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Detection, Classification and Localization of Faults of Transmission Lines using Wavelet Transform and Neural Network

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Abstract

In this work an algorithm is presented that allows to detect, classify, discriminate and locate the faults that can be presented in an energy transport line, based on high frequency information (travelling waves). For this, the Wavelet transform and two types or neural network architectures are used as analysis tools. For the validation of the proposed methodology, a four-bar 400 kV reduced power system was used, which was modeled in the ATP / EMTP electromagnetic transient program, to obtain the signals in the time domain. The results obtained show the validity of the methodology proposed, for the scenarios considered.

Keywords: Wavelet transform, Protection of high-voltage energy transport systems, fault location, neural networks, and traveling waves.

INTRODUCTION

One of the great areas of research that in recent times is having a great boom in the development of novel methods and quantity of publications in technical journals of international impact, is the one related to the location of the faults in both transport systems in high voltage as in sub-transmission and distribution systems.

In the case of this particular work, the analysis will focus on high voltage transport systems and is fundamentally due to the prevailing need to minimize the unavailability time of a line due to a fault.

The notable increase in demand coupled with new market strategies for electricity supply at all stages (generation, transportation, distribution and marketing) have led the transport system to grow in both size and complexity and additionally requires working more and more near the critical limits of stability.

All these points generate two important topics to cover:

A. The new requirements on protection systems in all its broad spectrum: selectivity, sensitivity, reliability, speed, adaptability, etc.
B. Greater precision in the location of permanent faults in order to reduce repair times and re-commissioning.

In order to adequately attack all these new conditions, it is essential to use modern techniques of analysis without dissociating from advances in the field of "hardware" for its effective and useful implementation.

There are two techniques that can be mentioned by their application in this specific field of work and that are precisely those that are going to be implemented in the present article:

1. Signal Analysis Techniques (Wavelet Transform).
2. Techniques of Artificial Intelligence (Neural Networks).

In general, the information obtained from voltage and current signals in the time domain is not sufficient and is generally used in the frequency domain [1-3].

Traditionally the Fourier transform (FT) has been used for this purpose; however, the particular analysis of non-periodic signals associated with electromagnetic phenomena such as a fault in a power system represents a problem for conventional FT. The localized Fourier transform (or Gabor transform) partially solves the problem, although it is limited by dependence on a fixed window width, which limits the combined time-frequency information.

The transmission lines generally transfer a considerable power to the centres of consumption, reason why when being out of service the power that supplied the line has to be supplied by some other line more near, this line that caters in addition, the power of the line out of operation could lead to overloading, resulting in the triggering of the protections, causing a cascade to be triggered, affecting the stability of the system and causing it to collapse. These factors would affect the continuity of the service and therefore the reliability of the service by the supplier. Reliable fault location algorithms will allow the location of the fault to be located in the shortest possible time, reducing the time that the line is out of service [1].

However, the Wavelet Transform (WT) uses variable window widths (short for high frequencies and longs for low frequencies) and allows in general to obtain adequate information combining the temporal event with the frequency spectrum. Therefore, it has been selected as an analysis tool in the present work.

On the other hand, it is the handling of that information extracted from the analysis and direct filtering of the signals of voltage and intensity, in order to obtain a precise result as to the concrete task that is wanted to undertake.

In the specific field of an algorithm of protection of energy transport lines, there is a classification of these tasks in function of the progressive scheme that must fulfil, from the detection of the event, until the decision is made to give or not to order of firing to the associated switch and can be succinctly divided as follows:

1. Fault detection.
2. Classification of the type of fault and identification of the phases involved.
3. Location of fault.

In particular, 2 and 3 are considered critical and, for them, will be used as support, neural networks.

Thus, in the case of classification, because it is a problem with discrete results, a probabilistic network (PNN) is used and for the case of fault localization, one that has the capacity to generalize for different scenarios, so that a radial base network (RBFNN).

The combined use of Wavelets with neural networks is not new [4] and the results obtained demonstrate their good functionality even in those scenarios involving series or electronic power compensators (FACTS).

Finally, the objective of this work is to present an algorithm that performs all the aforementioned tasks, primarily using the high frequency information of the signals (traveling wave), which is extracted by the WT and later processed by Neural Networks.

WAVELET TRANSFORM

For the purposes of this work Wavelet analysis can be interpreted as a technique that transforms a signal in the domain of time (current and / or voltage) to a domain called time-scale, in order to locate in time the different components of the frequency spectrum of the signal, made particularly useful for identifying transient signal components that can be used as a basis for developing high-speed protection algorithms, such as the traveling wave.

