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A statistical-based criterion for incipient fault detection in underground power cables established on voltage waveform characteristics

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ABSTRACT

The incipient faults which mainly occur due to the electric arc occurrence in the power cables with insulation defects are hardly detectable by the conventional protective relays, and over time can develop into a permanent fault in the system. Employing Kalman filter, this paper puts forward a method to detect the incipient faults and to discriminate them from other similar incidents in the power system. The proposed method is established on the comparison between the waveform of the measured voltage and fundamental component of the measured voltage, estimated by Kalman filter algorithm in the sending end of the cable during the fault. Employing the difference between the measured and estimated waveforms, the incipient fault detection and discrimination are carried out within two stages. In the first stage, event detection is relegalized by comparing the standard deviation of the obtained error with a certain threshold. The second stage is conducted to find the incipient fault based on the non-attenuating characteristic and quasi-periodic nature of the incipient fault. The feasibility of the proposed method is verified through computer simulation using four different electric arc models and also the acquired experimental data from real incipient faults.

1. Introduction

1.1. Background of fault incipient in underground power cables

The protection of the power networks against undesirable events, and increasing their reliability for continuity of operation has always been an important issue concerning the capability of power systems to deliver power. On this ground, prediction of possible faults can greatly help prevent such undesirable events and thus preserve the reliable operation of the power system. However, the power system faults are not always detectable by the conventional protective relays. Therefore, such faults should be detected by taking special techniques and methods into consideration.

The incipient faults, due to their short duration [1], mark an example for the group of faults that the conventional protective relays are unable to detect. These faults mainly occur due to electrical arcing in the sections of power cables with insulation defects [2]. Reoccurring with proportionately increased frequency characteristic by occurrence [1,2], the incipient faults can over time destroy the insulation of the cable, and turn into a permanent fault in the system [3,4]. Accordingly, an accurate method is required for desirably fast detection and discrimination of the incipient fault occurrence in the system among similar possible events.

The incipient faults are most significantly characterized by their short duration [1,2], and low voltage amplitude [2] comparing to the other system faults. The aforementioned inherent characteristics make it difficult for protective relays to detect the occurrence of incipient faults. The main features of the incipient faults are given by:

- These faults incept at positive and negative voltage peaks and extinguish at current zero crossings.
- The incipient fault duration can be variable from about ¼ of a cycle up to 4 cycles.
- Considering the low duration of the incipient faults and their low amplitude, the conventional protective relays are not capable of detecting these faults [2].
- The frequency characteristic of the incipient faults increases over the occurrence. The rate of such increase also grows by getting closer to turning into a permanent fault.
- At the fault location, the incipient fault is resembled by a distorted waveform, close to a square wave.

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Through the detection of the incipient faults, the occurrence of a permanent fault in the network can be predicted. The detection of the incipient faults is justified by the following reasons:

- Predicting the required proceedings before a complete power outage
- Determination and replacement of the faulty section before a permanent fault

1.2. Related works

So far, several studies have been published regarding the localization [1-18], and the detection [16-25] of the incipient faults. Frequency analysis together with wavelet has been utilized for incipient fault localization in [1,10]. By the employment of specially designed relays, the authors in [2] have presented a practical technique for incipient fault detection. The method presented in [3,4] is based on specifying the fault location by deriving the reactance. The authors in [5] have taken into consideration three various scenarios for incipient fault localization. In [6], localization has been carried out with the use of wavelet spectrum analysis of the first and second waves reaching the cable ends. The localization of the single- and three-phase incipient faults has been proposed to be conducted with the use of impedance measurement in [9] and with the use of capacitive effects in [8]. A method has been presented in [9] for incipient fault localization in overhead, and cable lines. The thermal model has been utilized for cable hot-spot detection in [11]. The authors in [12,15] have employed mathematical algorithms and a circuit model for the cable to localize incipient faults. In [13], the voltages and the currents have been analyzed to derive the impedance for incipient fault localization. In [14], the reactance concept in a similar manner as [3,4] has been employed to accurately specify the location of the incipient fault. In [16-18], some sensor based frameworks for fault detection and location were presented that were focused on smart distribution networks equipped with data loggers. In [19], through fast filtering of the voltages and currents in the sending end of the cable, incipient fault detection has been carried out in two stages. The authors in [20] have employed a mathematical model similar to the model in [12,15] for the detection of the incipient fault. Wavelet analysis and artificial intelligence methods have been employed for incipient fault detection in [23]. Taking into consideration the rotational current flows in the circuit, and also three different scenarios of three-phase cable junctions, the incipient fault detection has been put forward in [26]. Employing system identification based approaches and parameter estimation algorithms, incipient fault detection and location have been investigated in [27-30]. These algorithms are designed based on the analytical formulations and as a result, they have good accuracy comparing with the other previously published algorithms. In [31] an incipient fault identification method for distribution networks cables was proposed based on feature matching of power disturbance data. More specifically, a topic search algorithm was used to perform correlation matching, to identify incipient cable faults from a variety of abnormal conditions. In [32] the detection of the fault occurring in an underground cable system was proposed using extreme learning machine. In [33], based on the measurement of transfer function (TF) and deep learning approaches a novel aged cable segment detection and location was presented. In [34], a deep convolutional neural network (CNN) method was presented to recognize the early state of 10 kV single core cable based on sheath current. In [35], a precise approach based on cumulative SUM and adaptive linear neuron was proposed to detect incipient faults in underground cables. An algorithm based on a sparse auto-encoder and a deep belief network to form a deep neural network was presented in [36], to identify incipient faults in power cables. The algorithm can classify and identify various cable fault signals, without dependence on the preprocessing operations for the fault signals. In [37], utilizing restricted Boltzmann machine (RBM) and stacked auto-encoder (SAE), an algorithm was designed for the incipient fault identification in underground cables.

After the implementation of the incipient fault detection and localization methods, the accuracy and speed of the proposed method are put under evaluation in two stages. These evaluations are in the first stage conducted with the experimentally available data, and in the second stage using the gathered simulation data from some well-known electrical arc models. Several electrical arc models have been presented in the literature [38-42]. The Cassie arc model, presented in 1939, is principally suitable for electric arcs with high currents [38]. The Mayr arc model was first presented in 1943 [39]. In this model, it is considered that the arc conductance depends on the temperature. The Mayr arc model can accurately reflect the arc behavior for the currents near zero. Having modified and enhanced the Mayr arc model, the Schwarz arc model was presented in 1971 [40]. The time constant and cooling power are considered to depend on the conductance of the arc in the Schwarz model. The Habedank arc model is comprised of a series combination of circuit models for Mayr and Cassie arcs [41], and thus represents the advantages of both models, i.e., being suitable for both near-zero, and high currents. The modified Mayr arc model, presented in 1992 [42], considers the cooling power of the arc depending on the arc in the current. The Schavemaker model for electric arc, similar to the former, is obtained by modifying the Mayr model [42]. In this model, the time constant, and the cooling power are considered as functions of the input power of the model. The authors in lit. [42] have provided a review on the most practical arc models, and presented a thorough analysis by comparing the capabilities of each arc model.

