FAULT RECOGNITION ON TRANSMISSION LINES FOR AUTOMATIC RECLOSING

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Abstract - **This paper deals with the recognition of faults on three phase transmission lines in order to achieve a practical methodology to minimize overvoltage transients related to automatic reclosing. The main idea consists in defining optimum instants to close circuit breakers contacts to overcome the undesired phenomenon herein considered. The approach comprises two steps to the detection and the classification. The first is based on signal processing methods and the second on the theory of form recognition. Having in mind the search for fault detection procedures, Discrete Wavelet Transforms emerges as a powerful tool to underline amplitude and frequency discontinuities in a real-time recorded signal. The proposed method uses Daubechies 4 wavelets to carry out the detection and the duration of faults. Artificial Neural Networks and particularly a Multi-Layer Perceptron algorithm has shown to be quite effective at classifying the fault. Computational studies performances are carried out to highlight the overall approach and its efficacy.**

Keywords - **Artificial Neural Network, Discrete Wavelet Transform, Fault detection and classification, Transmission Lines, Transients.**

I. INTRODUCTION

Controlled switching has been a desirable method for stress reduction and in particular for diminishing switching overvoltages, becoming an issue of widespread interest to the utilities and manufacturers [1], [2]. Its benefit and feasibility were presented by CIGRE Task Force 13.00.1, with emphasis on mitigation of switching surges and related economical features [3], [4].

In this context, a methodology for automatic reclosing of a transmission was proposed on [5]. This work determines appropriate instants for the breaker switching based on zero crossings of the voltage signals from the line side and source-side. However, for an efficient reclosing, the algorithm needs to know which type of fault is occurring on the electrical system.

Many works concerning fault detection and classification have been carried out. They mostly use Discrete Wavelet Transforms [6] to perform the detection of fault. In this reference, Daubechies 4 wavelets are used. This family of wavelet has already demonstrated its efficiency for discontinuities detection in the previous works [7] [8].

For the classification, the use of Fuzzy-logic-based method has been given in [9] whist the Support Vector Machines (SVM) is applied in [8]. The first approach is quick and easier to implement, however, it is a little more limited in its efficiency. The SVM algorithm, in its turn, has shown to produce good results. Nevertheless, its convergence to a global minimum can only separate the input in two classes. Besides, its implementation is more difficult. A good compromise between the mentioned strategies is the use of Artificial Neural Networks (ANN). This is relatively efficient and rapid. Moreover, it is well adapted for discrete recorded signals. Reference [7] proposes a method to take into account the effect on lines in the vicinity when a fault occurs. This reference also gives the characteristics of an ANN, which was used to classify faults on transmission lines.

Within the above context, the goal of this work is to create a system able to detect and classify a line's fault in real-time. This is part of an experimental setup arrangement to be built using the Digital Signal Processor (DSP) TMS320F28335 from Texas Instrument to be connected to a Real Time Digital Simulator (RTDS). Using such arrangement, computational studies are to be carried out to validate the controlled switching methodology to minimize the disturbances related to the undesirable overvoltage transients.

II. FAULT RECOGNITION METHODOLOGY

Figure 1 describes the methodology used to recognize a fault on transmission lines. Basically, the algorithm is composed by two stages:

- Detection: using measured currents, this step is focused on verifying the existence of an eventual fault on the monitored electrical system. At this stage, the Discrete Wavelet Transform (DWT) is used to detect signals discontinuities associated to the recorded signals;
- Identification: once the transmission line short-circuit is detected, an Artificial Neural Network (ANN) is used to determine the type of the fault. This is based on measured voltages and currents.
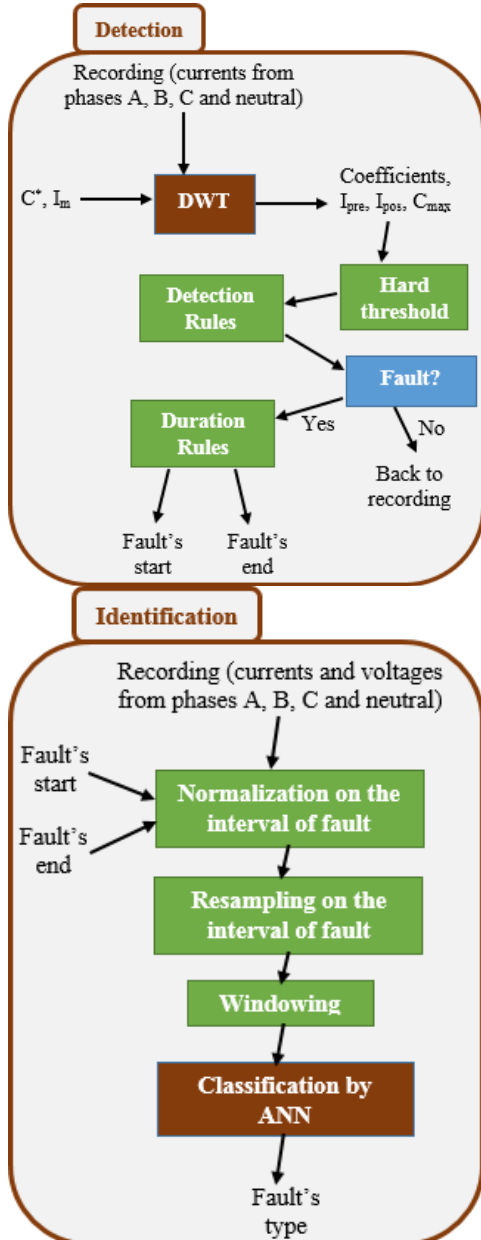

