Kalman filter and a fuzzy logic processor for series arcing fault detection in a home electrical network

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Abstract

This paper presents a method for detecting series arcing faults in AC home electrical networks. The proposed algorithm is based on both a Kalman filter, used for identifying fault symptoms and a decision block, which confirms the presence of a series arc fault to activate a tripping signal. The current measured at one end of the power line is estimated using a model of two steady-state variables (X1 and X2). Firstly, residuals and the third order difference of state X2 are used as input parameters of a Fuzzy logic processor for detecting fault symptoms. Secondly, the fault symptoms are processed by a detection logic block, which confirm the presence of an electrical arcing fault.

The algorithm is tested on a variety of loads in single or masking load configurations. Experimental results show that the method we propose can detect arcing faults efficiently, avoiding false tripping, whilst taking into account a high degree of diagnosis accuracy and average detection time.

Keywords: AC series arcing fault, Fuzzy logic processor, Kalman filter, adaptive threshold.

1. Introduction

Arcing fault detection in domestic networks has been an important subject for industrials and researchers for many years. In the USA, the safety standard UL 1699 dating from 1999, includes the requirements for arc fault interrupters (AFCIs) whilst in Europe, standard IEC 62606 is much more recent and has been at the forefront of the development of protective electric arc equipment for home use (50 Hz operating frequency and 230 V supply voltage). Protection devices are mainly based on the power line current and are inserted at the level of the general supply source in dwelling units. The challenge for fault detection algorithms is to work effectively with different circuit configurations where series arcing faults are difficult to identify. In this work, we focus on arc fault situations in presence of masking loads, whilst also taking into consideration the transient effect of starting loads.

The first difficulty in the development of AFCI lies in the choice of one or more optimal criteria. Different arcing fault detection approaches have been proposed in the literature, with spectrum analysis being the detection method most often used. Spectral analyze of the line current focusing on third and fifth harmonics [1–5] is performed in a variety of bands ranging from low frequencies up to 20 kHz. The approach presented in [6] analyzes the power spectral density of electromagnetic radiations.

Methods based on the temporal evolution of the current signal use the crest factor [7], inter-period correlations of current [8] or algebraic derivative of the line current [9].

Time-frequency methods are able to analyze non-stationary transient signals produced by arcing faults using essentially the Wavelet packet transform [10–12] and recently the Hilbert-Huang transform [13].

In this study, the detection method based on the Kalman Filter has the major advantage of allowing regular temporal estimation through an on-line digital processing structure unlike The other methods proposed in the literature which perform detection over a predefined sliding time window [1–14].

The Kalman filter and the extended kalman filter (EKF) are widely used in fault diagnosis [15–17]. The Kalman filter estimates instantaneous states from noisy (measurement) data recursively.

The use of Kalman filters for protection relays on high power systems developed in the 1980s by [18], provides state space models for voltages and currents. The work outlined in [19] associates an EKF and a support vector machine (SVM) to detect a parallel arcing fault. [20] presents a method based on two Kalman filters with different dynamics which detect incipient faults. This method is able to discriminate arcing faults from switching actions and load changes in an underground cable.

In [21], the Kalman filter is used to calculate eigenvalues which are compared to a predefined reference value (threshold) in order to identify the presence of an arc fault. However, this method was tested in stationary operating mode using mainly resistive household appliances as loads, with no inclusion of motor loads.

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An important part of the detection algorithm lies in the decision block which must operate reliably to confirm the presence of an arcing fault, respecting detection times imposed by standards UL 1699 and IEC 62606. Statistical techniques used for the selection of static thresholds presented in [22] are not sufficient to develop robust algorithms capable of avoiding false activation on circuit breakers. Another solution is to use a neural network or an SVM [23, 24]. However, they require long learning stages and are difficult to implement in a conventional electronic circuit board. In order to reconcile simplicity and efficiency, the strategy adopted in this work relies on an adaptive thresholding logic. The main part of the decision making is constituted by a Fuzzy logic processor largely used in recent years in fault diagnosis in photovoltaic and robotic systems [25–28] .

The major contribution of this article is the development of an arcing fault algorithm which is designed to reliably detect arcing fault events in stationary and transient operating modes in household appliances. Further, the algorithm incorporates more efficient fault detection and the prevention of nuisance tripping since it is is capable of distinguish arcing faults from load variations in the presence of masking configurations.

2. Proposed method

The block diagram of the whole system, represented in Fig. 1, consists mainly of a Kalman filter block and a decision part based on Fuzzy logic.