This is achieved thanks to the expansion of the signal through a linear decomposition that uses as base a set of functions called Wavelets, which arise from a function "Mother wavelet" (equation 1), which acts as a prototype to generate functions bases ("windows") whose width varies as the transform is evaluated.

$$\Psi_{\tau,S}(t) = \frac{1}{\sqrt{|S|}}\Psi\left(\frac{t-\tau}{S}\right) \tag{1}$$

Where "τ" (translation) is a parameter that is related to the location of the window as it moves through the signal, so this term will correspond to the time information in the transformed domain. On the other hand, "s" (scale) is a parameter that is related to the information in frequency of the signal, corresponding for each scale a certain band of frequencies and therefore defines the width of the window.

In practice, the mother wavelet cannot be a continuous function, but discrete values (j,k) must be chosen for the parameters (S,τ); this leads to the use of the Discrete Wavelet Transform (DWT), which is very efficient when implemented through multiresolution analysis (MRA).

For this purpose, the MRA is based on the appropriate selection of a scaling function φ that gives rise to two fundamental equations [5], the scale function $\varphi(t)$ and the wavelet function $\Psi(t)$ defined by (2) and (3), respectively.

$$\varphi(t) = \sum_k h(k)\sqrt{2}\varphi(2t-k)\; k \in Z \tag{2}$$

$$\Psi(t) = \sum_k h_1(k)\sqrt{2}\varphi(2t-k)\; k \in Z \tag{3}$$

These two equations are characterized by being recursive and by the discrete filters $h(k)$ and $h_1(k)$ representing the coefficients of the scaling function and the coefficients of the wavelet function, respectively. $h_1(k)$can be obtained from $h(k)$ as indicated in (4).

$$h_1(k) = (-1)^k h(1-k) k \in Z \tag{4}$$

The functions of scale and wavelet are a prototype of a class of orthogonal basis functions that generate a space $L^2(R)$ and that have the form indicated in (5) and (6).

$$\varphi_{j,k}(t) = 2^{j/2}\varphi(2^j t-k) j,k \in Z \tag{5}$$

$$\Psi_{j,k}(t) = 2^{j/2}\Psi(2^j t-k) j,k \in Z \tag{6}$$

Where the parameters "j" and "k" are the resolution and translation, respectively.

Therefore, with a set of functions $\varphi_{j,k}(t)$ and $\Psi_{j,k}(t)$ a function $f(t)$ can be represented as a series expansion in terms of these functions, (7).

$$f(t) = \sum_k a_j(k)\varphi_{j,k}(t) + \sum_k \sum_{j=0}^{J-1} d_j(k)\Psi_{j,k}(t) \tag{7}$$

In the first sum of (7) the coefficients $a_j(k)$ represent an approximation of $f(t)$, with a resolution of one point for every 2^j points of the original signal. In the second sum, the coefficients $d_j(k)$ represent the detail of the signal with different levels of resolution, which increases as the index "j" increases.

The coefficients $a_j(k)$and $d_j(k)$ thus constitute a way of expressing the DWT of the signal, and since the chosen base functions are orthogonal these coefficients can be calculated by the inner product as shown in (8) and (9).

$$a_j(k) \leq f(t), \varphi_{j,k}(t) \geq \sum_m h(m-2k)a_{j+1}(m) \quad (8)$$

$$d_j(k) \leq f(t), \Psi_{j,k}(t) \geq \sum_m h_1(m-2k)a_{j+1}(m) \quad (9)$$

The structure of these equations is a great advantage from the point of view of the implementation of a DWT calculation algorithm, since by applying the digital filter theory, the coefficients $a_j(k)$ and $d_j(k)$ defined by (8) and (9) can be evaluated in two stages; first, the convolution of the approximation coefficients of the scale "$j+1$" with the coefficients of the digital FIR filters $h(-n)$ and $h_1(-n)$, where the FIR filter implemented as $h(-n)$ is a low pass filter and is called a decomposition filter (LD) and the filter implemented as $h_1(-n)$ is a high pass filter and is called a decomposition filter (HD). Secondly, a reduction in the number of samples of the resulting signal is performed by selecting one of each two points (↓ 2). The described process can be repeated consecutively with the new a_j calculated coefficients, constituting a pyramidal structure or pyramidal algorithm of Mallat [5] as shown in Figure 1.

