**Proceedings of the Ninth IASTED European Conference**
**Power and Energy Systems (EuroPES 2009)**
**September 7 - 9, 2009 Palma de Mallorca, Spain**

# METHODOLOGY OF FAULT LOCATION FOR PREDICTIVE MAINTENANCE ON TRANSMISSION LINE

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**ABSTRACT**
This article presents a new methodology which monitors, on-line, the insulation condition of a transmission line and verifies anomalies in the operation before the power transmission has been interrupted, providing, this way, a predictive maintenance in transmission lines. This methodology uses harmonic decomposition of the leakage current for analyzing the insulation condition of the line and employs an artificial neural network for defect location. Experimental measurements were done to validate the simulated results.

**KEYWORDS**
Artificial Intelligence Applications in Energy and Power Sys;Fault Diagnosis;Power Transmission.

## 1. Introduction

Electric energy is one of the most important resources for economic development of a country, as well as, promoting satisfaction and welfare for society. Therefore Electric Power Systems (EPS) should guarantee a high level of reliability and maintenance of electric power delivery. However, due to the increase complexity of EPS, because of the constant necessity of energy and new links of the existent systems, interruptions in energy systems are more frequent.

This new and challenging scenery has demanded substantial improvement of the equipment for fault location, control and protection to guarantee reliability and economic operation of EPS in normal conditions or contingency. According to [1] the contingency situations are mostly of two kinds: fault or failure. Fault is an unpredicted deviation of at least one characteristic property or parameter of the system from acceptable, usual or standard condition, on the other hand, a failure is a permanent interruption of a system's ability to perform a required function under specified operation conditions.

Faults can occur in different parts of a EPS, but usually the most susceptible element is the Transmission Line (TL), it is caused especially because of its dimensions, functional complexity and exposure to the outside environment, these characteristics difficult the maintenance and monitoring. Faults can be caused by the occurrence of different types of phenomena, such as the end of lifetime of the equipment, environmental effects involving pollution problems, humidity or overheat, short-circuit in chain insulators, and also possible accidents like mechanical shock in towers or equipment, affecting many kinds of customers.

A precise fault location in transmission lines is very important because it can provide a faster maintenance and a short time of re-establishment of the system [2], [3].

This paper proposes a method for fault location on TL using the harmonic decomposition of the leakage current, its main tools are the mathematical model and the Artificial Neural Network (ANN). Real voltage and current data are acquired by analyzers installed in the two substations (SS). The methodology presented here is a registered international patent by number 0000220600491835 on April 19, 2006.

## 2. Methods for Fault Location of Transmission Lines Using Neural Networks

Fault Location on Transmission Lines has been largely discussed in the literature for years. Many of these articles consider only permanent faults, that unable a predictive maintenance.

Many different methodologies for fault location have been proposed by different authors, the two most common approaches are based on: i) the computation of the impedance by phasorial data of voltage and currents measured in one, two or three endings of the line; ii) the traveling wave method.

New concepts such as ANN and Wavelet Transformer (WT) had been employed successfully in fault location in TL [4]-[9].

The fault location methods that use ANN usually need the three phases of voltage and current data. The most used ANN in this kind of problem is the multilayer perceptron (with feed forward and backpropagation techniques for training). The ANN is fed by the data generated (simulated) by the Alternative Transients Program (ATP) software.

There are many articles that present not only methods for fault location [4], [5], [6], [7], [8] but also methods of fault detection and classification [4], [10].

Purushothama et al [6] presented two approaches using modified ANN to determine the fault location and the resistance of the fault. Protection relays were used to indicate the faulted line and the type of fault. The first approach uses only one terminal data and Eriksson's et al equation [11]. The input data are values of the three phases of voltage and current in situations of pre-fault and post-fault. Seven ANN were developed. The first one determines the type of fault, and the other six were made to locate the fault. The second approach uses voltage data of two ends of the TL. This approach is independent of current data or of resistance of the fault.

