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Performance assessment of swarm-assisted mean error estimation-based fault detection technique for transmission line protection

Ch.D. Prasad*, Paresh Kumar Nayak

Department of Electrical Engineering, Indian Institute of Technology (Indian School of Mines) Dhanbad, Dhanbad 826004 Jharkhand, India

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ABSTRACT

In this paper, a fast and computationally efficient fault detection algorithm is proposed for power transmission network protection using mean error estimation technique. In order to avoid false detection, instead of adopting the traditional trial and error-based approach, particle swarm optimization-assisted optimal threshold setting method is introduced in this paper. Performance of the proposed fault detection technique is tested for numerous fault and non-fault events generated on a two-bus test power system through MATLAB/SIMULINK software. The observations on results clearly show that using the proposed method even critical faults can be detected securely within a quarter cycle of the 50 Hz power system. The comparative assessment with two existing methods confirms the effectiveness of the proposed scheme.

1. Introduction

Fast and accurate detection and isolation of faults in power transmission networks greatly prevents possible component damage and ensures power system stability. Fault diagnosis in digital distance relaying-based transmission line protection scheme is carried out in three main steps: (1) sensing the fault; (2) classifying the fault type and faulty phase(s); and (3) estimating the location of the fault. Initiation of a fault is first sensed by the fault detector unit (FDU). The main function of FDU is to discriminate faults from normal system operating conditions and activates the fault classifier unit to determine the fault type. Once the fault type is identified, fault locator unit computes the distance of the fault from the relay for isolation of the fault. Thus, the overall performance of a relay depends very much on the speed and accuracy of the FDU [1,2]. The voltage and current waveforms of the power system deviate from the normal sinusoids at the initiation of a fault. The sample-to-sample and cycle-to-cycle comparison of current and/or voltage signals are the two straightforward techniques used by FDU for transmission line fault detection [3]. However, performances of these simple approaches are poor especially during certain extreme fault conditions (e.g. remote end and high resistance faults) due to the possibility of very small changes in the current magnitudes compared to the steady state operating conditions of the power system. Moreover, as these approaches are based on differential comparison principle, performances of these approaches are highly affected on noise, load change and the deviation of system frequency from the nominal value. To overcome the limitations of such simple approaches several advanced algorithms [3–21] have been proposed in the last few decades with an aim to accomplish fast and accurate detection of transmission line faults. A brief review on the relative merits and demerits of each of the available fault detection algorithms are provided below.

Traditionally, various fault detection algorithms are proposed based on the estimation of fundamental components of voltage and/or current signals. The methods employed for extraction of fundamental components of voltage and/or current signal include

* Corresponding author.
E-mail address: chdpindia@gmail.com (C.D. Prasad).

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discrete Fourier transform (DFT) [5], modified DFT [6], least square technique [7] and Kalman filtering [8]. Though the performances of steady state component-based fault detection schemes are accurate but have higher computational burden and also the processing time takes more than half a cycle of the fundamental period. Further, the performances of phasor estimation-based techniques are affected on noise, frequency deviation and fault inception time. The fault detection methods based on fault induced voltage and current travelling waves (TWs) are capable of detecting the fault in the first few milliseconds [9,10]. However, protection schemes based on TWs require high frequency sampling that ranges from several hundreds of kHz to 1 MHz. Thus, TW-based methods require high band width equipments [9], special transducers and high speed processors [10]. Hence, TW-based fault detection approaches are not economically viable.

The other group of fault detection methods are proposed based on moving sum [3] and cumulative sum (CUSUM) [4] of time domain current signals and have improved detection speed and accuracy compared to the traditional phasor-based methods. However, CUSUM method is affected by noise due to the consideration of drift parameter as peak magnitude of the current signal and also yields poor performance during certain extreme fault situations like high resistance faults and remote end faults [11]. To overcome the limitations of CUSUM-based fault detection technique, an adaptive cumulative sum (ACUSUM) method is proposed in [11], where the concept of dynamic drift parameter is introduced into the CUSUM approach. The methods based on Euclidean distance [12], determinant [13], and phase-space [14] are some other important fault detection techniques available in the literature. These methods compute absolute sum on a particular feature and have larger computational burden.

Fault detection algorithms based on the extraction of high frequency components of voltage and/or current signals using the time-frequency analysis methods such as wavelet transform (WT) [15,16] and S-transform (ST) [17] have drawn significant attention in recent years. Though, WT has good time-frequency resolution capabilities of non-stationary signals require multi-level filtering which make them computationally inefficient. The other challenges such as noise sensitivity and selection of proper mother wavelet impose difficulty in designing a systematic fault detection technique using WT. ST is less sensitive to noise. But, the drawback of ST is its redundancy. The computational intelligent techniques such as artificial neural networks [18], data mining [19], support vector machines [20], fuzzy systems [21] are also used for transmission line relaying applications. Besides complexity of the structures and training data, these techniques need large storage, computation time and multiple inputs for decision making. Classification and location estimation of a fault may be performed reliably by using computational intelligent techniques, but for fast detection of faults these techniques are not much attractive.

It is to be noted that all the aforementioned fault detection schemes adopt trial and error-based threshold setting approach for discriminating faults from non-fault transients. Such methods require extensive simulation studies for proper setting of the threshold which is time consuming. Also, using such approach of threshold setting reliability of the relay may not be guaranteed especially during extreme system operating conditions. Taking into account the computational burden, threshold selection procedure and fault detection speed, a simple method based on mean error estimation of current signal is presented in this paper with innovative swarm assistance. The method in [22] have proposed statistical process monitoring and fault diagnosis techniques for linear static processes using multivariate statistics framework, whereas the present work proposes particle swarm optimization (PSO)-assisted optimum threshold setting-based mean error estimation technique for transmission line fault detection. The proposed method computes the error between the actual and estimated samples of the current signal by approximating the small portion of the power frequency current signal into a straight line. Further, to ensure fast and reliable fault detection, the PSO algorithm [23–25] is employed for setting the optimum threshold value. Application of mean error estimation technique for transmission line fault detection and PSO assistance-based threshold setting are the two main contributions of the present work. The advantages of proposed method over the existing methods is that it has less computational burden, faster fault detection capability and it can be easily incorporated in the existing digital distance relaying scheme as it requires only one addition and one subtraction on the measured currents samples. The performance of the proposed fault detection algorithm is tested for a wide variety of fault and non-fault scenarios in a two-bus test power system and is found to be very fast and accurate.

The rest of the paper is organized as follows. The proposed method is presented in detail in Section 2. The results of the simulation studies are presented in Section 3. The comparative assessment of the proposed method with two existing techniques is provided in Section 4. Finally, the paper is concluded in Section 5.

2. Proposed method

The present work employs mean error estimation technique on three-phase currents for detection of transmission line faults. In order to ensure correct fault detection a PSO-assisted threshold setting method is adopted in this work. The detail calculation steps of the proposed method are provided below.

Let $x(i-1)$, $x(i)$ and $x(i+1)$ are the three consecutive samples in a pure sinusoidal waveform. For a straight line, the middle sample $x(i)$ is the average of the first sample $x(i-1)$ and third sample $x(i+1)$. However, when a portion of a sinusoidal waveform is approximated into a straight line, a small error exists between the actual and estimated sample. The error at i^{th} sample can be computed as

$$E(i) = x(i) - x_{\text{mean}}(i) \tag{1}$$

where $x_{\text{mean}}(i)$ is the estimated sample and is given by

$$x_{\text{mean}}(i) = \frac{x(i-1) + x(i+1)}{2} \tag{2}$$