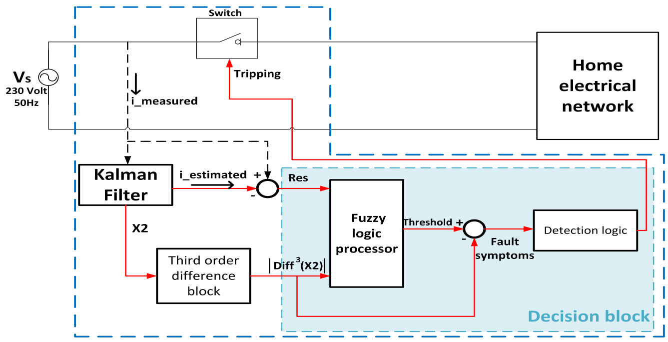

Figure 1: Scheme proposed for AC series arcing fault detection.

The kalman filter input is the current measured at one end of the power line (close to the source). The current signal is estimated by using the calculation of two-state variables X1 and X2 obtained from state equations. Residuals (Res) obtained from the subtraction between the measured current and its estimation and also the third order difference of state X2 are used by the decision block. This block consists of a Fuzzy logic processor responsible for generating fault symptoms which are processed by a detection logic block to confirm the presence of an arcing fault. Finally this block sends a tripping signal (TS) to activate a controlled switch in order to disconnect the power source from the power line.

The Kalman filter estimates a signal in the discrete domain and filters noises. The current signal in normal circuit operation can be represented by two phasors: the first with initial phase of 0 degree and the second with a 90 degree shift.

$$i(n) = X1 * cosw_o t - X2 * sinw_o t \tag{1}$$

Where X1 and X2 are independent, zero mean, Gaussian random variables and represent the real and imaginary parts. The system equations are then defined using a two-state model shown in [18].

$$\begin{bmatrix} X1(n+1) \\ X2(n+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X1(n) \\ X2(n) \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} i(n) \end{bmatrix} = \begin{bmatrix} cosw_o n\Delta t - sinw_o n\Delta t \end{bmatrix} \begin{bmatrix} X1(n) \\ X2(n) \end{bmatrix} + \begin{bmatrix} V(n) \end{bmatrix} \tag{3}$$

Equations (4) and (5) represent the state and measurement equations respectively.

3. Experimental environment

An experimental platform represented in Fig. 2 is used to create a database of current signatures under normal operation (switch is closed) and then in the presence of series arc faults (switch open). The database is used to evaluate the performance of the proposed method of detection. The experimental setup, consists of various domestic loads

Table 1: Loads used in the experimental platform.

Configuration	Appliance	Power [W]
Simple	Kettle	1200
	Halogen lamp	500
	Fan	60
	PC	300
	Drill	400
	Vacuum cleaner 1	1000
	Vacuum cleaner 2	1600
Parallel appliances	Halogen lamp // Halogen lamp	1000
	PC // PC	600
Masking type 1	Halogen lamp // R=80ohm	
	Vacuum cleaner 2 // R=80Ω	
	Drill // R=80Ω	
Masking type 2	Vacuum cleaner 2 // R=80Ω	
	Drill // R=80Ω	
Masking type 3	Vacuum cleaner 2 // R=80Ω	
	Drill // R=80Ω	
EMI filter 1	R=47Ω	
	Drill	
	Vacuum cleaner 2	
Disturbing appliance	Vacuum cleaner 1	
	PC	
	Drill	
	fluorescent lamp	
	Compressor	

supplied by the European domestic alternating voltage 230 Volts, 50Hz. The process of generating a series arcing fault is done using the opening contacts mode between two copper electrodes (6 millimeters diameters) according to IEC 62606 standard.

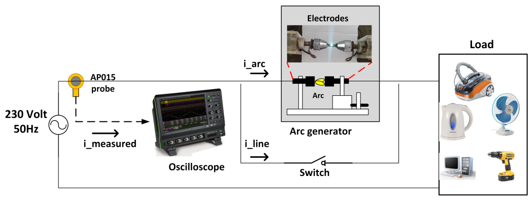

Figure 2: Experimental platform for series arc fault generation.

Measurements are recorded using an oscilloscope (Lecroy HDO 6104) at a sampling rate of 1MHz. Current measurements are made using a Lecroy AP015 current probe (75MHz bandwidth).

3.1. Series arc fault tests using typical domestic loads

Table I shows the characteristics of the main linear and non-linear household loads connected in the circuit. A database of current signatures is obtained using simple and combined loads configuration. The combination of different loads can be made according to several configurations presented in the standards UL 1699 and IEC 62606.

As fault detection is more difficult to achieve with combined loads (table I), household appliances are associated in parallel. Other tests are performed according to masking configurations presented in Fig. 3. In masking-type configurations a resistor of 80Ω generates a masking effect in the circuit.