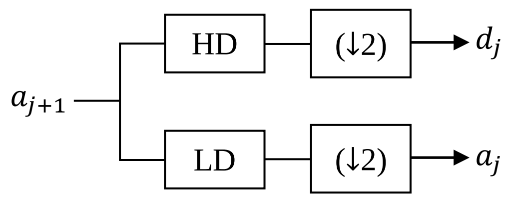

Figure 1: Representation of the decomposition process (multiresolution analysis), through the application of filter banks

NEURAL NETWORKS

One of the techniques that is currently used to estimate different variables in complex systems, from a limited amount of input parameters, are the neural networks [6]. This leads to taking as a starting point the use of RNA as a method of solution to the problem posed. However, one of the main problems when using neural networks is the correct selection of the architecture and input variables. However, this issue is of equal importance in any method used to estimate, so it is not a great disadvantage when comparing ANNs with some other similar tool used today. In the following sections we will go into detail about the aspects taken into account for the selection of input variables, according to their importance and relevance to the task required (classification or location of detected fault).

Nowadays there are types of ANN architectures (probabilistic, self-organizing, competitive, radial-based, etc.), which also use WT as conditioning element for input signals [4]. In the particular case of this publication, the types of ANN to be used, are the radial base and the probabilistic ones.

A. Radial Basis Neural Networks

Several works [7, 8, 9, 10, 11, 12 and 13] have shown a marked tendency to use radial-based networks, rather than retro-propagation, and have shown that these types of networks (RBFNN) have excellent properties for solving problems with nonlinear models since an approach to multidimensional functions.

So given the condition of possessing historical data represented by a pair of vectors (input and output) for training and assuming for the next step that the output is one-dimensional (which simplifies but does not subtract significant generality to the approach), you can define:

- Inputs:$X_i \in R^p$ with $i = 1,2, \dots n$
- Outputs:$d_i \in R$

The network with this function, implements a mapping of the type:

$$F(X): R^p \rightarrow R$$

Where:

$$F(X) = \sum_{i=1}^{M} \omega_i G_i(\|X - c_i\|) \quad (10)$$

Where $c_i \in R^p$, are the centers of the M base functions G_i(Gaussian exponential functions ofwidth σ_i)

$$G_i(\|X - c_i\|) = \exp\left(\frac{\|X - c_i\|^2}{\sigma_i}\right) \quad (11)$$

The vector containing the optimal weights $[\omega_i]_{i=1}^{M}$is calculated by minimizing the followingcost function:

$$\omega = (G^T G + \lambda G_0)^{-1} G^T d \quad (12)$$

An outline of such networks is shown in Figure 2, with "p" inputs and "n" outputs. Each of the "p" components of the input vector X arrive at the M base functions G_i, whose inputs are linearly combined with the weights ω_i, at each output $F_j(X)$.

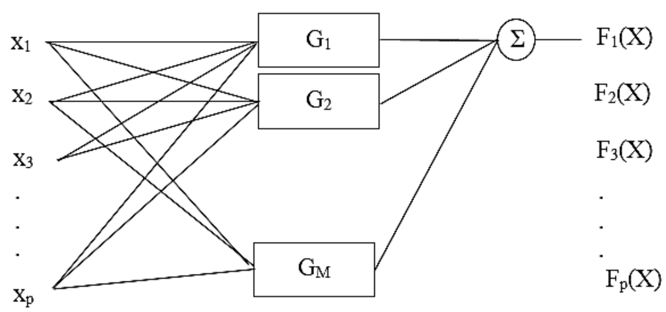

Figure 2: Schematic of a neural network with radial base architecture. "P"inputs, "n" outputs and M number of G_i functions

B. Probabilistic Neural Networks

The probabilistic neural network is ideal for classification problems [6] and falls within the group of non-parametric estimation techniques. This network is composed of three layers: The first corresponds to the inputs, an intermediate that can be of radial basis is a layer of categorization and the last one that throws the output is based on a competitive scheme.

The work is done as follows: The first layer calculates the distances from the input vector to the training vectors and produces a vector whose elements indicate the closeness between these two vectors (input / training). The second layer, sum the contributions for each class of inputs and thus produce a vector of probabilities. Finally, a transfer function of the competitive type takes the maximum of the probability vector and produces a binary output for the class classification (a "1" for the one with the highest probability and a "0" for the other positions of the vector).

The activation "function" for this case consists of the probability density (PD) between input and training patterns. As can be seen, there is no previous training for weight calculation, but the categorization layer calculates the PD for each input vector, comparing it with the training vectors for the pre-specified classes or output categories.

$$p_n(X) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{V_n}\varphi\left(\frac{x-x_i}{h_n}\right) \tag{13}$$

Where, n: is the size of the training vector.

$$V_n = \frac{1}{\sqrt{n}} \tag{14}$$

h_n: is the grouping factor.

