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Statistical decision-tree based fault classification scheme for protection of power transmission lines

J. Upendar *, C.P. Gupta [1], G.K. Singh [2]

Department of Electrical Engineering, Indian Institute of Technology, Roorkee, 247 667 Uttarakhand, India

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A B S T R A C T

This paper presents a statistical algorithm for classification of faults on power transmission lines. The proposed algorithm is based upon the wavelet transform of three phase currents measured at the sending end of a line and the Classification and Regression Tree (CART) method, a commonly available statistical method. Wavelet transform of current signal provides hidden information of a fault situation as an input to CART algorithm, which is used to classify different types of faults. The proposed technique is simulated using MATLAB/SIMULINK software and it is tested upon the data created with the fault analysis of the 400 kV sample transmission line considering wide variations in the operating conditions. The classification results are also compared with the results obtained using back propagation neural network.

1. Introduction

Transmission line protective relaying is an important aspect of a reliable power system operation. The faults do occur in power system network and are more frequent in transmission and distribution systems. Following the occurrence of a power system fault, the maintenance crew must find and fix the problem to restore the service as quickly as possible. Fast and accurate restoration of the service, reduces the loss of revenue and outage time. Therefore, these challenges reinforce the need to examine merits of different fault classification methods and various protection reinforcement schemes available to system planners, so as to achieve the highest possible incremental reliability and improvement in the system protection scheme under a variety of fault conditions.

Over the last two decades, owing to technological progress in computers and electronics, power system has been equipped with digital relays which offer a number of advantages over electromechanical relays. Event recorders used at remote terminal units transmit the data to the control center through the supervisory control and data acquisition (SCADA) systems. For complex fault or malfunction scenarios, identification of the fault type and malfunctioning devices may require extensive knowledge about the power system and its protective devices. Traditionally, fault diagnosis is performed off line by experienced engineers, but software tools emerging in present times for fault classification may provide more effective and flexible solution. To improve the accuracy and speed of fault classification, the information is stored in a database and intelligent systems in a control center can access the database for diagnosis of a fault type for further genesis.

In the past, several attempts have been made for fault classification using traveling wave, neural network and fuzzy logic based approaches. However, traveling wave methods [1] require high sampling rate and have problems in distinguishing between waves reflected from the fault and from the remote end of the line. Artificial neural network (ANN) based fault classification technique was reported in [1–4]. Although ANN-based approaches are quite successful in determining the correct fault type, the main disadvantage is that it requires considerable training effort for good performance, especially under a wide variation of operating conditions (such as system loading level, fault resistance and fault inception instance). Another disadvantage is that the training may end up in a local minimum e.g., contingencies may not converge to the desired value. When the learning gets stuck on local minima, the requisite performance will suffer. The application of fuzzy logic to classify the faults was used in relaying [5,6]. The benefit of fuzzy logic is that its knowledge representation is explicit, using simple "IF-THEN" relations. But logic-based expert systems have a combinatorial explosion problem [6] when it is applied to a large system. Again, the accuracy of fuzzy logic based schemes cannot be guaranteed for wide variations in the system conditions.

* Corresponding author.
E-mail addresses: jallaupendar@gmail.com (J. Upendar), cpg65fee@iitr.ernet.in (C.P. Gupta), gksngfee@iitr.ernet.in (G.K. Singh).
[1] Tel.: +91 1332 285594 (Off).
[2] Tel.: +91 1332 285070 (Off); fax: +91 1332 273560.

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In modern power systems, digital relays and fault recorders are installed at prime locations to monitor and record important information regarding power quality disturbances. Recently, wavelet based signal processing techniques have emerged as a powerful tool for feature extraction of power quality disturbances [7], data compression [8] and fault classification [9–11]. A pattern-recognition technique based on wavelet transform has been found to be an effective tool in monitoring and analyzing power system disturbances including power quality assessment [12] and system protection against faults. A technique based on comparison of currents in the corresponding phases of the two lines to detect faults and discriminate between faulty and healthy phases is proposed [13]. Wavelet transform-based fault classification using voltage and current signals of a simple transmission line is reported in [14].