1.3. Contributions

This paper presents a new method for incipient fault detection in underground power cables. The proposed method not only is capable of detecting the incipient faults, it can also discriminate the incipient faults from other similar events. The proposed algorithm employs only voltage signal at the sending end of the power cable and uses the dissimilarity between the signal and ideal sinusoidal function. More specifically, the proposed method is established on finding the estimation error between the estimated and original voltage signal.

The proposed algorithm is an event-triggered based method and it requires to identify the disturbance occurrence point in voltage signal. Owning to a sinusoidal waveform of the voltage signal during normal operation, it can be inferred that as long as the voltage signal preserves its sinusoidal behavior, no abnormal event has yet happened. Once any change happens, the waveform experiences momentary or even permanent deviation from the sinusoidal waveform. According to the latter deviation, the proposed change detection is designed based on the standard deviation of the estimated error so-called STD. (i.e. the error between the original voltage signal and the estimated fundamental component of the voltage signal). Note that the STD is calculated in each half-cycle. If the STD becomes higher than a certain threshold, the change is identified.

After the change point is identified, the behavior of the recorded voltage waveform should be analyzed for discrimination of the incipient fault from similar events. Note that similar events include capacitor bank switching, sudden load variation, harmonic load change, and short circuit fault. In general, in the case of capacitor bank switching, sudden load variation, and short circuit fault, the voltage waveform undergoes a sudden change but subsequently returns to following its sinusoidal behavior by the fundamental frequency. Moreover, during harmonic load change, the signal does not preserve the standard power system sinusoidal waveform, however, the signal shows a long-duration continuous periodical nature. Eventually, during an incipient fault, the voltage waveform deviates from 100% sinusoidal behavior and it has a discontinuous behavior. The discontinuity behavior of the incipient fault stands for arc fault on/off at the fault point. To detect the incipient fault and distinguish it from non-fault events, the proposed detection algorithm calculates the STD of the estimated error (i.e. the error between the original voltage signal and the estimated fundamental component of the voltage signal) for each half-cycle. Combining the STD and a counting criterion, the incipient fault is identified and discriminated from the similar events.

The contributions of the paper can be summarized as follows:

- The proposed method is based on the Kalman filter and due to the recursive nature of the algorithm, the proposed method can be implemented with a low computational burden.
- The proposed method utilizes a standard deviation based discrimination index which can solely (a) monitor and the abnormality of the signal and (b) detect the incipient fault with significantly low wrong discrimination with similar events include capacitor bank switching, sudden load variation, harmonic load change, and short circuit fault.
- Considering the fundamental mathematics of the proposed framework, it guarantees simplicity of the implementation, low complexity, speed, and accuracy compared with training based algorithm such as [15]. Also, unlike time-frequency-based incipient fault detection approaches [10,23], and [25], the proposed method does not require a high sampling rate and it has more immunity against noise. Also, these methods do not consider the impacts of harmonic load and short circuit fault.
- The incipient fault does not result in fast cable failure, however, the proposed method is designed to detect such a fault in less than 1 s and as a result, the proposed algorithm suitable for online application.

1.4. Paper organization

In the following, Section II discusses the electrical arcs models. A description of the proposed framework is given in Section III. Performance evaluation and discussion and also a comparison with the state-of-the-art are provided in Sections IV and V. Section VI provides some conclusions regarding this research studies.

2. Electric arcs model

The accurate analysis of the incipient fault requires suitable modeling. As for the complexity of the incipient fault occurrence conditions, so far, a suitable model for describing the behavior of the incipient fault from the first occurrence until turning into a permanent fault has not yet been presented in the literature. Nevertheless, the behavior of this fault can be described within the short intervals of its existence in the system, with the use of electric arc models. This way, even though the long-term process of the incipient fault turning into a permanent fault is not fully considered, however, the behavior of such a fault can be accurately reflected during its persistence. Therefore, it is primarily necessary to introduce the most practical arc models employed in incipient fault studies. It is worth mentioning that in the following formula presented for the arc models, the parameters i, u, and g correspond to the arc current, voltage, and linear conductance.

2.1. Cassie arc model

The Cassie arc model was first presented in the year 1939. This arc model is best suitable for modeling the electrical arcs with rather high current ratings. The parameter g, τ, and U_c in this model reflect the electrical conductance of the arc, the time constant of the model, and a constant specifying the voltage level of the arc model, respectively. In this study, the values for the parameters τ, and U_c are considered equal to 1.2×10^{-5}, and 4×10^{6} correspondingly. The Cassie arc model is described by the Eq. (1), given by

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{u^2}{U_c^2} - 1\right) \tag{1}$$

2.2. Modified Mayr arc model

The Mayr arc model was developed in 1943. In this model, the power loss from the thermal energy released by the arc is modeled. Therefore, it is a temperature-dependent model with a fixed cross-section area. The modified Mayr model for electrical arc was introduced in 1992. In this model, the cooling power of the arc depends on the arc current. The parameters C_i, and τ, reflect the current constant, time constant, and P_0 is a constant equal to 1. The parameters C_i, and τ are considered equal to 2000, and 9×10^{-6} in this model. The modified Mayr model is described by Eq. (2) as

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{ui}{P_0 + C_i|i|} - 1\right) \tag{2}$$

2.3. The Habedank arc model

The Habedank model for the electric arc is formed by the series connection of Mayr and Cassie arc models. This model, described by the equation given in (3), has the capabilities of both Mayr and Cassie models. Therefore, it is suitable for both the high current and low current electric arcs. The parameters g_c, and τ_c are arc conductance, and time constant in Cassie model, and the parameters g_m, and τ_m are the conductance, and time constant for Mayr arc model. The values considered in this study for the parameters U_c, τ_c, P_0, and τ_m are equal to 4×10^{6}, 1.2×10^{-4}, 1, and 12×10^{-5}, respectively.

$$\begin{aligned} &\frac{1}{g_c}\frac{dg_c}{dt} = \frac{1}{\tau_c}\left(\left(\frac{ug}{U_c g_c}\right)^2 - 1\right) \\ &\frac{1}{g_m}\frac{dg_m}{dt} = \frac{1}{\tau_m}\left(\frac{u^2 g^2}{P_0 g_m} - 1\right) \\ &\frac{1}{g} = \frac{1}{g_c} + \frac{1}{g_m} \end{aligned} \tag{3}$$

2.4. Schavemaker arc model

Likewise, the Schavemaker arc model is also obtained through the modification of the Mayr arc model. In this model, the time constant, and the cooling power are considered as functions of the input electric power of the arc model. In the formulation of the Schavemaker arc model, presented in (4), P_1 is the cooling constant, U_{arc} is a constant parameter depending on the arc voltage level, and P_0 is a constant parameter. In this study, the values 0.5, 2000, 0, and 9×10^{-6} are considered for P_1, U_{arc}, P_0, and τ respectively.