Purushothama et al also presented two distinct topologies of ANN, one is the multilayer perceptron, and the other one is Fahlaman's technique [12], i.e. cascade correlation technique.

Góes, Rodrigues and Da Silva [7] showed a new approach for fault location in three ends of TL using ANN. The ANN developed is to identify the fault leg using current data from only one terminal and the voltage data from three terminals of the TL. The three terminals data here are necessarily synchronized. The ANN used is a multilayer perceptron with 16 neurons in the input layer, 8 neurons in the hidden layer, and 3 in the output layer, 16-8-3. The simulation data were generated by ATP software. This method presented over 86% of correct identifications, however, the method is restrict because it shows only the fault leg for a phase/ground fault.

Ramos, Vellasco and Pacheco [8] presented a technique of a fault identification and location in TLs using ANNs and only one terminal data. In this article, five ANNs were developed. One of them was made only to classify the fault, the other four ANNs were made to locate the fault. The authors compare the results obtained with this technique against the well known Takagi method [13]. In this comparison the presented technique had some advantages, such as the locate precision, and the absolute error was less than 2%.

Most of the articles that use ANN for fault location do not use real data, all of them use the ATP software to generate the data set.

This article uses real data for the simulation and for the ANN design.

## 3. The Transmission Line Chosen

To develop a fault location methodology it is essential to monitor a TL. The monitoring must provide information such as voltage and current. These data are the input of the model.

The chosen transmission line was GUAMÁ – UTINGA – MIRAMAR that belongs to the Transmission System Tucuruí 230 kV (TUC 86 – 3003R – 5), as it is shown in Fig. 1. Only the stretch between the SS Guamá and SS Utinga belonging to Centrais Elétricas do Norte do Brasil – ELETRONORTE (Pará – Brazil) was monitored.

The constructive data of the TL Guamá – Utinga such as the tower structures, number of spans, porch and partial and total distances were provided by ELETRONORTE. There are 50 towers between the SS Guamá and Utinga, the average distance is 374.36m and the total distance is 19,049.68m. Two Power Sentinel 1133A analyzers were installed in each one of the substations, as shows Fig. 2. These analyzers are synchronized and are capable to provide voltage, current and power data up to the fiftieth harmonic, with 0,025% of precision. The data were stored and manipulated in a file to be used as input in the mathematical model.

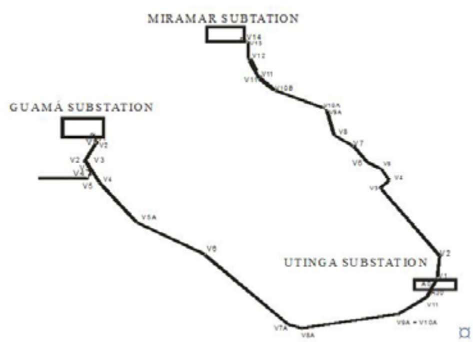
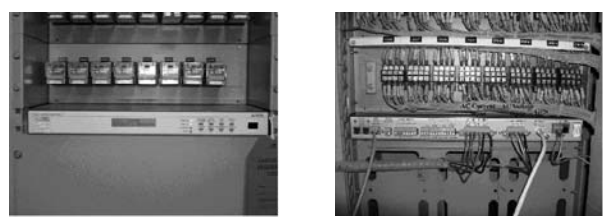



Fig. 1. Transmission line Guamá-Utinga-Miramar (ELETRONORTE).



(a) (b)

Fig. 2. Analyzer Power Sentinel 1133A installed in the substations Guamá and Utinga; (a) Front panel; (b) Back panel.

## 4. Mathematical Model and Simulation

### 4.1 The Chosen Model

Thinking in a simple mathematical model that could well represent the behavior of a real transmission line, the authors chooses the Π distributed model that is satisfactory for short and untransposed TL such as Guamá-Utinga. This model considered several sections in series, in agreement to [14].