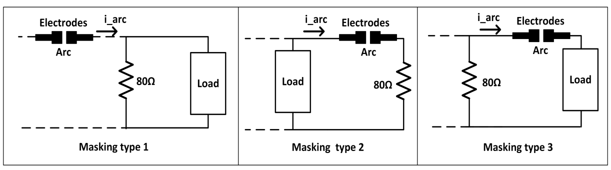

Figure 3: Different masking-type configurations.

The frequency rate of 100 kHz was selected in order to avoid an unnecessary computational burden for the algorithm implementation in an electronic circuit board (FPGA, DSP, etc).

A strategy for arcing fault detection based only on Res does not allow for effective detection. Thus, Res and the third order difference of X2 ($diff^3(X2)$) parameters can be combined to detect arcing faults. It can be seen that the association of these two parameters will allow arcing faults to be detected in the presence of motor loads under complex operating conditions (different masking load configurations, transient effects, variable speed and motor torque variations).

4. The decision part

The decision part plays a key role in the ability of the algorithm to avoid false tripping alarms.

4.1. Adaptive threshold using a Fuzzy logic processor

Based on the Fuzzy approach for threshold adaptation, we present our own topology displayed in Fig. 4. In our system Res and $|diff^3(X2)|$ are used as inputs of a Fuzzy logic processor (Mamdani FIS engine). These parameters deviate from zero even when no fault is present. The deviations in stationary operating mode are due mainly to measurement noises and unknown perturbation inputs. Furthermore, in transient operating mode these deviations vary dynamically and depend on appliance type and circuit configuration. The evaluation of these parameters therefore require a decision making process in order to reduce sensitivity to false alarms. In the adaptive thresholding logic shown in Fig. 4, the Fuzzy logic processor uses Fuzzy rules to sets an optimal threshold $\Delta J(Res, |diff^3(X2)|)$ which is then compared to $|diff^3(X2)|$ coefficients in order to generate fault symptoms.

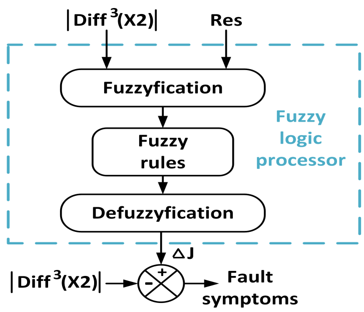

Figure 4: Fuzzy thresholding logic.

ΔJ increases or decreases under different fault scenarios (it includes varying operating conditions and uncertainties). The larger the difference between $|diff^3(X2)|$ coefficients and ΔJ the greater the possibility that a fault has occurred.

The mapping of crisp values into a representation by fuzzy sets is required. Thus, the fuzzyfication of Res, $|diff^3(X2)|$ and ΔJ are done through linguistic values.

4.2. Detection logic

The detection logic block shown in Fig. 5 guarantees correct fault detection. This block confirms the presence of an arcing fault and also reduces false tripping.

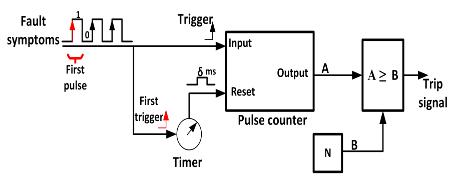

Figure 5: Detection logic.

In the process of confirming an arcing fault, the detection logic block starts by transforming the fault symptoms generated by the thresholding logic into binary pulses obtained with a comparator block. Then, a timing window of δ ms is then activated by the rising edge of the first binary pulse. An arcing fault is detected when N binary pulses are counted in a timing window. $\delta = 60$ ms and $N = 7$ are set experimentally in order to get a fast response in the circuit breaker.

5. Results

The blocks diagram shown in Fig. 1 was implemented using MATLAB. Different experimental tests were conducted in order to evaluate and validate the diagnostic accuracy of the detection algorithm.

In Fig. 6 the transient operating mode of the current using the first masking-type configuration (Fig. 3) for a halogen lamp, vacuum cleaner 2 and a drill is shown. The halogen lamp is started with a maximum power variation (section B) giving rise to a transient state which affects the Kalman filter dynamic. Consequently, residuals and $|diff^3(X2)|$ coefficients with high amplitudes are generated. However, the Fuzzy logic thresholding prevents fault symptoms being generated and, as a result, false tripping by the detection logic block is not produced. Finally, the arcing fault is confirmed and the tripping signal is sent after three wave cycles (60 ms).

In the case of current waves generated by vacuum cleaner 2, $|diff^3(X2)|$ coefficients are only affected by the presence of an arcing fault produced in section E, presenting high amplitudes. The detection logic block sends a tripping signal after 20ms.

The transient current behavior produced by a drill is presented in the whole of section F. The detection logic block sends a tripping signal after a wave cycle (20 ms).