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{ui}{\max(U_{arc}|i|, P_0 + P_1 ui)} - 1\right) \tag{4}$$

3. The proposed method

The proposed method is designed for inception fault detection in the underground power cables while the robustness of the method is guaranteed from different events in the network. The proposed method is conducted in two general stages: First finding change in the signal that triggers detection algorithm and second, applying a detection algorithm to discriminate of the incipient fault from capacitive switching and sudden load variations, harmonic loads, and short circuit fault events. The key point of implementing the proposed algorithm is to calculate the difference between the original signal and the estimated fundamental component of the signal. The fundamental component is calculated through Kalman filter and standard deviation of the estimation error is calculated (STD index) as the incipient fault detector. In the following, the aforementioned is described.

3.1. Fundamental component estimation using Kalman filter

The proposed approach puts forward a novel incipient fault detection scheme based on an index calculated from the measurements and estimations of the fault voltage signal. Such an end is attainable with the help of Kalman filter (KF) which is used to estimate the incipient fault voltage's fundamental component with a fast dynamic. As in the case of an incipient fault, voltage is not sinusoidal, the estimated fundamental component would not be able to follow the measurement signal, and thus a difference builds up between the measured voltage and its estimation. The proposed method utilizes this difference for event occurrence detection and early decision making.

As described, a fast dynamic KF is employed for the real-time estimation of the fundamental component of the voltage signal. Kalman filtering requires to be formulated based on the state-space representation of the estimation model, which is selected as a discrete sinusoid signal in the following:

$$S_n = a\cos(\omega_0 n + \varphi) \tag{5}$$

where the parameters a and φ represent the amplitude and the phase of the adopted sinusoid, respectively, and $\omega_0=2\pi f_0/f_s$, with voltage signal and sampling frequencies f_0 and f_s, and the time index n, correspondingly.

According to the trigonometric identities, a recursive relationship can be alternatively imagined for S_n as:

$$S_{n+1} + S_{n-1} = 2\cos(\omega_0)S_n + \psi_n \tag{6}$$

where the modeling errors, e.g., amplitude or frequency shifts, reflected by the additive term ψ_n, randomly generated with a zero mean.

Considering that the measured signal might be contaminated by noise or the other disturbing factors, the voltage signal can therefore be obtained as:

$$y_n = S_n + v_n \tag{7}$$

where the fundamental component of the voltage signal and its corresponding noise factor are denoted by S_n, and v_n, respectively. It is to note that v_n is generated randomly with zero mean value.

The state-space representation of the dynamic model for the fundamental component of the voltage signal estimation, required by the KF algorithm, is constructed based on (6) and (7) as:

$$\begin{aligned} X_{n+1} &= MX_n + b\psi_n \\ y_n &= h^T X_n + v_n \end{aligned} \tag{8}$$

where

$$X_n \doteq [S_n \quad S_{n-1}]^{-1}, \quad M \doteq \begin{bmatrix} 2\cos(\omega_0) & -1 \\ 1 & 0 \end{bmatrix},$$

$$b \doteq [1 \quad 0]^T, \quad \text{and } h \doteq [1 \quad 0]^T.$$

Taking the relationships obtained in the above into consideration, a classical iterative KF, as presented in the following, can be formulated to estimate the fundamental component of the voltage signal.

The classic KF algorithm procedure is as follows:

(i) The primary values for the state vector and its error covariance matrix ($\widehat{X}_n^-$ and P_n^-) are defined.

(ii) The filter gain at the sample time n is calculated by: $K_n = (P_n^- h/(h^T P_n^- h + r_n))$

(iii) The measurement at sample time n takes place and the estimated values are updated accordingly: $\widehat{X}_n^+ = \widehat{X}_n^- + K_n(y_n - h^T \widehat{X}_n^{-1})$ where, $q \doteq E\{\psi_n^2\}$, $r \doteq E\{v_n^2\}$, $\widehat{X}_n^- = \widehat{E}\{X_n | y_{n-1}, \ldots, y_n\}$ being the a Priori estimation of the state vector X_n at the sample time n affected by observations y_1 to y_{n-1}, $\widehat{X}_n^+ = \widehat{E}\{X_n | y_n, \ldots, y_1\}$ being the a Posteriari estimation of the state vector at the sample time n affected by observation y_n, corresponding to the a Priori and a Postriari error covariance matrixes P_n^- and P_n^+.

(iv) The error covariance is calculated after the measurement update at the sample time n by: $P_n^+ = P_n^- - K_n h^T P_n^-$

(v) The next step is projected the state ahead: $\widehat{X}_{n+1} = A_n \widehat{X}_n$, $\widehat{P}_{n+1} = A_n P_n^+ A_n^T + b q_n b^T$

(vi) The procedure is repeated from level (ii).

Accordingly, the voltage signal residual (VSR), used for event detection, is obtained as:

$$VSR_n = S_n - y_n \tag{9}$$

It should be noted that the steady-state operation of the filter corresponds to the stationary process models (q_n=q), and stationary observations (r_n=r), according to the KF algorithm procedure. The KF's dynamic response can be determined from the q/r ratio, by tuning the parameters of noise covariance matrixes q and r. These parameters can be tuned to reach a balance between the KF's noise sensitivity, and its dynamic response. During the implementation of the proposed algorithm, it is assumed the normalized signal is fed to the Kalman filter and q and r are selected 10^{-7} and 10^{-3} respectively. Calculating the VSR, the standard deviation (STD) is calculated for half-cycle as follows:

$$STD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left(VSR_n - \overline{VSR}\right)} \tag{10}$$

where, N is the number of samples in half-cycle.

3.2. Implementation

As mentioned previously, the waveform of the incipient fault has a harmonic nature. Accordingly, contrary to the sudden rise of the harmonic contents followed by a gradual descend as seen in the other faults, the occurrence of the incipient faults gives rise to the harmonic contents in the network for as long the fault persists. Furthermore, the short duration of the incipient faults, and their frequency of occurrence until turning into a permanent fault are two main features excluding them from the switching of the loads in the network.

As seen in Fig. 1, in the first stage, the signal is fed to the change detection algorithm sample by sample. Once the STD index becomes higher than a threshold (TH), the change is identified. After the identifying, the incipient fault is detected if the STD index remains higher than a certain threshold for 2 to 25 half-cycles in a period equal to 1 s. It is worth mentioning that during capacitor bank switching, sudden load variation, and short circuit fault, the STD index does not remain higher than the threshold for more than two half-cycles. Also, due to the continuous behavior of the harmonic load, the STD index remains higher than the threshold for the whole 100 consecutive half-cycles in the case of the harmonic load.

4. Simulation and experimental results

In this section, the performance of the proposed method is evaluated through experimental and computer simulation data. The evaluation results are analyzed in the following.