The simulation of the mathematical model was done by the program Simulink of MATLAB. Equation (1) can be found directly from Kirchoff's law for voltage.

$$\mathbf{V}(x,t) - \mathbf{V}(x+\Delta x,t) = \mathrm{R}'\Delta x\mathbf{I}(x,t) + \mathrm{L}'\Delta x\frac{\partial \mathbf{I}(x,t)}{\partial t} \quad (1)$$

The TL simulation is representative. It can be applied at any TL, therefore the simulation was done with only 10 towers, as it can be seen in Fig. 3.

The input parameters of simulations are: vectors with voltage and current data from the fundamental to $50^{th}$ harmonic obtained from local terminal; capacitance (C = 0.1634 nF); resistance (R = 1.0955Ω) and inductance (L = 31.88 mH) of the line, obtained in [15]. The output parameters are: computed vectors with voltage and current data from the fundamental to $49^{th}$ harmonic for remote terminal and the harmonic decomposition of the leakage current. The box Powergui is an internal routine of Simulink that provides perceptual harmonic decomposition using Fast Fourier Transformer. Fig. 4 describes a block diagram of Simulink of (1) representing one tower of the block diagram of Fig. 3.

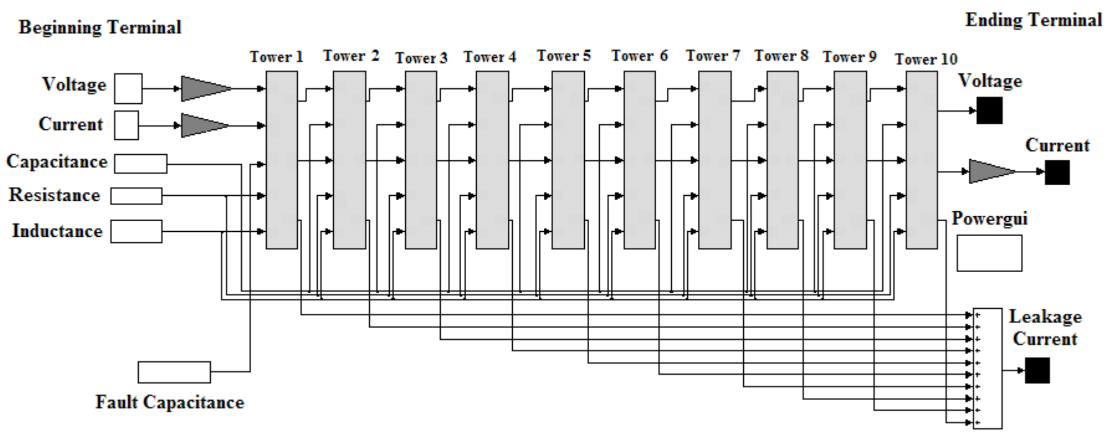



Fig. 3. Block diagram of the mathematical model.

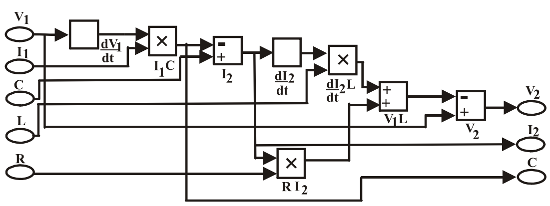


Fig. 4. $\pi$ model for each tower.

### 4.2 Determination of Leakage Current

The insulation conditions determine the state operation of the TL. As the insulation depends on the resistance and the dielectric strength of a TL, it was chosen, as variable of the model, the leakage current of the TL. The model validation was done by comparing the measured leakage current and the leakage current obtained by simulation.