Fig. 1. Proposed algorithm main steps

A. Fault Detection

Using TWD, this section describes the methodology used to detect the existence of a short-circuit on a transmission line.

1) Discrete Wavelet Transform

As presented on Figure 2, the fault detection divides the measured voltages and currents in distinct regions:
- Pre-fault: within this period, the electrical system is operating with normal voltages and currents;
- Fault: following, in accordance with the fault that has occurred, the transmission line is submitted to abnormal voltages and currents;
- Post-fault: once the circuit breaker is opened, the new voltages and currents will occur.
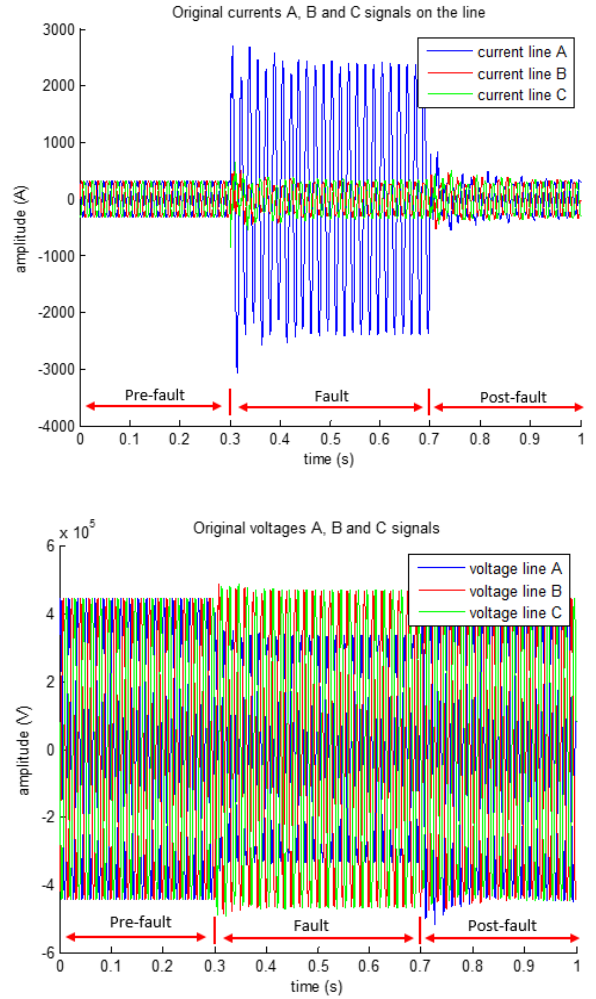

Fig. 2. Typical currents and voltages before, during and after the fault elimination

To verify the existence of a fault, the measured signals have to be scanned by time-frequency analysis tools, allowing the real-time detection of discontinuities on amplitude and/or frequency. That is the case for the Short Time Fourier Transform (STFT), the Pseudo-Wigner-Ville Transform (PWVT) or the Wavelets Transforms. Having in mind that the STFT is more adapted for long analysis and the PWVT is better in term of energy analysis, the advantages of wavelets are quick response, efficiency for discontinuities detection and the capacity of scanning discrete signals.

