow higher identification accuracy, especially for data with lower sampling rates.

One of the proposed features (MCC) is directly dependent on the sampling rate, so it needs to validate the impact of the sampling rate on the method's performance. The proposed fault line selection method is highly accurate only if arc fault occurs on a single appliance. Additional research focused on MVC_{50} vectors analysis should be conducted.

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