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Transmission line fault location using hybrid wavelet-Prony method and relief algorithm

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ABSTRACT

Context: Intelligent fault locating in transmission lines consists of three main steps: feature extraction, feature selection, and utilizing a learning tool.
Objective: The main objective of this paper is to propose a systematic approach for intelligent fault locating in transmission lines.
Method: This paper extracts a group of candidate features by applying a combination of the Wavelet Packet Decomposition (WPD) and Improved Prony Analysis (IPA) methods on single-ended voltage measurements. To have an accurate fault location estimate, useful and efficient features are selected among the candidate features using the regression relief algorithm. In this paper, performances of three regression learning tools including the Generalized Regression Neural Network (GRNN), *k*-Nearest Neighbor (*k*-NN) and the Random Forests (RF) in the fault location problem are evaluated and compared, and the best tool is introduced.
Results: Numerous training and test patterns are generated through simulation of various fault types in an untransposed transmission line based on different values of fault location, fault resistance, fault inception angle, and magnitude and direction of load current. The results of evaluation using theses patterns show the high efficiency and accuracy of the proposed approach. For various fault types in the test cases, the average values of fault location estimation errors are in the range of 0.153–0.202%.
Conclusion: Besides accuracy, the proposed fault locating method is immune against current signal measurement errors and it does not face the problems and costs related to the transmitting and synchronizing data of both line ends.

Introduction

Over the last few years, dozens of studies have been carried out on fault location in transmission lines and different methods and algorithms have been proposed based on either analytical models or machine learning algorithms. Several researches have been carried out to improve the efficiency of analytical methods [1–3]. Along with these efforts, improving the learning-based fault location methods has attracted the attention of many researchers. In the learning-based methods, this is the learning algorithm which is responsible for finding the hidden rules as well as sophisticated relations between patterns' features and fault location. The essential stages in implementation and execution of a learning-based algorithm are the application of an appropriate feature extraction method, selection of efficient features among the extracted ones, and utilization of an appropriate learning algorithm.

In the feature extraction stage, the measured data in a single, two or multiple terminals of the transmission network could be employed [4]. More reliable access to measured data, lower complexity and lower costs are some of the attractive benefits of using the single-ended measurements. Current and voltage signals are typically available in a terminal of the transmission line. Most of learning-based fault location methods use both current and voltage signals. However, the use of current signal may be associated with errors due to the current transformer (CT) saturation and considerable magnitude of the decaying DC component.

The learning-based methods proposed for fault locating in transmission lines have employed the Fourier Transform (FT) [5–11], Wavelet Transform (WT) [12–24], Prony Analysis (PA) [25], and the S-Transform (ST) [26] to extract features from current and voltage signals. In [27], valuable studies were performed to compare and evaluate different features extracted from steady-state and transient data and also by using the FT and WT methods. It should be emphasized that among the extractable features, the features with high correlation to fault location and with low sensitivity to effective parameters such

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as fault resistance, fault inception angle, and pre-fault current should be selected [11].

Different learning tools may exhibit different performances depending on the features included in patterns. Up to now, different tools like the Multilayer Perceptron Neural Network (MLPNN) [6–9,17,19,25,27], Radial Basis Function Neural Network (RBFNN) [5,22,26], Support Vector Machine (SVM) [20,21,24], Extreme Learning Machine (ELM) [20], Elman Recurrent Network (ERN) [18], Fuzzy Inference System (FIS) [13–16], Fuzzy Neural Network (FNN) [10,12,14–16], Adaptive Structural Neural Network (ASNN) [23], and k-Nearest Neighbor (k-NN) algorithm [11] have been used for fault locating in transmission lines.

Notwithstanding the fair performance of the above-cited learning-based fault location methods, most of them focused more on the implemented learning tools and less on the quality of input features. In most of these methods, even if new input features were proposed, the quality and efficiency of the proposed features were not analyzed independently of learning tools. On the other hand, the performance of learning tools usually depends on the structure considered for input patterns. The main purpose of this work is to design a novel, efficient and accurate fault location approach considering new extractable useful features and appropriate learning tools. Indeed, the core idea of this paper is to extract and select efficient features using appropriate tools and also to implement a suitable learning tool to improve the accuracy and performance in fault location. Fig. 1 presents the main stages in the current work.