And the function φ, is represented by:

$$\varphi(u) = \frac{1}{\sqrt{2\pi}}e^{-\frac{u^2}{2}} \tag{15}$$

PROPOSED METHODOLOGY

The general algorithm is divided into sequential tasks, as shown in Figure 3.

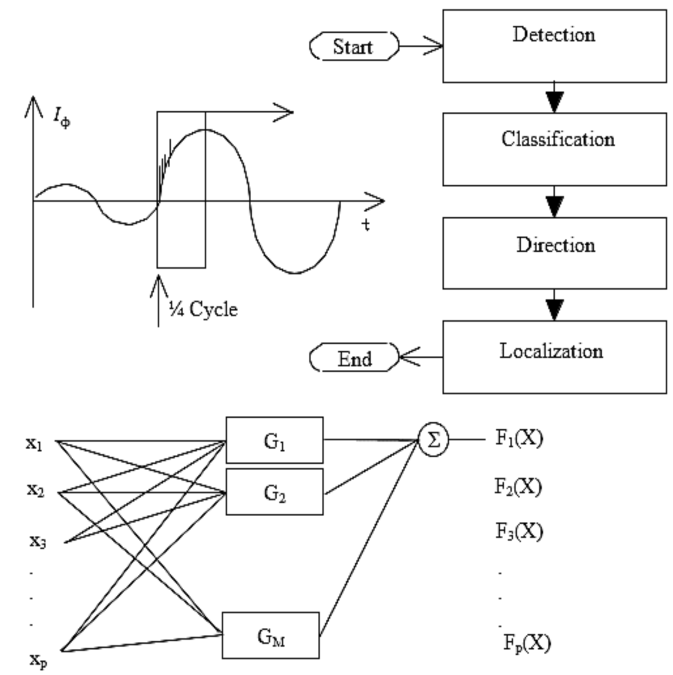

Figure 3: Task Scheduling Scheme

A. Fault Detection

This task seeks to start the algorithm, after detecting the occurrence of an event in the network. In general, the criterion commonly used in this respect is the condition that the effective value of the current in any of the system phases exceeds a preset threshold.

In this work, a threshold (M_{aj}) of the "Modulus Maxima" (MM) of detail 1 (d1) of the wavelet transform of the current signals in the modal domain, i.e.:

$$\left|MM_{d1}(I_\phi)\right| > M_{aj} \tag{16}$$

Where, $\phi = a, b\ or\ c$

It is defined as "Maximum Modulus" (MM), at the local maximum of the absolute value of the transform for a specific level of detail, within a defined time interval$(\varepsilon, \Delta t + \varepsilon)$.

$$MM = Max|WT(j,k)|_{t=\varepsilon}^{t=\Delta t+\varepsilon} \tag{17}$$

Where $WT\ (j,k)$ is the wavelet transform of the signal $f(t)$ on the scale "j".

The location of the MM in a time interval corresponds to the instant of occurrence of the maximum value of the transform in this period and its polarity is related to the direction of abrupt change of the signal. The advantages of working with this definition are, on the one hand, the significant reduction of the amount of information extracted from the signal, since it is reduced to the identification of singularities with a single coefficient other than zero and, finally, it constitutes a tool for to locate more precisely the instant (time) of occurrence of the singularity [14, 15].

B. Classification of the Fault and Selection of the Phases Involved

This task seeks to obtain, as a result, the type of fault existing, as well as the phases involved in it. As previously mentioned, a neural network will be used as support in the classification, of the probabilistic type.

The scheme of the network will have four neurons corresponding to the factors $[C_A,\ C_B, C_C\ and\ C_{ground}]$, where:

$$C_\phi = C_{\phi 1} + C_{\phi 5};\ \text{with}\ \phi = A, B, C\ and\ T \tag{18}$$

And,

$$C_{\phi i} = \sum_j \left|d_j^i\right|^2 \tag{19}$$

Where they are, they correspond to the coefficients of detail, for the phase ϕ and for the level of decomposition i. It should be noted that the term $C_{\phi i}$corresponds to a kind of spectral energy for the level of detail i, contained in a window of a quarter of a cycle immediately after the detection of the event.

In summary, the factors used as input for the classification network, possess frequency information for levels of detail 1 and 5.