To determinate the leakage current, it was used the Gauss' Law which enunciates that the flux of the electric field through a closed surface is equal to $1/\varepsilon_0$ times the net charge enclosed by the surface, [16], that was used to validate the model. Equating:

$$\oint_S \mathbf{E}.dS = \sum_{i=1}^{n} \frac{q_i}{\varepsilon_0} \quad (2)$$

where:

$\mathbf{E}$ → is the electric field;

$S$ → the surface;

$q_i$ → the electric charge.

In its differential form, (2) is also known as $1^{st}$ Maxwell's Equation.

$$\nabla.\mathbf{E} = \frac{\rho}{\varepsilon_0} \quad (3)$$

Where ρ is the volume charge density.

The theory of gaussian surfaces for closed surfaces assures that the algebraic sum of the currents that enter and go out of a closed surface is equal to zero (Fig. 5). Following this, the leakage current for the stretch of the TL is calculated by (4):

$$I_{Leakage} = I_{Guama\ SS} - I_{Utinga\ SS} \quad (4)$$

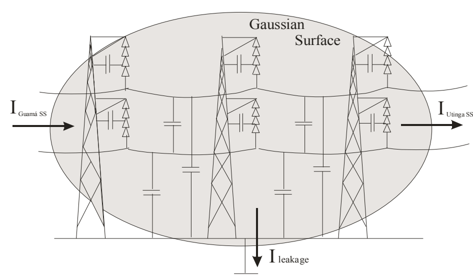
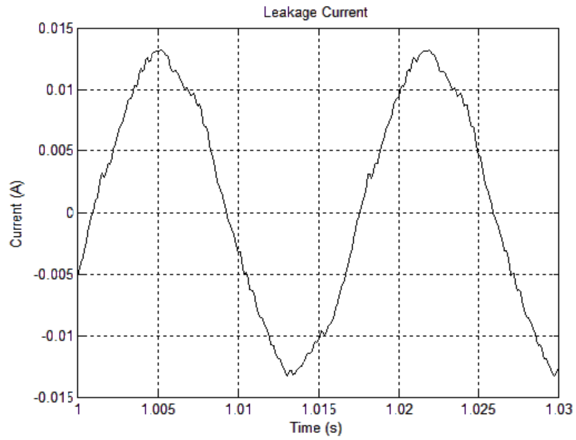



Fig. 5. Gaussian closed surface for the stretch of a TL.

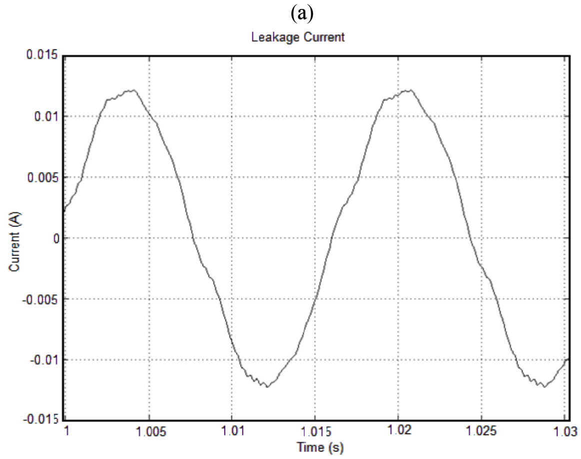
Gauss Law was used because of the complexity of the structures, since it is extremely hardworking considering all the existent nodes in a transmission line. It might exist leakage current in any of the nodes in a TL.

## 5. Validation of the Model

Observing Fig. 6 (a) and (b), we can compare the measured leakage current (experimental) and the simulated leakage current (theoretical), both shown at only one phase. It can be seen that the two wave forms are similar and that they have almost the same peak value. This comparison validates the model.




(a)




(b)

Fig. 6. Comparison between the measured and simulated leakage currents; (a) Measured leakage current; (b) Simulated leakage current.