This paper uses only the single-ended voltage measurements to extract efficient features for fault locating in transmission lines. In this regard, a combination of the Wavelet Packet Decomposition (WPD) and Improved Prony Analysis (IPA) methods is used to extract features out of one cycle of voltage signal after fault inception. Then, the regression relief algorithm is used to select efficient features. In this paper, among the representatives of three learning tool families, including the Generalized Regression Neural Network (GRNN), k-NN, and Random Forests (RF), the most appropriate one for fault locating is selected and used. It should be mentioned that the selection of efficient features and appropriate learning tool are performed using the patterns of the most probable fault type i.e. single-line-to-ground fault, and the obtained results are generalized to other fault types. A sample untransposed transmission line is considered for verifying the proposed method. Several fault cases are simulated through changing effective parameters such as fault type, fault location, fault resistance, fault inception angle, and magnitude and direction of pre-fault load current. The high efficiency and accuracy of the proposed approach is demonstrated using these simulated cases.

Tools and methods

The employed tools and methods for feature extraction and feature selection and also the considered learning tools are briefly introduced and described here.

Feature extraction tools

Wavelet Packet Decomposition (WPD)

The WPD is an extended version of the Discrete Wavelet Transform (DWT). Applying the DWT on non-stationary signals could result in the extraction of beneficial time–frequency information. The process of applying DWT includes passing a signal through a set of high-pass and low-pass quadrature mirror filters. During this process, at first the input discrete signal x is passed through the high-pass and low-pass filters at the same time. Then, the output signals of filters are downsampled through subsampling by 2. In next step, the output samples of high-pass filter (detail coefficients) are saved while those of the low-pass filter (approximation coefficients) are passed again through high-pass and low-pass filters and subsampled. This process is repeated for a specified number of times that have been considered for signal decomposition. The difference of WPD and DWT is that in the WPD, in addition to approximation coefficients, the detail coefficients are decomposed by high-pass and low-pass filters as well; resulting in a complete binary tree. Fig. 2 shows a schematic view of the WPD process along with the frequency range in different levels based on the Nyquist theorem. Applying the WPD provides us with more

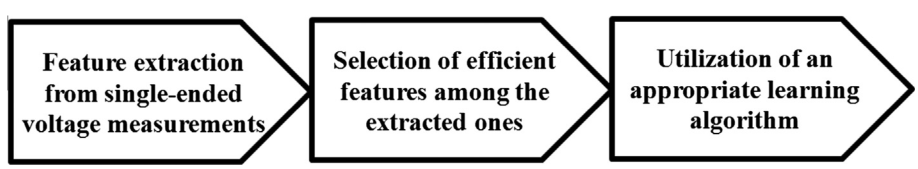

Fig. 1. The overall block diagram of the proposed work.

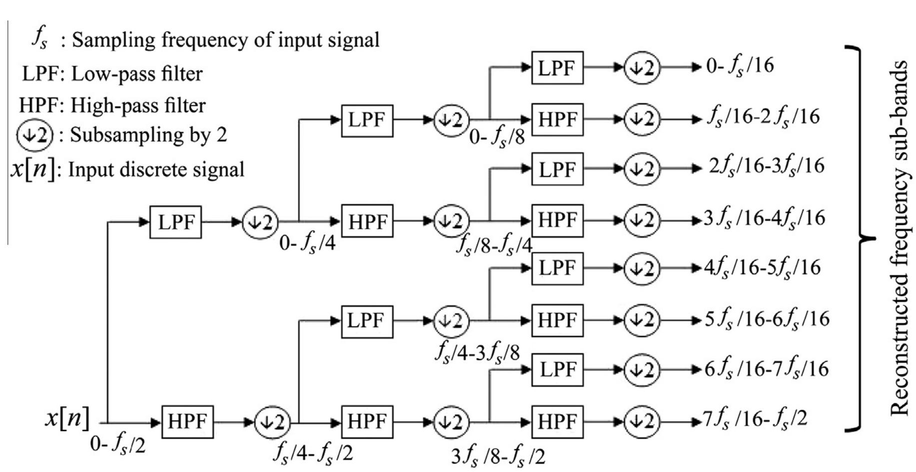

Fig. 2. Process of applying WPD in three levels.