It should be noted that in this work the daubechies 8 (dB8) is used as the wavelet function, applied to a signal sampled at 100kHz, corresponding to 2000 samples per cycle for a system with a fundamental frequency of 50Hz, so detail 1, according to the multiresolution scheme, would contain the information found in the frequency range of [2550kHz] and level 5 [1.6 - 3.1kHz].

For a better network behaviour, the input vector is normalized, using as the base quantity, the highest value recorded for that particular vector, as follows:

$$V_c = \left[\frac{C_a}{C_{base}}, \frac{C_b}{C_{base}}, \frac{C_v}{C_{base}}, \frac{C_{ground}}{C_{base}}\right] \tag{20}$$

$$\text{Where, } C_{base} = \max\left(C_a, C_b, C_c \text{ and } C_{ground}\right) \tag{21}$$

And the output, corresponds to the classification of the lack of binary type, with the following scheme:

Output = [FT, FA, FB, FC] (22)

Where Fx, they take values of "0" or "1", depending on whether it is involved in the fault, earth, phase A, phase B or phase C, respectively.

C. Fault Location

For the location of the faults, the method of the traveling waves was used, extracting the relevant information through the WT and having as support in the identification, a neural network of the type RBFNN. There are many methods for locating faults in electrical systems and a brief classification could be as indicated in the Figure 5:

In the case of the present work, the information of the components of high frequency (traveling wave), obtained from the first level of detail of the wavelet transform (and more specifically of the MM_{d1}) will be used.

In general, the analysis of traveling waves produced by an event in the system is performed in the modal domain, since this simplifies the complexity of the coupling between phases and the effect of the earth plane on the propagation of the electromagnetic wave. The signals that are preferably used for this purpose are the voltage signals, recorded in a particular node of the system.

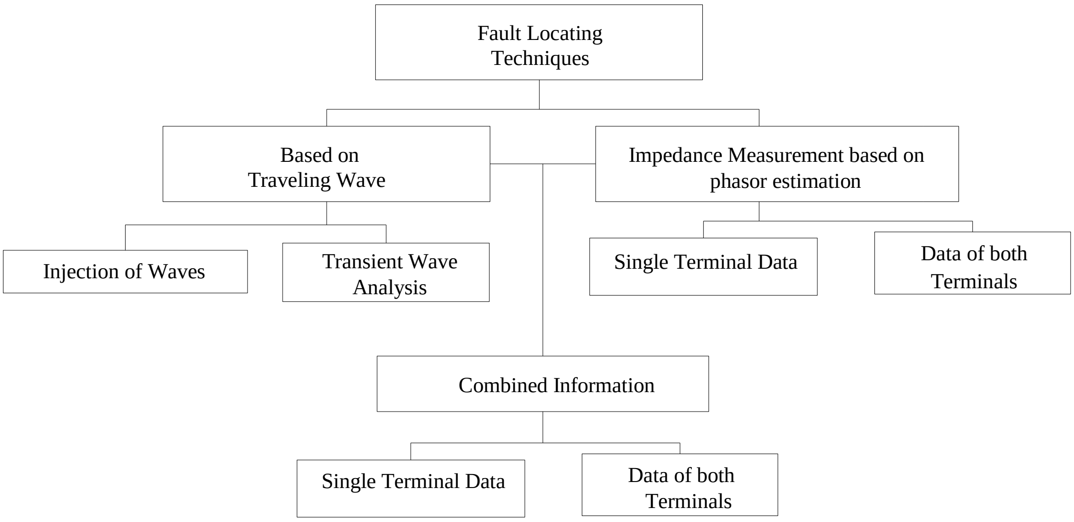

Figure 5: Classification of localization techniques

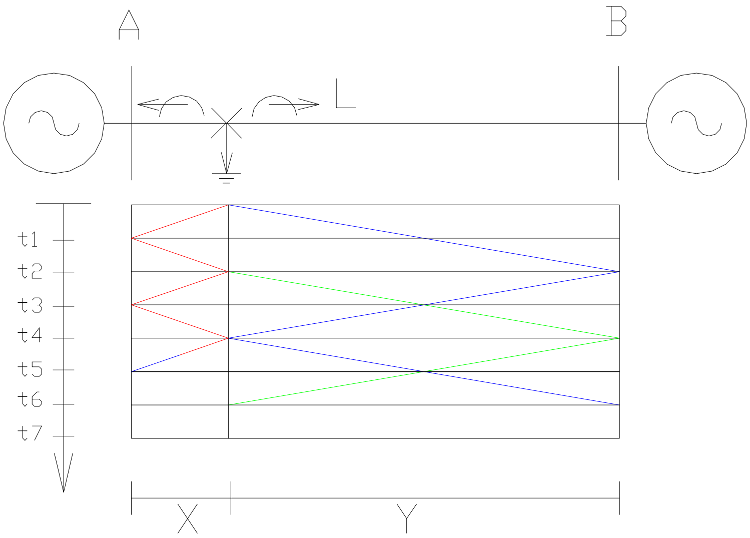

Figure 6: Lattice diagram, for the case of Fault 3φ, with $X < Y$

The scheme that shows in a simplified way the phenomenon of the traveling waves and the effect of the reflections and transmissions according to the edge conditions present, is shown in the Figure 6.