In this context, the Discrete Wavelet Transform is used in this paper to obtain the coefficients that indicate the presence of the fault. Moreover, DWT was already tested for fault

detection [6-8] and particularly, Daubechies 4 wavelets (D4), is well adapted for abrupt changes in signals' behaviors.

According to [6], the D4 coefficients for DWT are:

$$h_0 = \frac{1+\sqrt{3}}{4} = g_3 \qquad (1)$$

$$h_1 = \frac{3+\sqrt{3}}{4} = -g_2 \qquad (2)$$

$$h_2 = \frac{3-\sqrt{3}}{4} = g_1 \qquad (3)$$

$$h_3 = \frac{1-\sqrt{3}}{4} = -g_0 \qquad (4)$$

Where:
- h_i - Coefficients of D4 mother wavelet (i=0 to 3).
- g_i - Coefficients of a D4 child wavelet (i=0 to 3).

Knowing these coefficients, the DWT allows the calculation of the wavelet coefficients c_i of the input signals, as given by (5).

$$c_i = \sum_{k=0}^{3} g_k \times s(2i+k) \qquad (5)$$

Where:
- i - Index of a coefficient wavelet value.
- s - Signal on which the D4-DWT is to be applied.

It should be highlighted that the signals' discontinuities during a fault are more visible if currents' wavelet coefficients are used instead the voltages ones. Following the methodology presented in [7], the currents coefficients c_i are used to detect the existence of a fault on the transmission line, using the following parameters:

- C_{max}: absolute maximum of the calculated wavelet coefficients c_i.
- I_{pre} and I_{pos}: respectively, the pick values of the currents in the first and the last recorded cycle.

The length of the wavelet coefficients array is equal to the integer directly inferior to $\frac{N-3}{2}$ and the values are given by the equation (5).

This algorithm allows the detection and the temporal localization of an eventual discontinuity in a signal, herein represented by the short-circuit faults. Once the fault is detected, the beginning and the end can be deduced by following duration rules.

2) Hard threshold

The hard threshold step consists in defining a threshold and setting all the values below to zero. This method is applied on the wavelet coefficients arrays in order to stress the highest values, which indexes correspond to the positions of discontinuities. For the focused application, the method still follows reference [7], taking a threshold, which depends on C_{max}, as define in (6).

$$c_i \geq 0.1 \times C_{max} \Rightarrow c_i = c_i$$
$$c_i < 0.1 \times C_{max} \Rightarrow c_i = 0 \qquad (6)$$

This step improves the accuracy and the rightness of the detection and the temporal localization of an eventual fault.

3) Detection rules

To cope with this, it was necessary to establish detection rules to eliminate the cases of unlinked faults discontinuities. This stage is described in [7], which defines four conditions:

1. If $C_{max} < C^*$, there is no fault.
2. If $C_{max} \geq C^*$, $I_{pre} < 0.2 \times I_{pos}$ and $I_{pos} > I_m$, there is no fault
3. If $C_{max} \geq C^*$ and $|I_{pre} - I_{pos}| < 0.1 \times \max(I_{pre}, I_{pos})$, there is no fault
4. For all other cases, a fault is detected

These rules are applied with all the recorded phases' currents. If a particular phase corresponds to the fourth rule, a fault is detected and the determination of its duration can begin. Otherwise, the algorithm leads to the recording phase.

4) Duration rules

When a fault is detected, it is possible to determine its start and its end by using the currents' wavelet coefficients. Indeed, the fault's start and end are located at the discontinuities in the recorded signals. As multiple phases can be involved in the fault, some duration rules [7] help to choose moments for the fault's start and end, as described in the following points:

1. Identify the index of the first non-null wavelet coefficient for the currents of every phases and of the neutral.
2. The index of the fault's start is defined as the highest index of those determined in the point 1.
3. Identify the index of the last non-null wavelet coefficient for the currents of every phases.
4. The index of the fault's end is defined as the highest index of those determined in the point 3.
5. Identify the index of the last non-null wavelet coefficient for the neutral current.
6. If the index found in the point 4 is highest than the point 5's one, the index of the fault's end is the one determined at point 5.
7. The indexes of the fault's start and end must be doubled to correspond to the indexes of the recorded signals.

Because there is a possibility of non-detection of the fault's end risk, it is necessary to take a minimal interval of fault of 500 values from the fault's start. If the end is not found, it is set at the end of the record. This procedure allows the process of the fault identification.

Then, for the algorithm is to be implemented in the DSP, a maximal number of values in the interval of fault is arbitrary fixed to 5000. If the fault's end is too far, the interval of fault is reduced to the first 5000 values from the fault's start.

