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Fault location in a series compensated transmission line based on wavelet packet decomposition and support vector regression

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ABSTRACT

This paper proposes a novel transmission line fault location scheme, combining wavelet packet decomposition (WPD) and support vector regression (SVR). Various types of faults at different locations, fault resistance and fault inception angles on a series compensated 400 kV–285.65 km power system transmission line are investigated. The system only utilizes a single-end measurements. WPD is used to extract distinctive fault features from 1/2 cycle of post fault signals after noises have been eliminated by a low pass filter, and SVR is trained with features obtained from WPD. After training, SVR was then used in precise location of fault on the transmission line. The result shows that fault location on transmission line can be determined rapidly and correctly irrespective of fault impedance.

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1. Introduction

Faults often occur in power transmission system, which cause supply interruptions, damages to equipments and affect the power quality. Therefore, accurate fault location estimation is very important in power transmission system in order to restore power supply as soon as possible with minimum interruption. In addition it is imperative that faults on electric power transmission lines are quickly located and cleared, in order to improve the return on investment of power utilities. Accurate location of faults on power transmission systems can save time and resources for the electric utility industry.

In general, transmission line fault location techniques could be divide into two broad categories based on the number of terminal data used, namely single end/terminal[1–6] and multi-terminals techniques [7–10]. Each of these categories could still be subdivided further depending on the type measurements used in various algorithms, impedance estimation technique, [11–16,6], traveling wave based technique [5] and statistical or computational intelligence techniques [17,2,18]. Impedance based algorithms usually use both voltage and current measurements, while other algorithms like traveling wave methods and intelligent or pattern recognition methods can use either current or voltage measurement [19] to reduce the complexity and volume of data needed in fault location estimation. Some schemes use different combinations of some of the afore mentioned methods [20,21]

The line impedance method is realized by comparing the impedance obtained from the line model, considering possible faults in each node of the network with the equivalent impedance of the system. This method could be grossly affected by load conditions, high grounding resistance, and most notably the presence of series capacitor banks. Fault location based on traveling wave method is accomplished by precisely time-tagging of wave fronts as they cross a known point, typically at substations. Although, traveling wave methods have been reported to be accurate compared to Impedance based techniques, however, traveling wave method has some major challenges [17]: the requirement of high sampling rate, the associated computational burden of processing comparatively large data, and the possibility of misidentification of faults due to excessive attenuation of signals, especially for remote faults or close in faults have been a concern.

Generally, most computational intelligent methods have basically two stages in tandem. The first stage is used for signal pre-processing and features extraction. It is used for obtaining fault signature from measurements taken at the terminals of transmission lines. The second part involves classifiers or regressor algorithm schemes. Fault signatures obtained from the first stage is usually used in training intelligent schemes of the second stage. Consequently, fault classification and fault location are achieved. Many intelligent methods have been proposed. Joorabian et al. [22] used discrete Fourier transform (DFT) to extract features and used the radial basis function neural network (RBFNN) to estimate fault

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location. Samantaray et al. [23] applied hyperbolic S-transform (HS-transform) to yield the change in energy and standard deviation at the appropriate window variation and applied the RBFNN to find out fault location. Samantaray et al. [24] employed discrete wavelet transform to yield change in energy and standard deviation which are used to train and test the RBFNN to provide fault location from the relaying point accurately. Chunju et al. [25] applied DWT and wavelet fuzzy neural network to estimate fault location. DWT is applied to extract fault characteristics from the fault signals and the wavelet fuzzy neural network is used to find out fault location. Ekici et al. [26] proposed an intelligent method by combining the DWT and the Elman_(tm)s recurrent networks. Ekici et al. [27] applied wavelet packet transform (WPT) as extraction algorithm and BP neural network as fault locator. Both current and voltage signals were used in [22–26]. One cycle pre-fault and one cycle post-fault were considered in [23–25], half cycle of pre-fault and half cycle of post-fault in [27,26], and one cycle in [22].

In this paper, a new fault location scheme for power transmission line that uses a wavelet packet decomposition (WPD) for feature extraction and a support vector regression (SVR) for fault location is presented. One of the challenges in fault location scheme is the trade-off between the accuracy and data window size. Unlike other schemes that were highlighted earlier, which used a minimum of 1 cycle data window, the proposed scheme uses 1/2 a cycle data window. The method is demonstrated on a power transmission system with 400 kV–285.65 km transmission line. Various types of faults are initiated at different locations along the transmission line at various inception angles. The pre-fault and post fault phase data collected at line buses are first passed through a low pass filter to reduce the effect of noise. WPT was then used to extract fault signatures from 1/2 cycle post fault data; a support vector regression scheme then used the fault features to estimate the fault location. The results obtained were subjected to error analysis, which indicated that the proposed method can correctly and rapidly locate the faults with different fault type and different fault inceptions.