Depending on this diagram, the incident waves recorded at knots A and B can be obtained and with this information the distance to the fault can be calculated from the end 1 (measuring) (X) or from the knot B(Y), based on the following expressions:

$$X := \frac{v.(t_3 - t_1)}{2} \tag{23}$$

$$Y := \frac{v.(t_6 - t_2)}{2} \tag{24}$$

Where, v is the propagation velocity of the electromagnetic wave for the mode m, used $(\alpha, \beta\ or\ 0)$.

The accuracy of the localization under this premise depends on the accuracy in recording such time intervals. This depends significantly on the frequency of sampling and on the detection and accurate identification of the incidence of each signal.

It should be noted that the cases where $X > Y$ or $X < Y$ are different and the analysis for the identification of the waves that correspond to the trip in that interval and to distinguish them from those that can come from the reflections in the remote nodes is not trivial. In [17], the authors presented a way of solving the problem in part, through the use of cross-correlation functions.

In this particular case, a neural network will be used so that, based on a considerable number of trainings, it is able to recognize the wave pattern that occurs in the measurement node and, depending on it, establish the distance to the lack

The architecture of the selected network is as follows: seven inputs, one hidden layer of 10 neurons (quantity selected empirically, depending on the tests performed) and the output composed by a neuron corresponding to the location of the fault.

The input vector contains the position and polarity of the first seven peaks of the detected MM_{d1} for mode α (the position is represented in the number of times the sampling step).

$$VL = [P_1 \cdot X_1, P_2 \cdot X_2, P_3 \cdot X_3, P_4 \cdot X_4, P_5 \cdot X_5, P_6 \cdot X_6, P_7 \cdot X_7] \tag{25}$$

Where:

P_n is the polarity of the MM_{d1}^n and X_n is the position in time (in times of the sampling step), within the window of ¼ cycle considered.

And the output vector will be directly the location of the fault in percentage of the total length.

$$Output = [L_{fault}(\%)] \tag{26}$$

SIMULATION RESULTS

A. Simulation Parameters

The cases considered for the evaluation of the algorithm, for the particular system previously described, were the following:

1. Type of fault: The eleven types of possible faults (AG, BG, CG, ABC, BCG, CAG, AB, BC, CA, ABC and ABCG) were considered.
2. Fault impedance (resistive only - Rf): 100Ω, 300Ω, 500Ω.
3. Fault timing: 0.23 sec.
4. Fault location: 5 to 195 km.