## 6. Methodology and Simulation Results

A fault due to cable problems or insulation problems causes changes in the capacitance value [17]. Therefore, faults were simulated by changing the capacitance value in a determined tower while the others remain with the same value (unchanged). A fault condition was introduced by the 'fault capacitance' block, see Fig. 3. Faults were simulated in every tower using the capacitance values: $C_0 = 1.6345 \times 10^{-10}F$ (Normal condition of operation); $C_1 = 2.7488 \times 10^{-10}F$; $C_1 = 4.6230 \times 10^{-10}F$; $C_3 = 7.7749 \times 10^{-10}F$; $C_4 = 13.0757 \times 10^{-10}F$; $C_0$ is the capacitance value for the normal condition of operation. This value was obtained using the Finite Element Method in [18], other values were obtained through a logarithmical space between $C_0$ and eight times this value. It was done to create a good set of pattern to infeed the ANN.

The simulation provided 41 data sets, including one of normal condition operation and 10 of each fault condition simulated. The harmonic decomposition is stored as percents of the fundamental wave, thus it was considered only 48 values of each harmonic decomposition. The input and output data were used to feed the ANN.

Fig. 7, 8, 9 show the harmonic spectrums of the leakage current for a fault in the beginning, in the middle and in the end of the TL generated using the capacitance $C_3$.

It can be concluded that the harmonic decomposition of a fault in the beginning of the TL is different from a fault in the end.

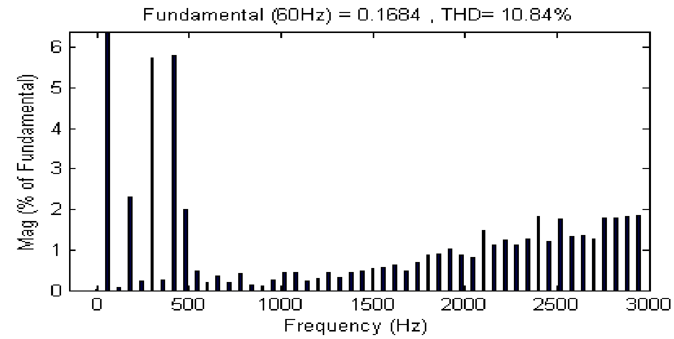



Fig. 7. Harmonic spectrum of the leakage current for a fault in the 1st tower and capacitance $C_3$.

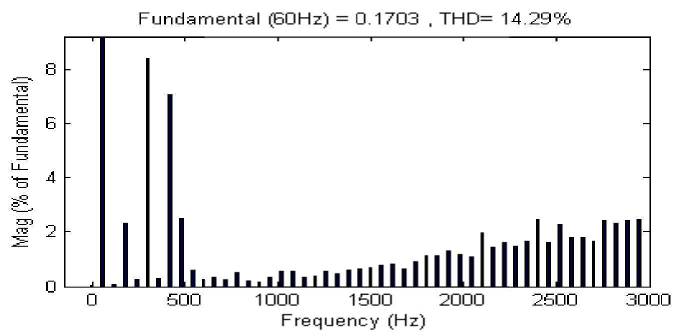



Fig. 8. Harmonic spectrum of the leakage current for a fault in the 5th tower and capacitance $C_3$.

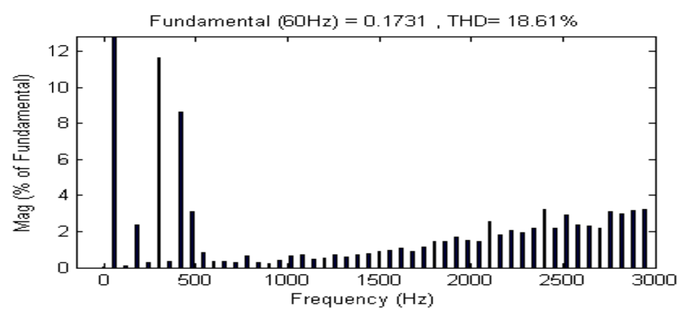



Fig. 9. Harmonic spectrum of the leakage current for a fault in the 10th tower and capacitance $C_3$

## 7. The Artificial Neural Network Developed

An ANN was developed and programmed to provide the fault location and the value of capacitance that generates that fault, using just the harmonic decomposition of the leakage current. Thus it can be known a priori if the TL requires immediate maintenance or if it can be programmed.