4.1. Computer simulation test system

The testbed adopted for this study, as shown in Fig. 2, is comprised of a simple feeder with an input voltage of 10 kV. The feeder under study is an underground three-phase cable supplying a three-phase load at the receiving end. For the sake of the analysis, the test system is simulated in PSCAD environment, the incipient faults are applied to the cable along its length, and the voltage data are recorded utilizing a data logger with

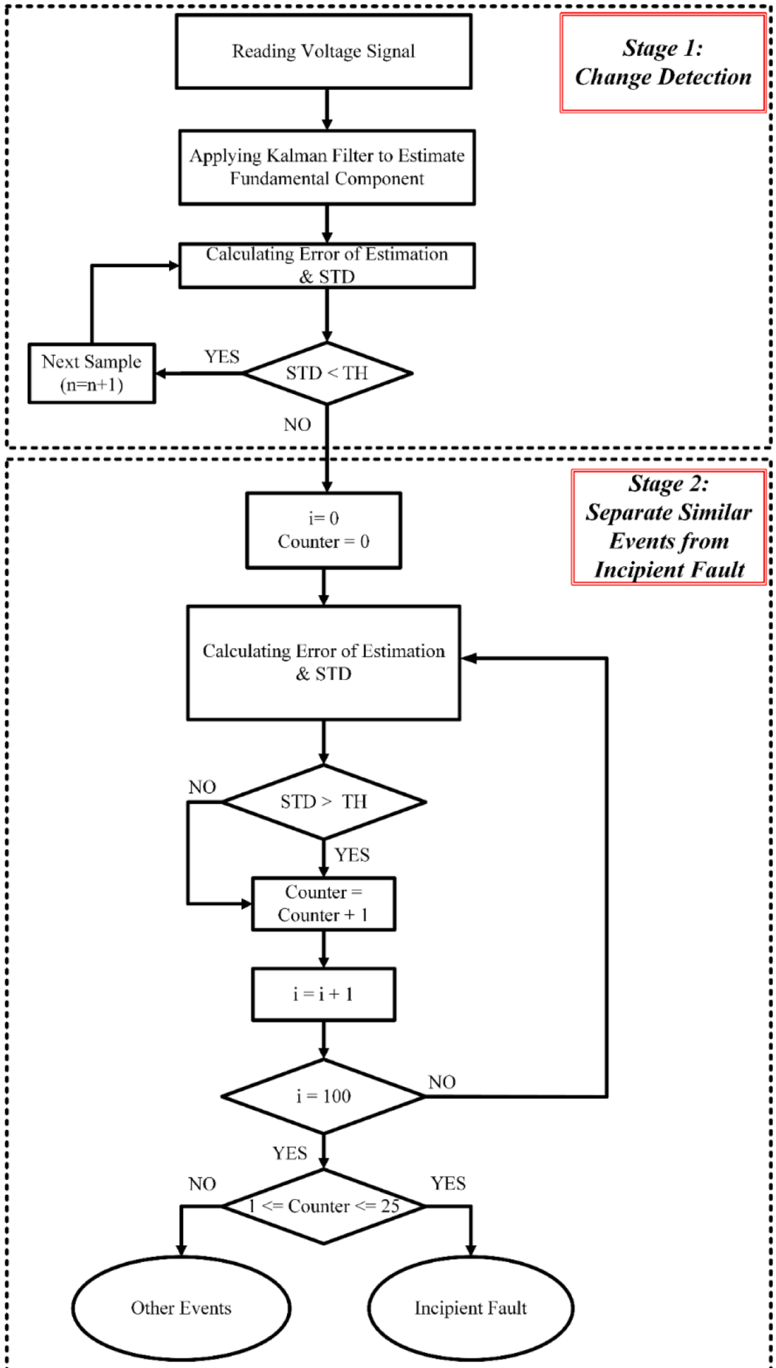

Fig. 1. The flowchart diagram of the proposed method.

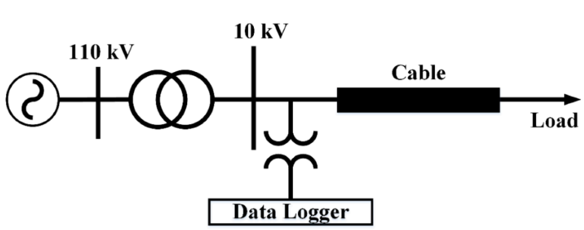

Fig. 2. The single-line representation of the test feeder.

a sampling time of 500 μs at the sending end of the cable. The specifications for the under-study system are as follows:

- $V = 10$ kV
- Frequency = 50 Hz
- Load = 0.022 (H) + 9 (Ω) (assumed 500A current in consumer side)
- Length of line = 10 km
- Cable size = 1 × 300 / RM 25
- Time simulation = 2 s

The properties of the under-study cable are as follows:

- Standard IEC6052

- Layers = CU/SC/XLPE/SC/SCT/CWS/PVC
- (Because of software limitation for simulation, just 3 layers of it simulated that contain Core, Insulation, Sheath)
- Cable size = 1 × 300 / RM 25 (25 stranded cable)
- The thickness of the insulation layer = 3.4 mm
- The thickness of the sheath layer = 2.1 mm
- The core diameter = 38.9 mm
- The weight of cable = 3644 kg/km
- The distance between cables = 0.5 m
- The depth of burial = 1 m

In order to thoroughly evaluate the performance of the proposed method, the incipient faults have been applied to the system under study, considering different scenarios, taking into consideration the following parameters:

- Applying arc fault at different fault location (from 1 km to 9 km from the voltage recorder)
- Applying different arc fault at different time instance (positive polarity voltage peak, negative polarity voltage peak, zero crossings of the voltage signal, random instance of voltage signal)
- Applying different arc fault with different time constant during fault
- Applying different load changes at a different location from voltage metering
- Applying multiple motor starting to simulate entrance of parallel loads at the end of the cable
- Applying different capacitive, inductive load changes and motor starting at different time instance (positive polarity voltage peak, negative polarity voltage peak, zero crossings of the voltage signal, random instance of voltage signal)
- Considering the different level of random noise with the signal to noise ratio between 40 dB to 60 dB

The threshold value is selected based on plenty of simulations in different scenarios. To obtain threshold, an algorithm named "Otsu thresholding method" was utilized which is a well-known and reliable method, employed in different engineering fields [43-47].

In the following, the implementation of "Otsu thresholding method" in the proposed method is described in more detail.

1) In the first step, a Probability Function Density (PDF) is assigned to the desired parameter for different conditions such as inception fault and load changes scenarios (in the proposed method, PDFs should be assigned for standard deviation).
2) In the second step, a normal function based curve should be fitted for each case.
3) In the third step, the intersection point of the PDF curves regarding the normal and fault cases is selected as the threshold value.