B. Fault Identification

Once the interval of fault is found, the identification stage can be started. Several steps are necessary to organize the measured data for the ANN to classify the fault. This is described in the sequence.

1) Normalization
During the interval of fault, the absolute maximum values for currents and voltages are determined and used to normalize the measured data. This step is important because the signals have to follow a certain pattern so as to avoid possible disturbances to the classifier.

2) Resampling
In general, voltages and currents are measured with different sample frequencies, depending on the equipment used for monitoring. In this context, the algorithm resamples the measured data with a minimal frequency of recording is 1200Hz. This step is necessary to create a pattern for the discrete values used by the ANN.

3) Windowing
To prepare the input of the classifier, it is necessary to choose samples from each recorded signal. According to [7], the five first samples of each signal from the fault's start are recorded in a vector, which will be the input of the classifier. A 40-lengthed vector is created as follows: first, it has the samples from the currents (phases A, B, C and neutral in this order) and then, the samples from the tensions (same order as the currents).

4) Classification by ANN
Considering the recognition theories, various algorithms are possible to build an Artificial Neural Network. This paper uses a Multi-Layer Perceptron (MLP), which is a particular ANN.

The output values are rounded to reach 0 (false) or 1 (true). A false value indicates the phase has not been recognized as involved in the fault. The true value indicates the contrary, as described on Table I.

Table I - Correspondence between outputs and fault types

Fault's type		Output 1	Output 2	Output 3	Output 4
Phase-to-earth	AT	1	0	0	1
	BT	0	1	0	1
	CT	0	0	1	1
Biphasic	AB	1	1	0	0
	AC	1	0	1	0
	BC	0	1	1	0
Phase-to-phase-to-earth	ABT	1	1	0	1
	ACT	1	0	1	1
	BCT	0	1	1	1
Triphasic	ABC	1	1	1	0
	ABCT	1	1	1	1
Unrecognized type		Other output			

If the output values do not correspond to one of the 11 fault possibilities, the algorithm returns an unrecognized type of fault. This last response denotes the fault identification did not succeed, but, at least, the algorithm detected a fault and localized it temporally.

Such ANN needs a training, which can take a lot of time until it converge. The learning algorithm is to be given in section III.

III. COMPUTATIONAL MODELLING

This section details the experiment and the created system to perform the recognition of faults on transmission lines. As already stated, this algorithm is intended to be implemented in the DSP TMS320F28335 and tested with a Real Time Digital Simulator (RTDS). However, before the hardware development, some computational tests were carried out with Matlab and with a C program. This is explained as follows.

1) Discrete Wavelet Transform
At first, the chosen Discrete Wavelet Transform has been implemented with Matlab in order to simplify the comprehension of the results by curves representations. The algorithm allowed the detection of discontinuities in signals. Because, it has to be integrated to a DSP, the method was also implemented in C. In the C program, signals are read and studied separately because of memory constraints.

2) ANN

The Artificial Neural Network was also created in Matlab and in C. The algorithm is composed of nodes. Each node, except the inputs, owns an activation function, which expression depends on attributed weights and bias and on the values of the previous step of nodes.

A representation of the MLP is given in Figure 3, with N=40, M=30 and L=4 in this experiment. In this work, 40 nodes in input compose the proposed ANN, corresponding to the 40 values of the created input vector. Then, 30 hidden nodes represent the first step of the classification. Finally, the chosen ANN owns 4 output nodes whose values varies between 0 and 1.
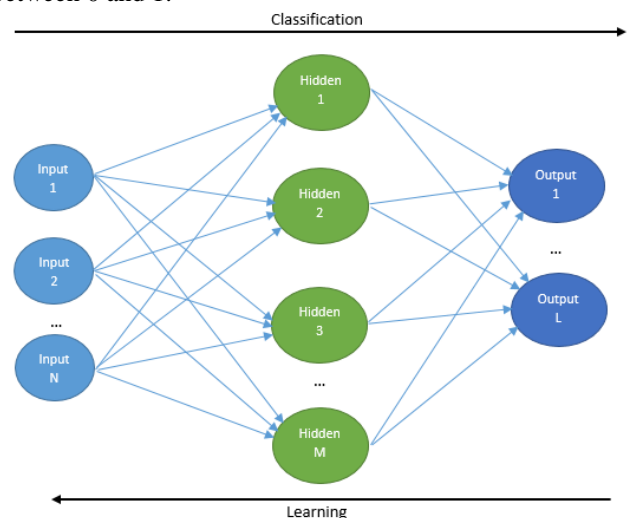

