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Classification of lightning stroke on transmission line using multi-resolution analysis and machine learning

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A B S T R A C T

One of most important elements of Electric Power Systems (EPS) is the transmission line (TL), which is permanently under adverse conditions especially lightning strokes. At the moment, those phenomena have been the root cause of short circuits and the most important cause of mal-operation of transmission line protection relays. Thus, this paper develops the classification of lightning transient signals with and without fault. Multi-resolution analysis (MRA) is used to analyze those signals considering five mother wavelets and different decomposition levels of three phase voltages. In this manner, Spectral Energy and Machine Learning as Artificial Neural Network, K-Nearest Neighbors and Support Vector Machine are employed to classify those signals. On the other hand, the developed work in this paper analyzes most important parameters of lightning strokes, which are essentials in producing conditions with and without fault. Results show that the methodology presents an acceptable performance.

1. Introduction

It is well known, that for a long time, electric power has been a very important part of modern day life, whose principal objective is supplying electric power maintaining a very high level of continuity of service [1]. Nevertheless, abnormal or intolerable conditions especially lightning strokes can cause short circuits, i.e. faults, being transmission lines (TLs) the most affected [2–4].

Lightning strokes on TL are manifested in two ways. First, when their over-voltages are higher than voltages that can withstand the basic insulator level (BIL), generating a ground fault. Second, when over-voltages caused by lightning are not greater than BIL; therefore a fault is not produced [5]. Moreover, since that lightning has a very unpredicted behavior [5], their elimination or total reduction on TLs is impossible, thus at the moment it is the most important disturbing phenomenon for the functioning of EPS [5–9,19]. Records reported by different organizations indicate that those signals cause the highest percentage of power outages and mal-operation of protection relays. Hence, different countries like United States of America, Canada, Argentina, Japan, Mexico, Brazil, Malaysia and others have experimented catastrophic consequences as blackouts due to lightning strokes [2,7,10–18].

On this context, TLs are equipped with protection relays, which are continuously monitoring those phenomena [20], being impedance estimation relays and transient based protection (TBP) the most used protection techniques [20–22]. However, they suffer from some drawbacks of reliability due to atmospheric discharges presence, which have not been solved yet [8,23,24].

As regards distance relays, they respond to the impedance between relay location and fault location [20,25,26], this technique is very popular in practical applications. Nevertheless, their operation time depends on the length of the sampling window [20,23], which currently cannot be less than 1–3 cycles. Thus, their actuation time often reaches 50–70 ms to analyze lightning strokes. On the contrary, unlike the previous technique, TBP is related to the analysis of high frequency components [20–22], which carry the very first information about signals [21,22,27]; improving the operation time from some cycles to a quarter cycle. However, transient signals caused by atmospheric discharges that produce and do not produce fault are not well distinguished by those protection algorithms, leading to mal-operation of those relays [8,28,29].

On the other hand, since the intensity and frequency of storms worldwide increase due to global warming [45,46], there is a very high probability that lightning impacts on TLs [47]. Hence, protection relays have to provide maximum sensitivity, identifying faults as quickly as possible, but avoiding their operation under all permissible condition like lightning without fault [30–33].

In order to solve those previous drawbacks, recent approaches particularly based on Wavelet Transform (WT) have been reported

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by a number of researchers, which extract energy spectrums of different frequency bands [8,9,34–39,64–67]. Moreover, as stated previously, the flash performance is random [5]. Hence, the lightning strokes classification on TLs has to be investigated considering their most important parameters, which are essentials in producing flashover [40–42] (see Section 3). Therefore, atmospheric discharges with different flash peak current magnitudes, positive and negative polarity, tower footing resistances (TFR), lightning stroke on tower, on phase directly and others must be considered [43,44]. However, from bibliographic review it is possible to see that specific conditions of lightning strokes are analyzed, omitting crucial parameters in their performance [40,48]. Previous research considered some flash current magnitudes (3–15 kA), omitting wide flash currents range (15–250 kA). Those pieces of research analyzed only a Footing Tower Resistance (FTR) value and one polarity (10 Ω/positive), respectively. On the other hand, lightning may hit on any stretch of TLs. However, previous research analyzed the lightning stroke on the midpoint of TLs, omitting their total length.