According to Fig. 3, the cross section of two PDFs is selected as the threshold, and as a result, the threshold is 0.0225. Note that the threshold is obtained for one cycles after disturbance inception. Fig. 3 also shows the STD index has very wide range for incipient fault, while the value of non-incipient fault is highly limited. The performance of the proposed method considering 6287 scenarios including 1007 non-incipient fault, and 5280 incipient fault has been evaluated, and the obtained results are tabulated in Table 1. As a result, the proposed method is able to detect the true event with an accuracy of about 99%.

4.2. Computer simulation results

This section is dedicated to the performance evaluation of the STD index for different incipient fault and other events. As illustrated in Fig. 4, the incipient fault is applied at $t = 0.3$ s. According to Figs. 4.c, f, i, and l, the error of estimation has led to a change in the STD index. Also, according to the proposed method, in Figs. 4.c, f, i, and l, the STD can identify the incipient fault after fault inception, the STD index remains above the threshold for almost 20 half-cycle.

Fig. 5 shows the performance of the proposed algorithm under load change and capacitor bank switching. As one can see in Figs.5.c and f, after change detection, the STD index goes under the threshold after one cycle and as a result, both signals are identified as non-incipient fault events. The same result can be concluded for short circuit fault as shown in Fig. 6. As it can be seen in Fig. 6.c, the STD index identifies a change in the signal given in Fig. 6.a, however, it rapidly goes and remains under the threshold.

4.3. Performance evaluation under harmonic load

To show the performance of the proposed method under harmonic load condition, three recorded voltage signals of the cable that feeds an electric arc furnace (EAF) are provided in Fig. 7 with sampling time equal to 128 μs. The EAF is known as the largest nonlinear harmonic load which contains very rich even, odd and inter-harmonic contents that its harmonic components have time-variant behavior. According to Figs. 8.a, c, and e, the voltage signals data measured at cable sending end are provided for 2 s duration. As one can see in Figs. 7. c, f, and i, the STD index remains above the threshold with continuous behavior for 2 s. Furthermore, it does not fall below the threshold for more than 1 s (100 half-cycle). As a result, the proposed algorithm identifies the signals as

Table 1
The accuracy of the proposed algorithm True Event detection .

Event	Arc model	No. of tests	Accuracy
Incipient fault	Cassie	1320	99.6%
Incipient fault	Modified Mayr	1320	99.3%
Incipient fault	Habedank	1320	99.1%
Incipient fault	Schavemaker	1320	98.5%
Capacitive switching	–	347	98.9%
Sudden load change	–	660	98.8%

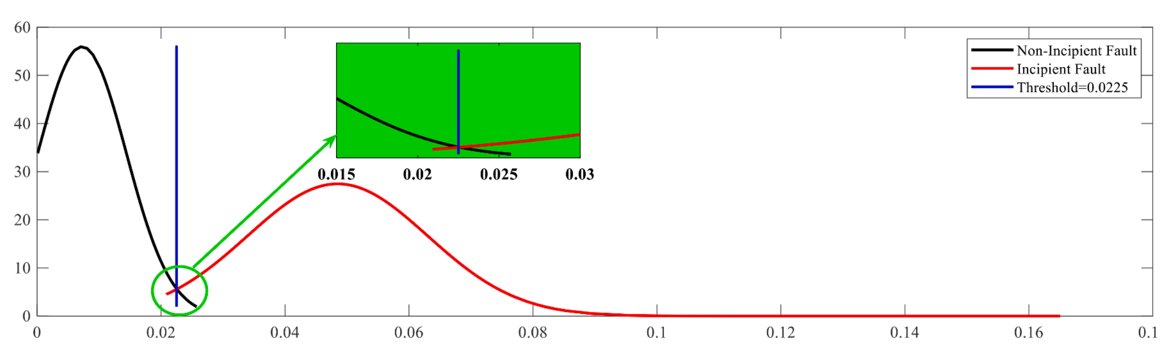

Fig. 3. Selecting threshold .