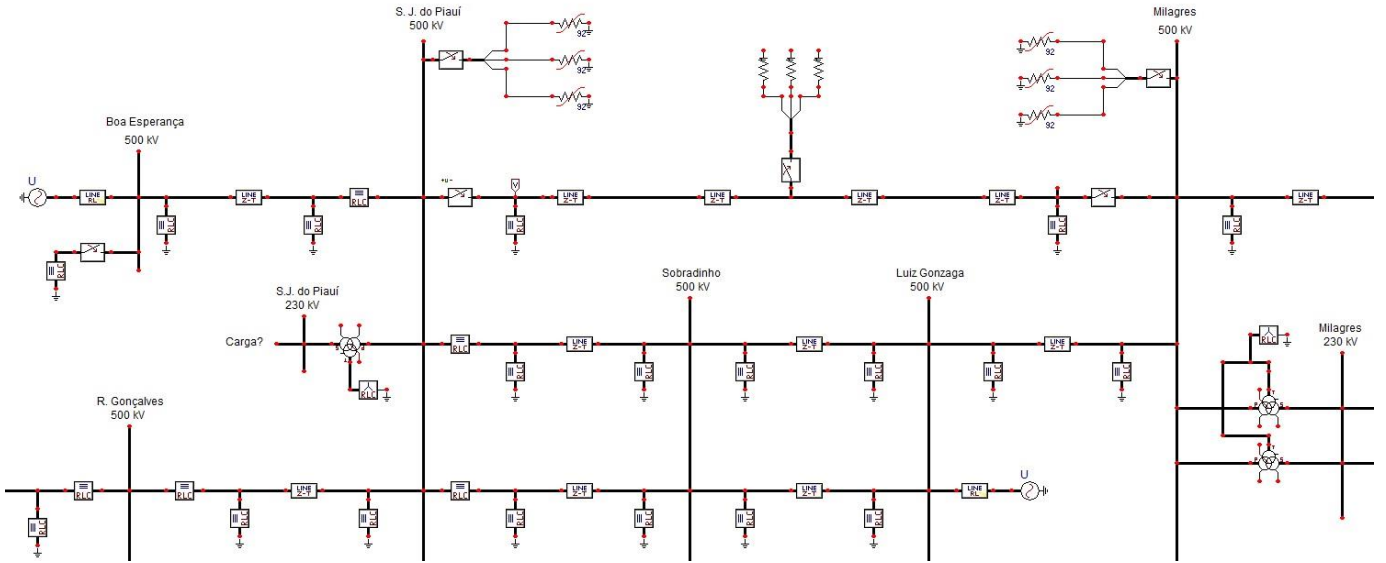Fig. 3. Principle and representation of a Multi-Layer Perceptron

Fig. 4. Simulated electrical system

With each hidden and output node, weights are attributed to the values of the previous step of nodes and to the biases associated to the concerned node. The returned values are the sums of these calculated coefficients. At the beginning, biases and weights are arbitrary defined to -1. Then, the learning algorithm is going to change these values to improve the performances of the classifier.

3) Learning algorithm for the ANN

The C program is to be integrated to the final module used on the DSP TMS320F28335. Thus, the learning algorithm was only carried out with Matlab. This provides easy ways to train the algorithm.

To the ANN learning procedure, it is necessary to know the fault's type before the classification. In this way, the learning algorithm can use the difference between the reality or the desired output and the calculated output. According to the method of back-propagation, which is owned by every MLP, this difference is transmitted to the hidden nodes. Then, the weights are recalculated to correspond to the demanded output, with the given input.

The algorithm needs a learning coefficient, which in this experiment was arbitrary set to 0.7. Moreover, a number of iterations is set to 1500 to allow the learning algorithm to converge. Simulations with various fault's types have been carried out to train the algorithm. The following methodology has been used:

- Manually simulations: initially, the program has been tested with manually simulations created on Matlab. The goal was to test independently every part of the algorithm.
- Using voltages and currents from ATP (Alternative Transient Program) software, a phase-to-earth fault on a transmission system has been simulated. Using the simulated voltages and currents, the DWT and the ANN programs in Matlab and in C were tested. This

has helped the learning algorithm to determine more appropriated weights.

