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A hybrid method for arcing faults detection in large distribution networks

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ABSTRACT

This paper presents a reliable protection scheme for high impedance fault (HIF) detection in large and complex electrical distribution networks. The proposed algorithm uses dynamic features extracted by stationary wavelet transform and feeds them to a support vector machine-based decision making system. HIF occurrence is detected according to the normalized changes of the features extracted from three post-disturbance data windows. To provide more security, the output of the main fault classifier is compared with the outputs of three other classifiers in a voting system for final decision making. The results of simulations of a real distribution system demonstrate that the proposed scheme is able to detect a wide range of arcing faults, from a few amperes to hundreds of amperes, with high level of security against non-HIF phenomena.

1. Introduction

Automatic detection of high impedance faults (HIFs) in electrical distribution systems has been investigated by utilities and researchers from the late 1970's [1] and is still in progress [2–6]. Due to high impedance of the circuit against the current flow and low voltage level of distribution system, fault currents can have such low magnitudes that conventional protection devices such as overcurrent relays or fuses may be unable to detect them. According to the published reports, fault current magnitude can be as low as one ampere up to hundreds of amperes [7]. Although, HIFs are not usually a serious danger to system components, they could cause a serious hazard to public safety as well as potential risk of fire, so must be detected quickly. Proposing a reliable method being able to detect all HIFs in a distribution system with high level of security is still a challenge, due to the fact that a sensitive method may result in low security and a high secure method may reduce dependability [7,8]. Although current magnitudes of HIFs are low, these low current faults are usually accompanied by arc [1] and exhibit features like asymmetry in the waveform, the existence and randomness of energy distribution in harmonics and subharmonics that can be employed for designing an HIF detection system. There are two main stages in each HIF detection system: feature extraction and decision making. By employing modern microprocessor based protection devices, there are many digital signal processing tools that can be used for feature extraction from the measured signals; such as Fourier based transforms [1,9–12], mathematical morphology [13,14], time-frequency based transforms [2,3,5,15,16] or Kalman Filter [17]. After extracting the required features, the decision about occurrence of HIF has to be made. A simple way for implementation of a decision making system is to set proper thresholds for the selected features as has been done in [2,4,9,11]. Setting proper thresholds requires comprehensive studies on system load characteristics under various operating conditions. However, in a large distribution system with a vast variety of loads, these studies are impractical [18]. To overcome this problem, pattern recognition tools such as decision tree [12], neural networks [6,13,17] and support vector machines (SVM) [5,10,14] have been used.

The main problem in discrimination of HIF from non-HIF phenomena (such as harmonic loading, capacitor switching, transformer energizing, and insulation leakage current) is that there are features, applicable for HIF detection, which may have similar values or even larger in non-HIF events. Furthermore, the extracted features may have different values in different hours of a day and in different days of a year [18]. Therefore, an HIF detection method can claim to have high level of security, whenever it withstands

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Nomenclature

j	the decomposition level in wavelet transform
a_j	the approximation coefficients of signal S at jth decomposition level (scale j)
d_j	the detail (wavelet) coefficients of signal S at jth decomposition level
N_j	the total number of samples at the jth decomposition level
$WQ_{D_j}^{[S](VI)}$	wavelet reactive power at the jth decomposition level
$WP_{D_j}^{[S](VI)}$	wavelet active power at the jth decomposition level
$Wrms_{D_j}^{[S](I)}$	root mean square (RMS) of the detail coefficients at the jth decomposition level of current signal (I)
$WEE_{D_j}^{[S](I)}$	wavelet energy entropy of detail coefficients at at the jth decomposition level of current signal (I)
$Wstd_{D_j}^{[S](I)}$	standard deviation at the jth decomposition level of current signal (I)
$\boldsymbol{F}_{\boldsymbol{total}}^{[\boldsymbol{Dsrb}]-(\boldsymbol{VI})}$	the total normalized disturbance feature set extracted from voltage and current signals
$\boldsymbol{F}_{\boldsymbol{total}}^{[\boldsymbol{Dsrb}]-(\boldsymbol{I})}$	the total normalized disturbance feature set extracted only from current signals
$\boldsymbol{S}^{[Pre1]}$	pre-disturbance data window of signal $\boldsymbol{S}$ (phase voltages and currents)), according to Fig. 2
$\boldsymbol{S}^{[Post1]}$, $\boldsymbol{S}^{[Post2]}$, $\boldsymbol{S}^{[Pos1]}$	post-disturbance data window of signal $\boldsymbol{S}$ (phase voltages and currents), according to Fig. 2
$\{\boldsymbol{F_{Post1\text{-}/Pre}}\}$, $\{\boldsymbol{F_{Post2\text{-}/Pre}}\}$, $\{\boldsymbol{F_{Post4\text{-}/Pre}}\}$	normalized changes in features of post-disturbance data windows ($\boldsymbol{S}^{[Post1]}$, $\boldsymbol{S}^{[Post2]}$, $\boldsymbol{S}^{[Post3]}$) with respect to the pre-disturbance data window features($\boldsymbol{S}^{[Pre]}$)