B. Results

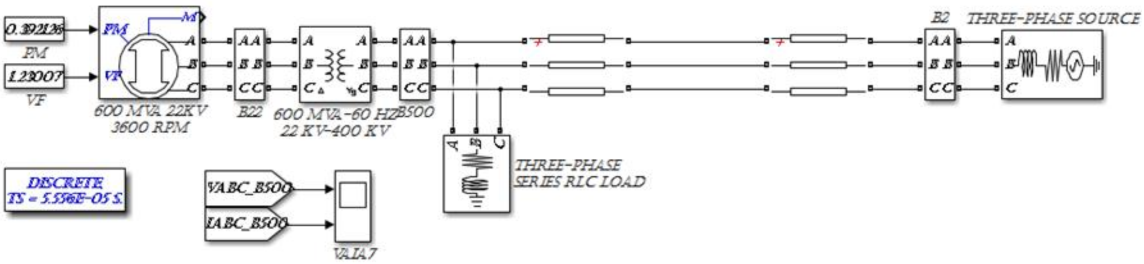

Figure 7: Simulink model without fault

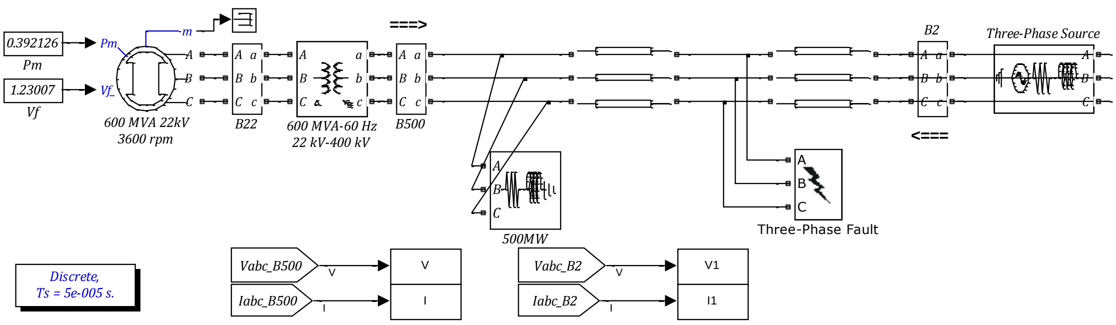

Figure 8: Simulink model considered for the evaluation of the proposed system

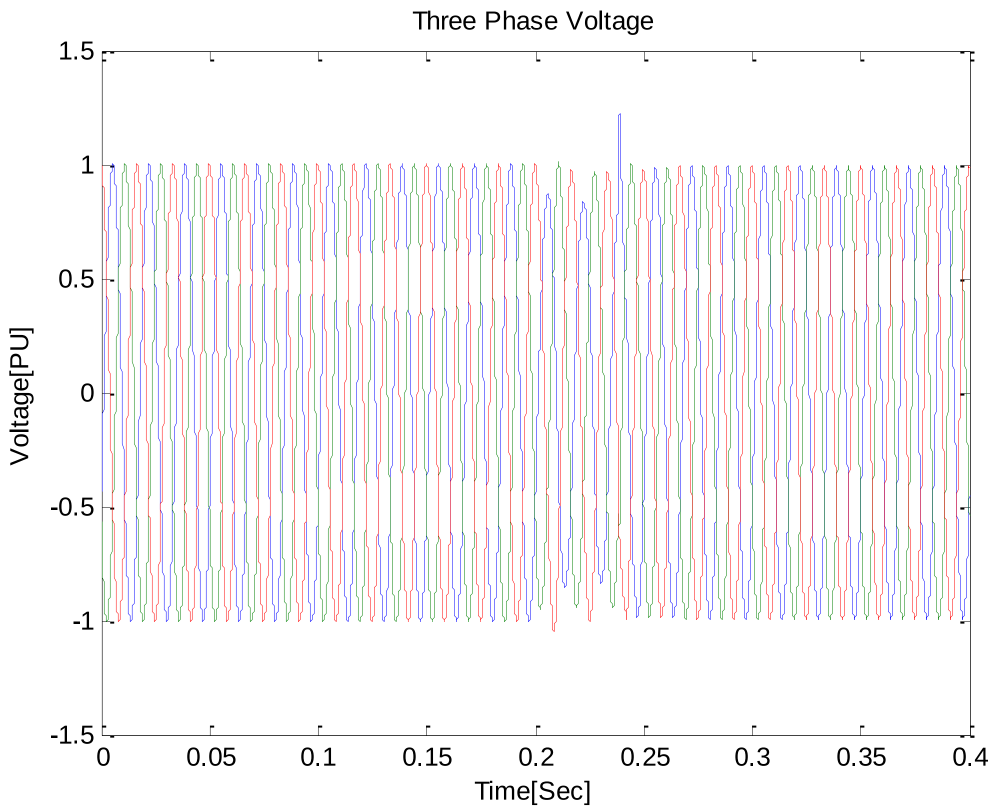

Figure 9: Voltage response of three phase circuit

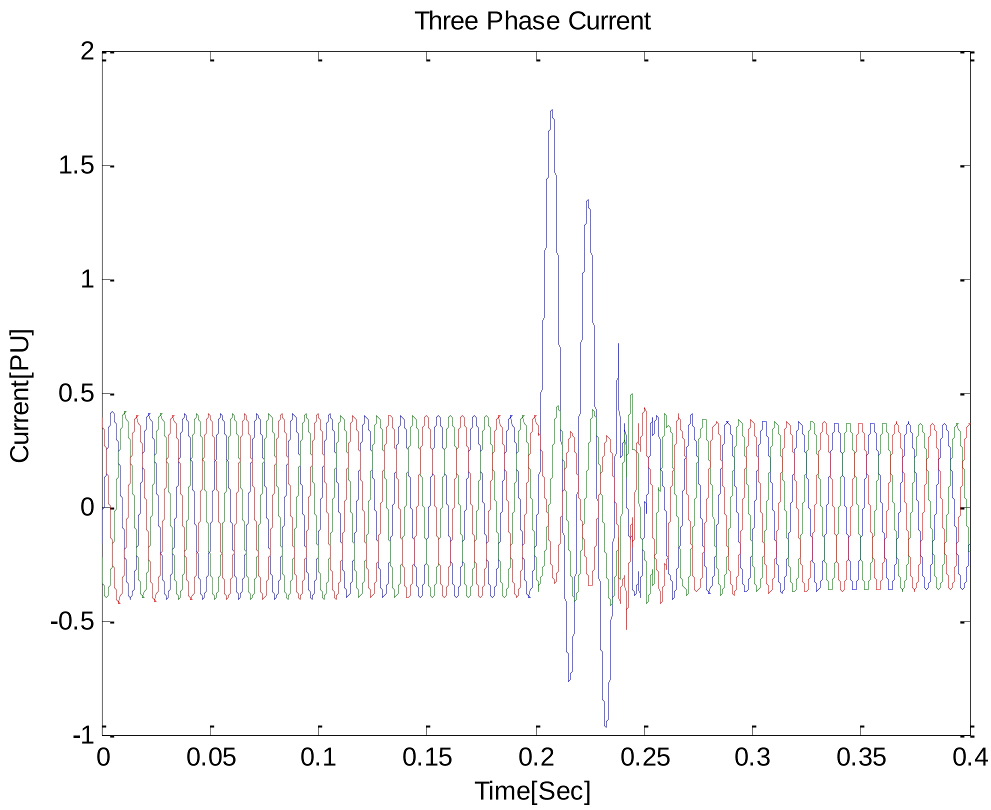

Figure 10: ABC fault in three phase circuit

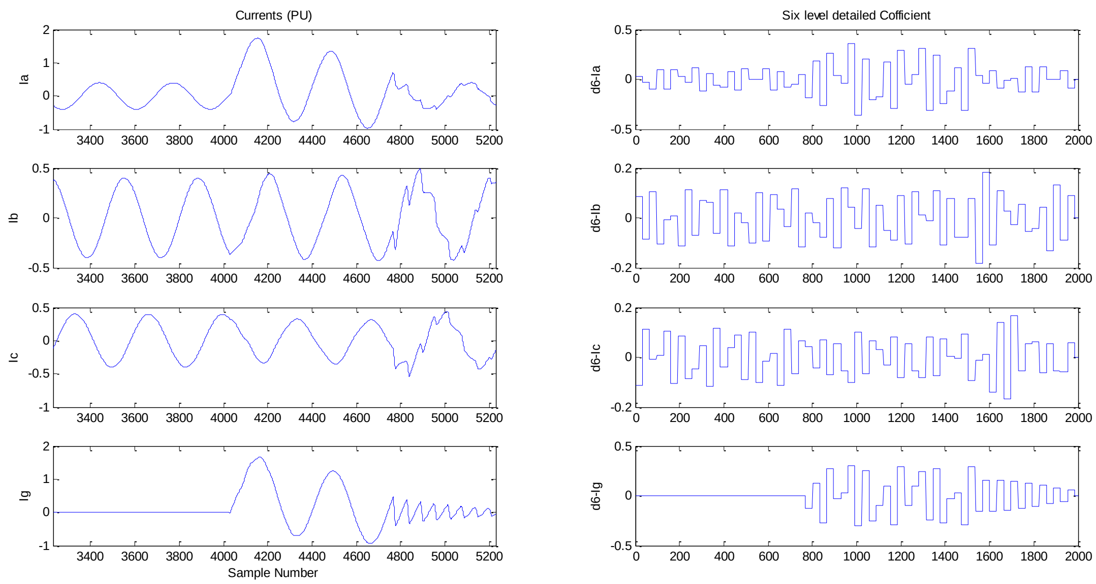

Figure 11: Detailed coefficient for various faults

CONCLUSIONS

This paper describes the application of Wavelet analysis and neural networks for the protection of energy transport lines. Based on the analysis of Wavelets theory and the simulation of line protection, the potentialities and advantages of the Wavelet multiresolution analysis and in particular the "Modulus Maxima", to obtain and analyze the transient components of voltage and current signals, highlighting in these methodologies the relative low computational effort, allowing them to be used as part of a high protection system speed.In the different tasks studied, we observed the effectiveness of each of the algorithms and criteria proposed, highlighting the case of classification and location of faults.

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