Until this moment, approximately 20 learning simulations were made. Now, the C program is able to recognize a phase A to earth T fault with signals similar to the ATP-simulated ones. The other phase-to-earth faults are not all recognized because of the few number of training sections.

IV. CASE STUDY

This section presents the results of a case study using the electrical system identified in Figure 4. A phase-to-earth fault, involving the phase A is simulated on the transmission line between two busbars. The fault duration is 0.4 s, starting at 0.3s and ending at 0.7s.

Figure 5 shows the ATP-simulated voltages and currents signals, with a phase-to-earth fault. As shown in Figure 6, the D4-DWT allows the detection of the fault's start and its end.
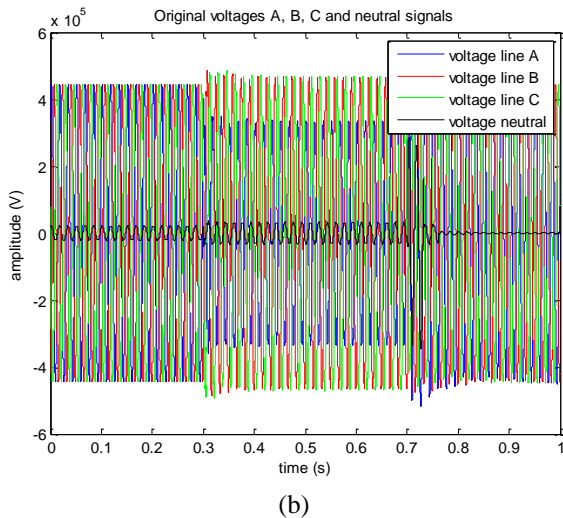

(a)

(b)
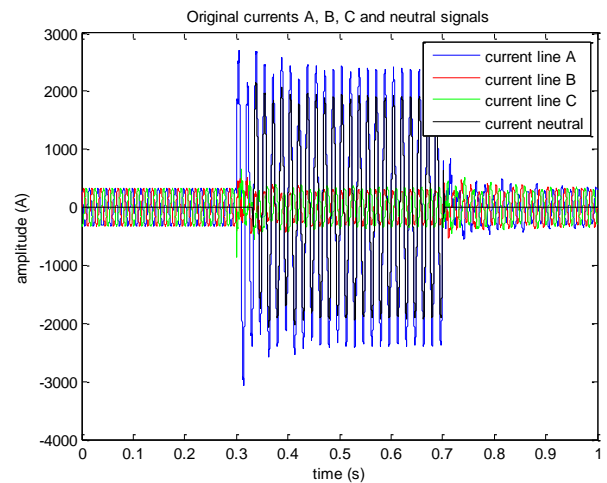
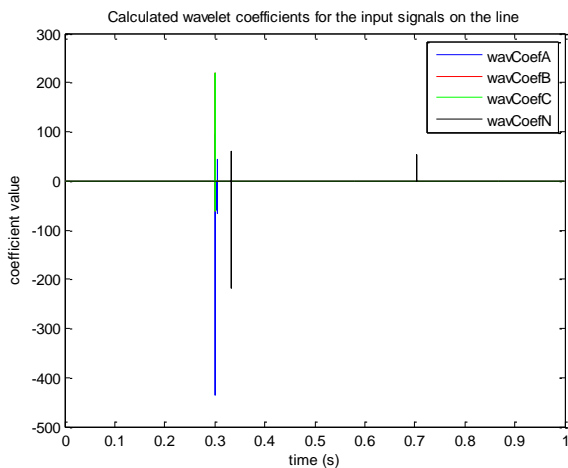Fig. 5. ATP-simulated currents (a) and voltages (b) related to a phase-to-earth fault.

Fig. 6. Wavelet coefficients of the line's currents with phase-to-earth fault AT simulated with ATP.

Concerning the ANN, the authors recognize that the learning algorithm still needs more simulations to converge to reliable weight values. With the previous ATP simulation, results are encouraging because some faults are already well classed, whereas the training involved just few simulations.

V. CONCLUSIONS

The recognition of a fault on transmission lines is important in the context of automatic reclosing. Depending on the fault's type, a particular algorithm is chosen to reclose

the transmission as soon as possible, avoiding subsequent material damages [5].

Multiple tests must be carried out with a RTDS with the DSP implemented. These steps allow the verification and the validation of this part of the automatic reclosing system.

At this moment, the method containing D4-DWT and ANN has shown to be quite promising. The initial results have demonstrated a good agreement with the expected performance.

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