against a variety of phenomena that can arise those features similar to HIF phenomenon at comparable values. In this paper, a novel method for HIF detection is proposed that is capable of detecting a wide range of HIFs (for both modelled and measured HIFs from field tests) only by using currents and voltages at the outgoing point of the main substation of a large and complex distribution network with high reliability and accuracy. The proposed method employs:

- The stationary wavelet transform (SWT) to extract normalized dynamic features (which are less dependent on the operating conditions as they are normalized and are more reliable as they are dynamic or slope-based instead of static) and applying them to SVM as the classifiers;
- A voting classification system that aggregates the outputs of trained SVMs for three sets of features (extracted from three post-disturbance data windows) to classify each event with more reliability;
- A logical decision making system that evaluates the degree of certainty of HIF occurrence against that of non-HIFs to make a more secure final decision.

To investigate the performance of the proposed scheme, a real large and complex 20 kV distribution system, including static, dynamic and nonlinear loads was simulated in the EMTP - RV environment. Various events like switching different types of loads, capacitor bank switching, transformer energizing, low impedance faults, and modelled high impedance faults were simulated. The results of these simulations as well as the records of measured HIFs from field tests were analysed to investigate the performance of the algorithm. The sampling rate used by the algorithm is 6400 Hz or 128 samples per cycle in a 50 Hz system; which is in the order of available commercial distribution IEDs.

The rest of this paper is organized as follows. In Section 2, the selected features based on applying stationary wavelet transform to currents and voltages at the outgoing of sub-transmission substation are described. The proposed scheme for HIF detection is presented in Section 3, including formulation of normalized dynamic feature extraction and the proposed decision making system. The details of distribution system modelling and simulations are presented in Section 4. Section 5 is devoted to the results of implementing the proposed method for HIF detection and comparing it with the other methods. This section is followed by a summarized conclusion.

2. Selected features for HIF discriminating

Discrete wavelet transform (DWT) decomposes a discrete signal into different frequency bands, preserving the temporal structure at each decomposition level. Stationary wavelet transform (SWT) is also a wavelet based transform for discrete signals which has the important characteristic of shift-invariance [19,20]. In this paper, SWT is employed as the main tool for feature extraction. The sampled voltages and currents are decomposed by SWT and then, selected features at different decomposition levels are calculated and prepared for further processing. The following variables are the ones selected in this work for generating features for the proposed method, while their corresponding relations are also given. Though the proposed method applies SWT to find the following features, DWT is also employed as an alternative to have comparative investigations.

***Reactive Power* ($\boldsymbol{W_Q}$):** Active power of measured voltage and current signals can be calculated by SWT decomposition [21,22] as follows:

$$WP_{D_j}^{(VI)} = \frac{1}{N_j}\sum_{n=1}^{N_j} d_j^{(I)}(n)d_j^{(V)}(n) \tag{1}$$

$$WP_{A_j}^{(VI)} = \frac{1}{N_j}\sum_{n=1}^{N_j} a_j^{(I)}(n)a_j^{(V)}(n) \tag{2}$$

where a_j and d_j stand for the approximation and detail coefficients of signal S and N_j is the total number of samples at the jth decomposition level (scale j).

The apparent power at each wavelet decomposition level can be defined as multiplication of the root mean square (RMS) of voltage coefficients to current coefficients of the same level:

$$WS_{Dj}^{(VI)} = \boldsymbol{rms}(d_j^{(V)}(n))\boldsymbol{rms}(d_j^{(I)}(n)) \tag{3}$$

Finally, the wavelet reactive power at each decomposition level can be obtained as:

$$WQ_{Dj}^{(VI)} = \sqrt{\left(WS_{Dj}^{(VI)}\right)^2 - \left(WP_{Dj}^{(VI)}\right)^2} \tag{4}$$

***Wavelet RMS* (*Wrms*):** Root mean square (RMS) of the detail components at the jth decomposition level is calculated by:

$$Wrms_{D_j}^{(S)} = \sqrt{\frac{1}{N_j}\sum\nolimits_{n=1}^{N_j}\left(d_j^{(S)}(n)\right)^2} \tag{5}$$