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Fault locating in large distribution systems by empirical mode decomposition and core vector regression

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ABSTRACT

This paper proposes an intelligent fault locating method using a new signal analysis technique called Empirical Mode Decomposition (EMD) and Core Vector Regression (CVR) for large distribution systems. The conventional fault locators are based on the measurement of post-fault line impedance suffering from the factors such as path fault impedance, system configuration and line loading, so that they have low accuracy. On the other hand, because of the vast range of resistances, the negative impact of damping factors affects the performance of travelling wave-based fault locators in large distribution systems. To overcome these problems, this paper uses a minimum measuring device to meet the acceptable observation of transient waves and presents a novel method for locating phase to ground faults in a large distribution system using CVR. Inspecting the energy content of transient voltage around the path characteristic frequencies by EMD can provide a suitable fault pattern to CVR. Training of the proposed algorithm needs little time and small amount of memory in comparison with the existing methods. Presented algorithm is examined on IEEE 34-bus test system which shows satisfactory results. Then, the results are compared with the method of recent papers based on Artificial Neural Networks (ANNs).

1. Introduction

Power quality is an important issue for power systems, especially power distribution systems. An accurate fault locating technique can decrease interruption time and costs, and it is essential to find the fault point. In [1–6] power frequency of voltage and current fault waves is used to find the fault location. Refs. [7–9] developed different methods based on combined impedance-travelling wave methods and combined wavelet-fuzzy approach to find the fault location on transmission lines. Travelling wave-based methods are more efficient for fault locating in distribution systems in comparison with traditional one, which are based on measurement of post-fault line impedance [10–22].

Traditional methods which estimate the path impedance with fundamental voltages and currents at the main feeder are impractical for distribution networks due to the complex nature of large distribution networks with huge number of radial branches.

Time-Domain Reflectometry (TDR) is a well-known technique used for locating faults on transmission lines [11,12]. TDR is based on the distinction between the reflected wave from the fault point and the remote bus. In large distribution networks TDR signals cannot be interpreted easily for locating faults because of the reflections of many Tee connections. The disruptive characteristics of distribution lines as well as many reflection factors cause the monitoring of transient waves to be impossible with TDR, thereby inefficient to locate them [22]. Besides, the accuracy of this method is strongly influenced by noise sources (e.g. corona and partial discharge) around the equipments. A new approach for complexity reduction of TDR-based methods in distribution networks is signal processing-based methods; such as Continuous Wavelet Transform (CWT) proposed in [18,19]. In [4,5,15–17] Artificial Neural Network (ANN) which is a well-known machine learning technique was introduced for fault locating on distribution lines, which reduced the problems of traditional methods considerably.

High-frequency fault waveforms are used as an important feature for ANN in [15–17]. In [16] maximum values of Discrete Wavelet Transform (DWT) of phases A, B, C and zero sequence for post-fault voltage and current waveforms are used as ANN input features. Although this method minimizes the influence of load conditions, it adds the effect of inception angle because of using

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the maximum values of transient components. Combination of Support Vector Machine (SVM) and ANN are used for fault locating in radial distribution systems while steady state three phase voltages and currents are considered as inputs [5].

In [17] frequency and amplitude of the transient currents are used as ANN inputs. This method minimizes inception angle impact via elimination of low-frequency modes. Based on the energy content of signals around the Path Characteristic Frequencies (PCFs) of travelling waves, fault locating is done in [18–20]. Inspecting the peak values of energy spectrum around the PCFs in radial distribution systems is another approach for locating of faults [18,19]. In [22] a new method has been proposed for fault locating in small radial distribution systems based on the energy of transient voltage signals. That reference used wavelet transform and ANN for specifying the location of faults based on PCFs. Due to complex nature of large radial distribution systems with different Tee connections, aforementioned methods are not accurate enough because of ANN structure and existence of just one measuring device.

Furthermore, a new signal processing technique which is used in this paper called Empirical Mode Decomposition (EMD) has received much attention in a number of research areas [23]. EMD can decompose a signal based on interpolation point's criterion into a number of Amplitude and Frequency Modulated (AM/FM) with zero mean, called Intrinsic Mode Functions (IMFs). Some recent studies on EMD showed specific aspects of its performance [23–25]. In [25] genetic algorithm optimization approach is used to have good criteria for selection of interpolation points. Another type of EMD with a good performance called doubly-iterative EMD is introduced in [24,26] which estimates interpolation points based on the extracted optimized criteria in [25], leading to improve overall decomposition performance. As EMD is used for feature extraction of the transient voltage signal in this study, it is described in details in Section 3.1.