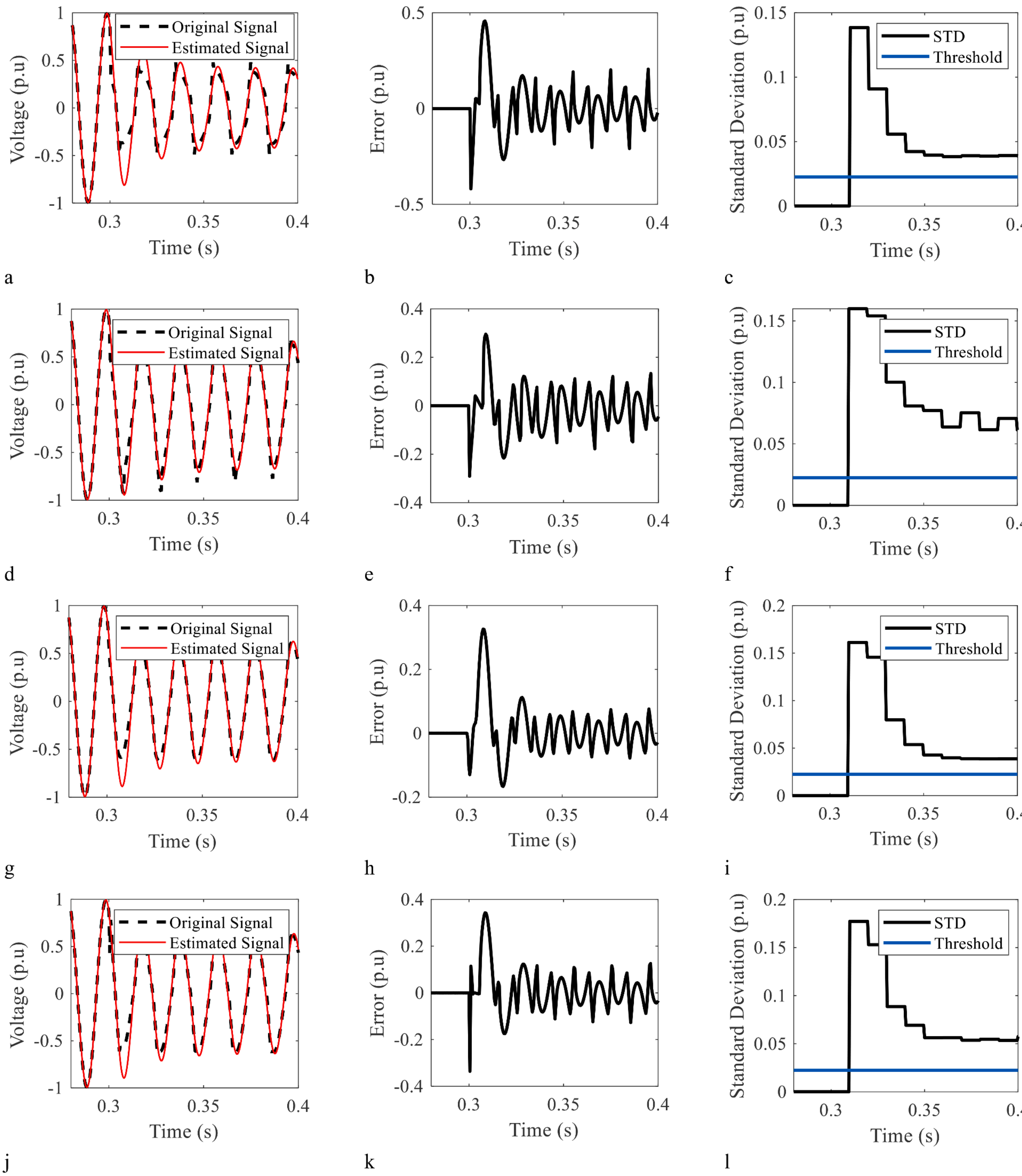

Fig. 4. Performance evaluation of the proposed method for different arc fault model using simulation data (a), Original and estimated voltage signal of Cassie arc model, (b) Error of the estimation, (c), STD index, (d), Original and estimated voltage signal of Mayr arc model, (e) Error of the estimation, (f), STD index, (g), Original and estimated voltage signal of Habedank arc model, (h) Error of the estimation, (i), STD index, (j), Original and estimated voltage signal of Schavemaker arc model, (k) Error of the estimation, (l), STD index.

the harmonic load.

4.4. Performance evaluation with experimental data

Having evaluated the performance of the proposed method by the computer simulation data acquired using verified electric arc models, in this subsection, the proposed method is tested through the experimentally recorded data. In the experimental under-study system, there had been disturbances observed in electronic power loads and also UPSs. The real-life data are adopted from [19]. More specifically, in Fig. 8a single line diagram of a part of the network, in which the field data have been measured, is presented. In this figure, some information on the system and the considered feeders are presented. The measured data are recorded from F2, which has a 6 km underground cable (type XLPE).

The test system has the following specifications:

- 110 kV grid: Vn = 110 kV; Short Circuit Positive Sequence Impedance: 0.7 + j6.5Ω.
- 110/10 kV transformer (YY): Nominal Rated Apparent Power: 50 MVA; Impedance Voltage= 12%.

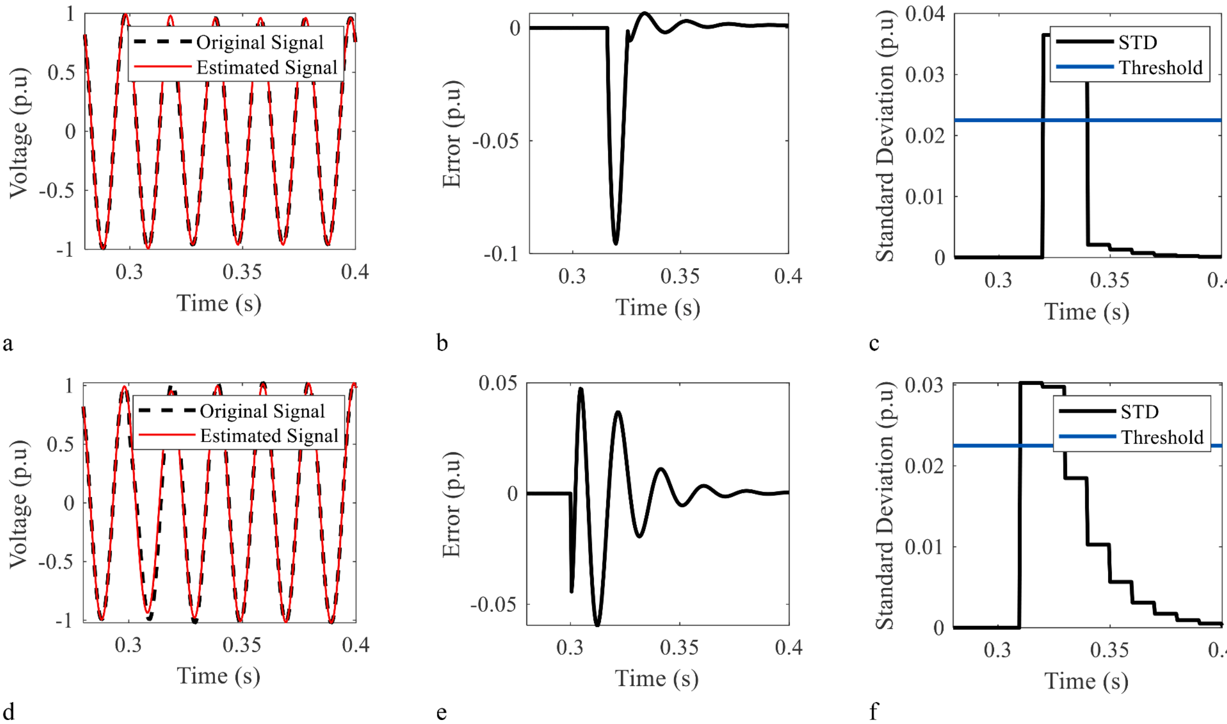

Fig. 5. Performance evaluation of the proposed method for inductive load change and capacitor bank switching using simulation data (a), Original and estimated voltage signal of inductive load change, (b) Error of the estimation, (c), STD index, (d), Original and estimated voltage signal of capacitor bank switching, (e) Error of the estimation, (f) STD index.

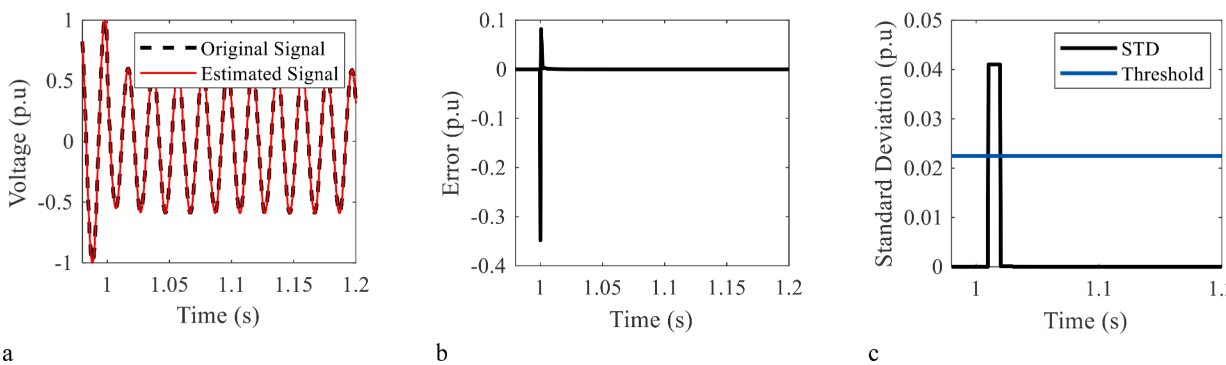

Fig. 6. Performance evaluation of the proposed method for single line to ground short circuit fault using simulation data (a), Original and estimated voltage signal, (b) Error of the estimation, (c) STD index.