This paper is organized into six(6) sections, the first section is an introduction. In the Section 2 we discuss features extraction using wavelet packet decomposition and in Section 3 application of support vector regression machine was discussed. The new scheme and simulations are described in Section 4, while result and discussion is presented in Section 6. Finally, Section 7 is the conclusion.

2. Feature extraction based on wavelet packet decomposition

Feature extraction algorithms are valuable tools, which transform high dimensional data to a lower one with an equivalent information content. Hence, feature extraction is always used to reduce the dimensionality of data, which consequently reduce the complexity of classification or regression scheme.

Discrete wavelet transform (DWT) and wavelet packet decomposition are powerful tools that have been applied in various fields, data compression, signal denoising, feature extraction just to mention just a few. They are orthogonal wavelet decomposition procedure where a signal is passed through several filters. However, in WPD the number of processing filters is more than what is used for DWT. Fig. 1 shows the splitting of a signal using DWT into approximation and detail coefficients. The information lost between two successive approximations is captured in the detail coefficients, the successive details are never reanalyzed. For an n-level decomposition, there are $n+1$ possible ways to decompose or encode a signal.

Unlike DWT, in the WPD, both the detail and approximation coefficients are decomposed as shown in Fig. 2. For n levels of decomposition the WPD produces $2n$ different sets of coefficients (or nodes). WPD is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis.

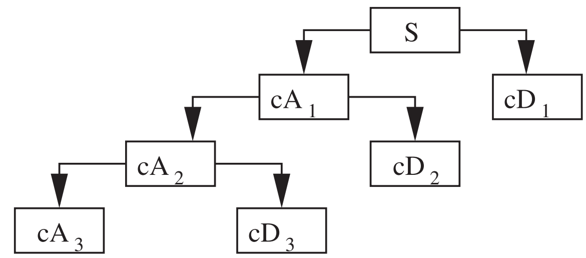

Fig. 1. Discrete wavelets transform decomposition tree.

Corresponding to the wavelet, are two finite impulse filters, a low-pass filter $h\,(k)$ and a high-pass filter $g\,(k)$. Using these two filters, the following sequence of recursive functions can be defined.

$$W_{2n}(x) = \sqrt{2}\sum_{k=0}^{2N-1} h(k)W_n(2x-k) \tag{1}$$

$$W_{2n+1}(x) = \sqrt{2}\sum_{k=0}^{2N-1} g(k)W_n(2x-k) \tag{2}$$

where $W_0 = \phi(x)$ is the scaling function and $W_1 = \psi(x)$ is the wavelet function. A wavelet packet function, is in form of

$$W_{j,n,k}(x) = 2^{j/2}W^n(2^{-j}x-k) \tag{3}$$

To measure a specific time–frequency information in a signal, we simply take the inner product of the signal and that particular basis function. The wavelet packet coefficients of a function f can be computed by

$$W_{j,n,k} = < f, W_{j,n,k} > = \int f(x)W_{j,n,k}(x)dt \tag{4}$$

Computing the full WPD of a discrete time signal involves applying both filters to the discrete time signal and then recursively to each intermediate signals. WPD decomposes the signal utilizing both low-frequency components and the high-frequency components. This flexibility of a rich collection of abundant information with arbitrary time–frequency resolution allows extraction of features that combine non-stationary and stationary characteristics.

Each coefficient of WPD measures a specific sub-band frequency content in a signal indexed by the scale parameters j and modulation parameter n. These coefficients are feature representations of the original signal in different wavelet packet bases. The sub-band energies of WPD nodes can be used to represent certain features of signals [28]. WPD sub-band energies is defined as the sum of square of coefficients of wavelet packet node.

$$e_{j,n} = \sum_k W^2_{j,n,k}(x) \tag{5}$$

3. Support vector regression

Support vector machines (SVMs) were first developed as a support vector classification (SVC) to solve classification problems, within the area of statistical learning theory and structural risk minimization [29–31]. Although SVMs have been used for fault classification, and transmission lines parameter estimation for fault locations, it can also be applied to regression problems [32] by an alternative loss function. These SVMs are called support vector regression.

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