A better solution in comparison with ANN can be provided by the Least Squares Support Vector Machine (LS-SVM). SVM and LS-SVM are preferable, because their ability is independent of input data dimension [27]. Due to these advantages, SVM and LS-SVM are being more admissible than ANN for fault locating.

SVM algorithm solves a quadratic programming (QP); if m is the number of training data, then training time and space complexity will be commensurate with m^3 and m^2 respectively [28]. SVM and LS-SVM algorithms suffer from long training time and large amount of memory requirement for large dataset.

Refs. [29–32] described Core Vector Machine (CVM) and Core Vector Regression (CVR) as fast machine learning methods. CVM is a combination of computational geometry techniques with SVM training which can be used for with any linear and nonlinear kernels.

The training time and space complexity of this algorithm is commensurate with the number of training data (m). Although CVM is nearly the same as SVM in terms of performance, it is faster, and needs less training time and memory, and produces much fewer support vectors when the number of training dataset augments [29]. These merits make CVM more admissible than SVM, LS-SVM and ANN for fault locating in large distribution systems.

This paper aims to extend the presented concepts in [22] to derive a more regular pattern by using a new fault locator based on EMD and CVM. The transient voltage waves of both single-end and double-end networks for different faults are analyzed to show the efficiency of the proposed method for different conditions in distribution systems. The energy of sub signals (IMFs) extracted by EMD is computed and used as inputs for CVM. Based on the concept of the EMD, different IMFs are extracted from the main transient voltage waves for fault locating in a large radial distribution network. Also the results of CVR method are compared with ANN to show the effectiveness of the proposed technique over the existing studies with ANN.

This paper is structured as follows. In Section 2, travelling wave theory and PCFs are described. Section 3 introduces fault feature extraction based on EMD. CVM and CVR algorithms are described briefly in Section 4. This is followed by CVR and ANN based fault locators in Section 5. The results are discussed in Section 6.

2. Travelling wave theory and PCFs

After occurring faults, travelling waves propagate along network's paths in both directions from the fault points, and are reflected until they arrive to the fault locations. Travelling waves can be theoretically assessed by solving the voltage and current equations along the lines considering the long line model. Solving voltage equations can lead to following equations [33]:

$$[V(x)] = e^{+x[\gamma]}[V_+] + e^{-x[\gamma]}[V_-] \tag{1}$$

The first term is the propagated voltage wave and the second term is the reflected voltage wave. The propagation constant matrix $[\gamma^2]$ is computed by multiplying of the impedance of lines and admittance matrices.

$$[\gamma^2] = [Z][Y] \tag{2}$$

where, in a single phase line, γ is calculated as:

$$\gamma = \alpha + j\beta = \sqrt{(R + jL\omega)(G + jC\omega)} \tag{3}$$

where α and β are attenuation and phase constants respectively.

For a better theoretical explanation of propagation role in distribution systems and a reasonable approximation, various faults are modeled. Fig. 1 shows IEEE 34-bus test distribution system which is simulated by ATP/EMTP simulator. The data of IEEE 34-bus distribution system have been noted in Appendix A. ATP/EMTP simulator considers the skin effect and the effect of all three lines of this system on faulted line.

In distribution systems, fault-originated waves are attenuated along the paths with the factors such as transmission and reflection coefficients at junctions as well as the resistance lines. Depending on the network topology and fault location, the number of effective paths leading to measuring points differs in length and total attenuation in the first reciprocation. In this section it is shown that how the frequency and attenuation of paths can introduce fault characteristic pattern in a typical distribution system.

In this section the concept of the proposed methodology is demonstrated by developing propagation equations of a desired fault location. Suppose a fault occurs at 0.2 km between buses 824 and 828 (i.e. case 1). Fault simulations in the time domain indicated that recorded transient signals include characteristic frequency (f_p) related to each path. Travelling along the paths with speed v cause each wave at measuring points has a transient frequency in range of path characteristic [19].

$$f_p = \frac{v}{n_p L_p} \tag{4}$$

where v is the travelling speed which is close to light speed, L_P is the length of the Pth path, and n_p is the number of times that a wave has to travel along Pth path until it obtains again the same polarity at the measuring point. For the paths reach to loads $n_p = 2$; and for junctions and fault points $n_p = 4$. Therefore, sixteen paths are identified for the first case fault. Table 1 shows all paths that travelling waves propagate through them with the characteristic frequencies leading to the measuring points.

According to Table 1 paths #1–#7 are associated to measuring device of bus 800 and paths #8–#16 are associated to measuring device of bus 854. Forward and backward travelling waves which