- F1, F2, and F3 (Overhead lines): AL/ST, 70/12, 24 km in total.
- F2 (Underground cable): N2XS2Y, 3 × 1 × 185, 6 km in total.
- F4 (Cable): NKBA 3 × 70, 3 km.
- Capacitor bank: 1 MVAR, 3MVAR, 4MVAR.

The experimental data in this paper have been logged with the use of a data logger at the sending end of a power cable by a sampling frequency of 4200 Hz. The data suggested fault occurrence at highly limited durations and ratings. After inspecting the cable junctions, it had been observed that the insulation of the cable is damaged in one phase, giving rise to incipient fault occurrence [16]. The recorded voltage signals have been fed to the proposed method. As one can see in Figs. 10c, f, and i, the STD index robustly detect the incipient fault in very few cycles after the change has happened.

5. Comparison with the state-of-the-art

Given the fact that the incipient fault detection in power cables is rather a hot topic regarding the protection of the power systems, numerous studies have been carried out on this subject in the literature, each proposing a technique or algorithm for incipient fault detection in the network. Due to the high extent of the literature published on this subject, some of the most recently published incipient fault detection methods have been selected for the comparative evaluation of the proposed method of this paper. The selected methods from state-of-the-art are described in the following.

5.1. *First method [19]*

An incipient fault detection method has been provided in [19] by which the voltages and currents are measured in the sending end of the line, and are estimated with the use of a combined method based on the Kalman filter and least square technique. The variance of the differences between the measured voltages and their corresponding estimation are provided in C_m, and the differences between the measured and the estimated currents are provided in R_n. Now, by comparing these values

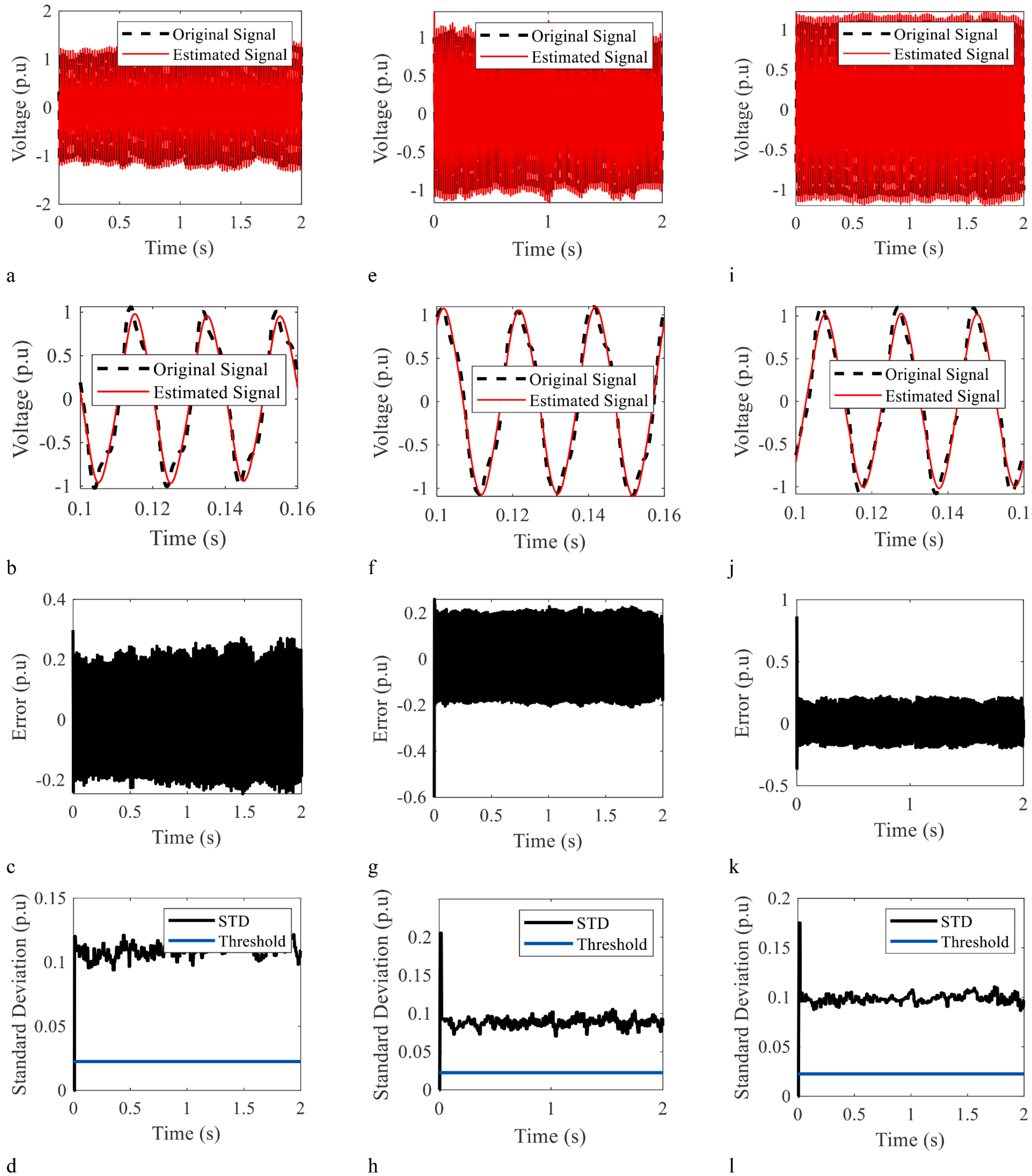

Fig. 7. Performance evaluation of the proposed method for harmonic load condition using field data measurement (a), Original and estimated of the first voltage signal, (b), Zoom on Fig. 7.a, (c) Error of the estimation, (d), STD index, (e), Original and estimated of the second voltage signal, (f), Zoom on Fig. 7.e, (g) Error of the estimation, (h), STD index, (i), Original and estimated of the third voltage signal, (j), Zoom on Fig. 7.i, (k) Error of the estimation, (l), STD index.

to the threshold value, obtained from various tests, the final decision is made. In the first step, the comparison to the threshold value is conducted for current, and in case of confirmation, the voltage is then analyzed. If both stages confirm, the event is verified as an incipient fault. It should be mentioned that when the values are obtained smaller than the threshold, the occurred event would not be an incipient fault. Comparing with the proposed method, this method does not consider the impacts of harmonic load and short circuit fault.