Fault symptoms in transient conditions under the first masking type configuration are effectively obtained in spite of the parallel ($R = 80\Omega$) resistor which masks arcing faults.

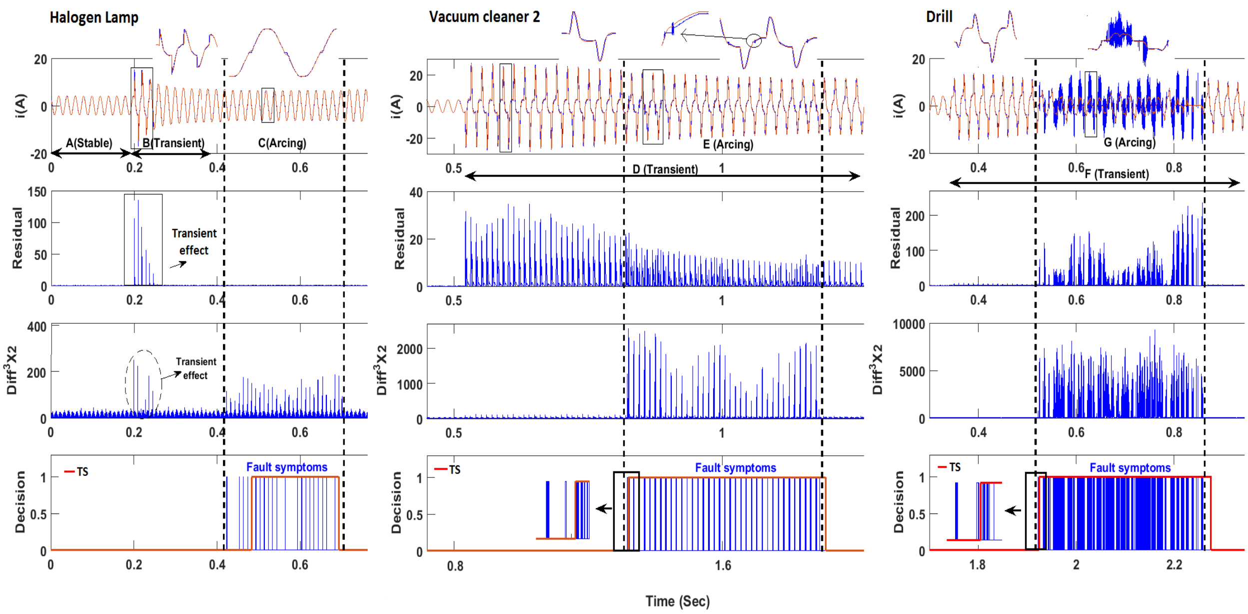

Figure 6: Sub-case 2: transient current (masking-type 1) of an halogen lamp, vacuum cleaner 2 and a drill.

Table IV summarizes the performances obtained by all the tests carried out in the laboratory.

Table 2: Summary of results.

Operation Mode	Load Configuration		No. of Tests	Diagnosis Accuracy (%)	Average Detection Time (ms)
Stationary	Simple		20	100	60
	Parallel		4	100	40
Transient	Simple		8	100	20
	Parallel		7	100	30
	Masking		18	100	60
	EMI filter		4	100	40
	Disturbing Load	Drill	3	100	20
		V. cleaner1	2	100	30
		PC	2	100	30
		F. lamp	2	100	35
		Compressor	4	75	40

6. Conclusion and future work

AC series arcing fault detection using conventional algorithms are much more difficult to achieve in presence of non-linear household appliances during the transient phase rather than in a steady-state. Furthermore, the performance of these algorithms often can be affected by load variations, different masking load configurations and disturbing appliances which are generally presented in real working conditions. In order to overcome these constrains, we have proposed an algorithm based on a Kalman filter and Fuzzy logic. The generation of Res and $|diff^3(X2)|$ coefficients obtained essentially from a Kalman filter with a fast dynamic response provide us with a first arcing fault detection approach. A second step allows us to select different fault symptoms and to confirm the arcing fault through the use of a decision part. The core of the decision part is composed by a Fuzzy logic processor which generates a threshold with different amplitude levels. This adaptive threshold mechanism makes an important contribution to the present research since it allows a significant reduction in false fault symptoms, which could lead to false tripping by the detection logic block. Finally, this block confirms an arcing fault after counting seven fault pulses in a timing window of $\delta = 60$ ms experimentally determined. The results obtained in both stationary and transient operation mode satisfy the triggering time imposed by standards UL 1699 and IEC 62606 with a 230 V supply voltage. Future work aims to test loads under the influence of EMI perturbations according to EN 61000-4-4, EN 61000-4-5 and EN 61000-4-11 standards.

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