Based on the above said, it is imperative to develop methodologies for classifying lightning strokes on TLs; this paper develops a features extraction–classification problem. Accordingly, by using MRA and different mother wavelets (see Section 4.2) lightning stroke signals are decomposed in different decomposition levels, extracting information useful to analyze those phenomena. Later on, by using Spectral Energy and Machine Learning techniques as K-Nearest Neighbors (K-NN), Artificial Neural Network (ANN) and Support Vector Machine (SVM), those features extracted though MRA are classified. It is necessary to note that Machine Learning techniques at the moment have not been proposed for this purpose.

Finally, in order to determine which technique gives the best performance, this research presents a comparison among those techniques. Results show that methodology developed in this work presents an acceptable performance.

2. Mathematical tools

2.1. Multi-resolution analysis

Wavelet Transform (WT) represents time-varying signals into a time-scale (frequency) domain, so it is particularly useful to analyze transient signals. Accordingly, by using functions of translation τ and scale s, the window function ψ (mother wavelet) is moved and dilated automatically during the analysis [49].

Moreover, Discrete Wavelet Transform (DWT) has been used in protection relays, the function of translation and scale must be selected as discrete values. Where, DWT is based on multi-resolution analysis (MRA) or sub-band coding shown in Fig. 1.

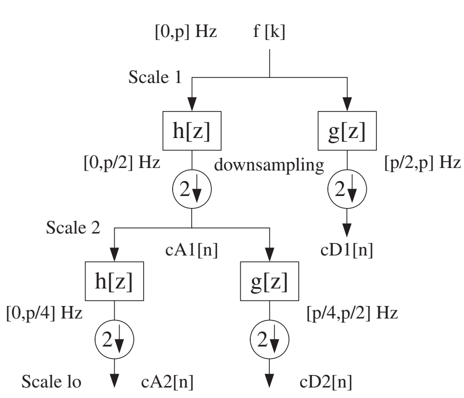

Fig. 1. Wavelet filters bank.

From this figure it is possible to see that a discrete signal $f[k]$ passes through two mid-band digital filters, a high-pass filter $g[z]$ and a low-pass filter $h[z]$, which produce detail (cDl) and approximation (cAl) coefficients, respectively. These filters cover various frequency ranges depending on the decomposition level (j) of the original signal [50].

2.2. Artificial Neural Network

The basic processing elements of neural networks are called artificial neurons, where effects of input signals are represented by the connection of weights, and the transfer function represents the nonlinear characteristic exhibited by neurons. Therefore, the neuron impulse is calculated as the weighted sum of input signals, which are transformed by the transfer function [51]. The basic functioning of an artificial neuron can be represented as a vector as follows:

$$y = f(u) = f\left(\sum_{j}^{n} w_j x_j\right) \tag{1}$$

where, w_j is the weight vector, x_j is the input vector and $f(u)$ is referred to an activation function. The variable u is defined as a scalar product of the weight and input vectors such as:

$$u = w_1x_1 + w_2x_2 + \cdots + w_nx_n = w'x = \sum_{j}^{n} w_j x_j \tag{2}$$

The output value Y is computed as:

$$Y = f(u) = \begin{cases} 1 & \text{if} \quad wx \geqslant u \\ 0 & \text{otherwise} \end{cases}$$

2.3. K-Nearest Neighbors

This technique is based simply on remembering all examples which are used in the training stage. Then, when new data are presented to the learning system, they are classified according to behavior nearest data [52,53]. For instance, Fig. 2a shows the classification process based on KNN, it has data of two different classes represented by squares and circles. On this context, the aim is to identify the class of a new signal x represented by rhombus. Then, it is necessary to determine the closer signal to this testing signal, assigning the corresponding class as class 2 (see Fig. 2b). However, it is clear that any signal represented by a square can be within data corresponding to circles as is shown in Fig. 2c, thus there is a possible error and the signal x is classified as square, i.e. class 1. In order to solve this drawback, a greater number of neighbors to classify the new signal can be employed, i.e. using a small portion of data for example $k = 4$, it is possible to see that the new signal belongs to the class 2 (see Fig. 2d). As regards to the proximity, this is defined in terms of a distance metric, being the Euclidean the most used. However, there are other measures like Euclidean squared City-block and Chebyshev.

2.4. Support Vector Machine

The aim of SVM is to separate data of opposite class using a function or hyper plane [54]. Nevertheless, there are many possible linear classifiers that can separate the data, so the aim of SVM is to get only one by maximizing the distance between it and the nearest data point of each class.

Given a data set, with $1 \leqslant i \leqslant l$, l is the size of the sample

$$(x_1, y_1), \ldots, (x_i, y_i) \quad \in \quad Xx\{\pm 1\} \tag{4}$$