5.2. *Second method [25]*

Utilizing support vector machine (SVM), and s-transform matrix, an incipient fault detection method is introduced in [25]. In this method, using the s-transform (ST) matrix, indexes ST of magnitude-time voltage (STMV), and ST of frequency-time voltage (STFV), as fully described in the main paper, are calculated in each phase. Afterward, these indexes are compared to threshold values regarding each index, the final decision regarding the incipient fault occurrence is made. Moreover, this paper provides other indexes such as STMV and STFV, all of which are obtained through trial and error, and other tests. This method employs

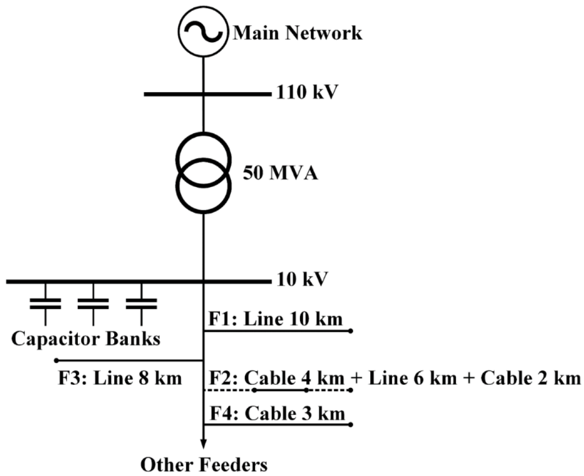

Fig. 8. a single line diagram of a part of the network for the field data measurement .

the SVM for verification, and by clustering the data using the kernel function $e^{-\frac{|x-y|^2}{2\alpha^2}}$,$\alpha = 0.2$ within a multidimensional space, the final decision of incipient fault detection is made. Although the method of this paper represents high accuracy, as of being a multistage method, however, most of the indices provided in this method are obtained by trial and error. Moreover, even though the provided laboratory data confirm this method, a slight change in the real condition can violate all the provided indices which are obtained from the provided data. Moreover, unlike the proposed method, this method does not consider the impacts of harmonic load and short circuit fault.

As can be seen in Table 2, the superiority of the proposed method in comparison to other methods is verified. It is inferred from the results in Table 2 that the proposed method is capable of detecting incipient faults more accurately than the methods presented in lit. [19], and [25].

6. Conclusion

The stability of the power systems and their protection against undesired events is highly important in nowadays power networks. One of the most important issues threatening the power networks' continuity of operation is the incipient fault phenomenon. These faults mainly occur in the splices of the underground cables, due to the mechanical stress of the cable insulation or also the atmospheric conditions. In this paper, a novel method has been proposed for fast and accurate incipient fault detection. The proposed method employs Kalman filter for fast estimation of the voltage waveform in the sending end of the cable, and then by subtracting the estimated and the recorded voltage waveforms, extracts the distortion in the voltage signal. Thereafter, an index is calculated by calculating the standard deviation of the distortion in the difference of the estimated and recorded voltages. This index is then compared to a pre-set threshold value to detect the incipient fault occurrence. As for the incipient faults inherently representing a harmonic behavior rising momentarily and then damping after several cycles, the incipient fault detection procedure can be performed by STD index within the counting the cycles after event inception as the index for incipient fault detection. The advantages of the proposed method are its high fault detection speed and high accuracy compared to the other methods (above 99% accuracy within 6272 sample cases), utilizing only monitoring in the input terminal of the cable, and fault detection without complex mathematical relations, considering only the inherent features of the incipient faults, verifying its superiority over other methods.

Table 2
Comparison of the performances of different incipient fault detection methods.

Method	% of correct identifying incipient fault
[19]	92%
[25]	90%
Proposed method	99%

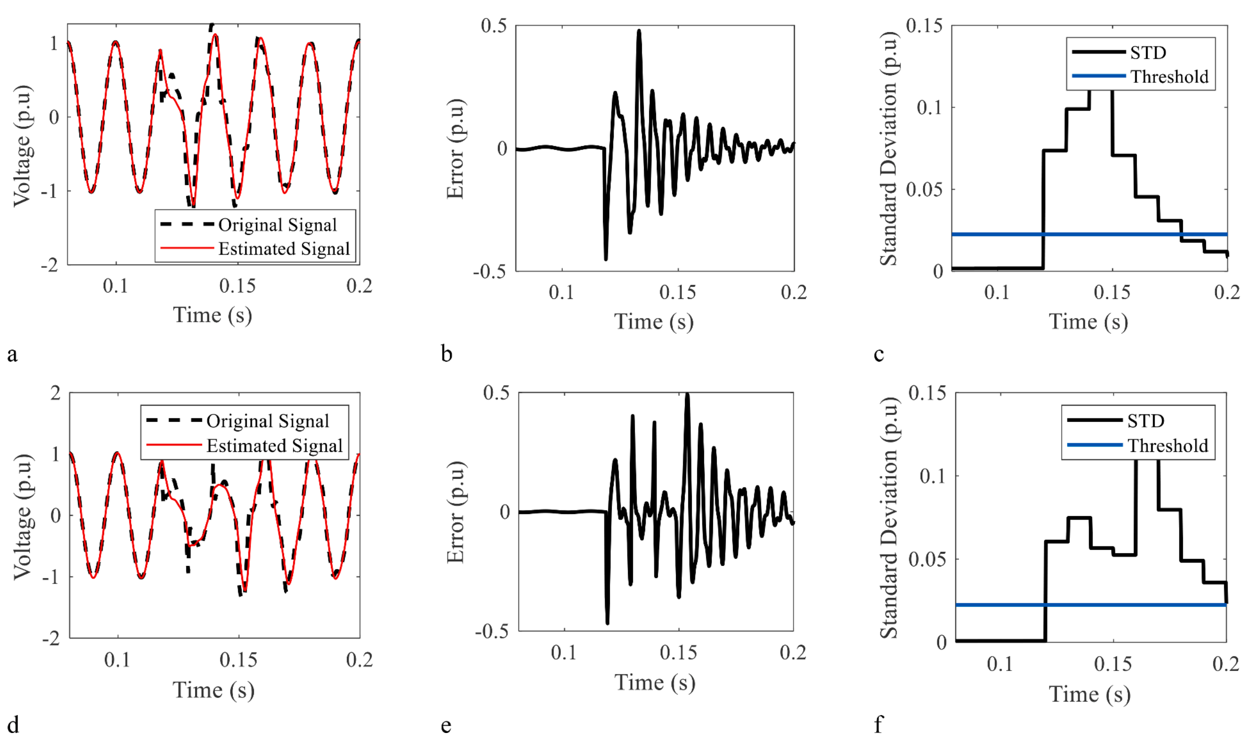

Fig. 10. Performance evaluation of the proposed method for incipient fault using field data measurement (a), Original and estimated voltage signal, (b) Error of the estimation, (c), STD index, (d), Original and estimated voltage signal, (e) Error of the estimation, (f), STD index.

CRediT authorship contribution statement

Haidar Samet: Conceptualization, Methodology, Project administration, Supervision, Writing - original draft, Writing - review & editing, Data curation, Visualization. **Mohsen Tajdinian:** Investigation, Supervision, Software, Writing - original draft, Writing - review & editing, Data curation, Visualization, Validation, Formal analysis. **Saeed Khaleghian:** Methodology, Software, Writing - original draft, Visualization, Validation, Formal analysis. **Teymoor Ghanbari:** Investigation, Project administration, Supervision, Writing - original draft, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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