More recently, the CART methodology [15,16] has caught the interest of a wide community of applied mathematicians and digital signal/image processing engineers. Built around ideas of recursive partitioning, it develops, based on an analysis of noisy data, a piecewise constant reconstruction, where the pieces are terminal nodes of a data-driven recursive partition. Since its inception in the last decade, the CART methodology of tree-structured adaptive nonparametric regression has been widely used in statistical data analysis. For example, in health risk analysis [15], it was used to classify heart attack patients into two groups: those who will survive 30 days (low risk) and those who will not (high risk). After examining 19 variables including age and blood pressure, the classification tree was formed using CART and it was observed that 89% of low risk and 75% of high risk patients were correctly classified. Again CART was used for pollution monitoring to study the relationship between air pollution concentration and housing values [15]. In [17], CART was used for deciding the value of the house depending upon various variables (like crime rate, tax rate, air pollution, number of rooms, distance to employment sectors and accessibility to road highways) and also for investing the risk factor related to bankruptcy in banking sector. It was also used in household food-insecurity analysis [18], for identifying indicators of vulnerability to famine and chronic food insecurity from the information collected from household survey in Bangladesh and Ethiopia, that provide the indication of households most likely to be food insecure. The information used as input consists of calories available per person per day for various households. Then the households were separated into two groups – food insecure and food secure. CART was widely used for data pruning in image coding [19–22].

This paper presents an application of a new statistical decision-tree based fault classification technique using CART for transmission lines. In many of the previous papers/research, it is observed that, the fault classification is mainly implemented with the help of threshold values. But, because of non-linearity nature of these threshold values under various operating conditions, it is difficult to determine these threshold values. In our proposed fault classification algorithm, the advantage of CART is that it is nonparametric in nature. CART does not require any variables to be selected in advance. CART algorithm will itself identify the most significant variables and eliminate non-significant one. CART results are invariant to monotone transformations of its independent variables. By changing one or several variables to its logarithm or square root will not change the structure of the tree. Based on its own analysis, it will analyze the large amount of data within a short period. The proposed method is capable of providing a reliable and fast estimation of fault types on the basis of measurement of three phase currents using wavelet transform (WT). The method classifies whether a normal state, single-line-to-ground, double-line-to-ground, phase-to-phase or a three-phase fault has occurred. The proposed algorithm is tested on a 400-kV two terminal transmission line simulated using MATLAB/SIMULINK®. The performance of the proposed technique is analyzed by comparing the fault classification results with Back-Propagation Neural Network (BPNN) method for the same test data considering a wide variation in system condition. Fault signals in each case are extracted to several scales using wavelet transforms and certain selected features of wavelet transformed signals are used as input for a training process of the proposed statistical algorithm.

2. Wavelet analysis

Wavelet analysis [23] is a mathematical technique for signal processing and is inherently suited for non-stationary and non-periodic wide-band signals. It helps in archiving the localization both in frequency and time. Wavelet analysis involves an appropriate wavelet function called "mother wavelet" and performs analysis using shifted and dilated versions of this wavelet. The continuous wavelet transform (CWT) of a continuous signal $x(t)$ is defined as

$$\mathrm{CWT}(a,b) = \int_{\infty}^{-\infty} x(t)\Psi^*_{a,b}dt \tag{1}$$

where $\Psi(t)$ is the mother wavelet and other wavelets $\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi^*_{a,b}(\frac{t-b}{a})$ are its dilated and translated versions, the constants a and b being dilation (scale) and translation (time shift) parameters, respectively. The CWT at different scales and locations provides variable time–frequency information of the signal.The digitally-implementable counterpart of CWT known as discrete wavelet transform (DWT), is the one which is used for the proposed fault classification. The DWT of a signal $x(t)$ is defined as

$$\mathrm{DWT}(x,m,n) = \frac{1}{\sqrt{a_0^m}}\sum_m\sum_n x(k)\Psi^*\left(\frac{k-nb_0a_0^m}{a_0^m}\right) \tag{2}$$

where $a = a_0^m$ and $b = nb_0a_0^m$; a_0, b_0 being fixed constants are generally taken as $a_0 = 2$ and $b_0 = 1$. k, m *and* n are integer variables.

The actual implementation of DWT is done by multi-resolution analysis (MRA) [24]. The original signal is analyzed at different frequency bands with different resolutions. The signal is decomposed into a smooth approximation version and a detail version. The approximation is further decomposed into an approximation and a detail; and the process is repeated. This decomposition of the original signal is obtained through successive high-pass and low-pass filtering of the signal. The successive stages of decomposition are known as levels. The MRA details at various levels contain the features for the detection and classification of faults.

3. Classification and regression tree method

Classification and Regression Tree (CART) [15] is a classification method which uses historical data to construct decision trees. The aim of a classification and regression tree is to partition the input data in a tree-structured fashion, and to construct an efficient algorithm which provides a piecewise-constant estimator f or a classifier φ by fitting to the data in each cell of the partition. This algorithm is based on binary tree-structured partitions and on a penalized criterion that permits to select some "good" tree-structured estimators among a huge collection of trees. In practice, it yields some easy-to-interpret and easy-to-compute estimators. More precisely, given a training sample of observations, the CART algorithm consists in constructing a large tree from the observations by minimizing at each step some impurity function and then, in pruning the thus constructed tree to obtain a finite sequence of nested trees thanks to a penalized criterion whose penalty term is proportional to the number of leaves. Decision trees are then used