The inputs of ANN are harmonic decompositions of leakage current obtained from simulation. The simulation provides 41 data sets organized and joined in one file by a small routine. Each line of this file corresponds to one harmonic decomposition. The first one is the harmonic decomposition of the normal condition of operation, the other forty are fault condition. Thus the input parameter is a $48 \times 41$ matrix. This matrix was dimensioned to an

$8 \times 246$ matrix. The output values are the fault location and capacitance, these two parameters are together in an output $2 \times 41$ matrix. Fig. 10 shows an organization chart that describes the procedure done since the measure of electric parameters until the computation of the fault location and the capacitance value.

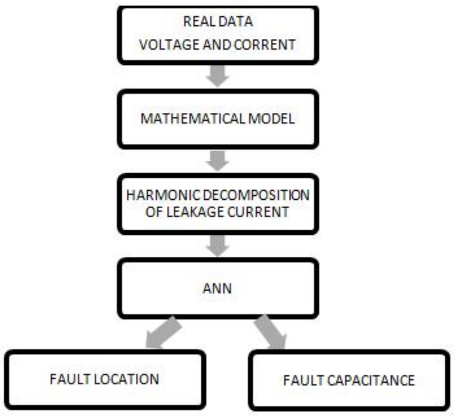



Fig. 10. Organization chart of the methodology.

At first, the ANN was made with only one hidden layer, but the training time was too long and the results were unsatisfactory. A good architecture found (considering the number of neurons) was 8-16-12-2 (it was necessary here, two hidden layers). The ANN uses, as transfer function, logsigmoid (logsig – MATLAB) in the first three layers and the linear function (purelin – MATLAB) on the last one. Other architectures were tested, some of them presented better results for faults in the beginning of the TL, others, on the other hand, presented better results in the end or in the middle of the TL. In all cases, backpropagation with resilient training, [19], was used.

## 8. Results

Two aspects were considered to validate the ANN. Firstly the ANN should reach the proposed goal, in other words, it should show results substantially close to the input data in a very short period of time. If well succeeded, the ANN has to be submitted to a data test, different from the data training. In these tests, it was used two distinct values of capacitance, $C' = 3\times10^{-10}$F and $C'' = 8\times10^{-10}$ F, for each tower.

Initially the ANN was simulated with a goal of 0.05 (average error for the location variable). Considering this goal, the output for the data training were very close to the data input, but in this situation the results for a sample test were not so good, probably it happened because the ANN had been over-trained and, consequently, it loses the generalization capability.

Many different values for the goal were tested. A good response was found for the goal 0.1. This goal was reached in only 1817 epochs and in less than one minute. For this goal the training results were not so close to the data input, see Table 1, but the tests results were very satisfactory, see Table 2.

In Tables 1, 2, the capacitance that causes the faults are represented by the letter C and the location of the fault is represented by $\ell$. Here $\ell = 0$ indicate the normal condition of operation, other values of $\ell$ indicates a fault situation.

TABLE 1
Results for a training using a goal of 0.1.

| TRAINING DATA | | ANN OUTPUT | |
|---|---|---|---|
| C $(10^{-10})$ F | $\ell$ | C $(10^{-10})$ F | $\ell$ |
| 1.6344 | 0 | 1.7298 | 0.0587 |
| 2.7449 | 1 | 2.7567 | 0.9989 |
| | 2 | 2.9101 | 2.0481 |
| | 3 | 2.7015 | 2.9560 |
| | 4 | 4.5005 | 4.4947 |
| | 5 | 2.3009 | 4.8363 |
| | 6 | 2.6189 | 6.1987 |
| | 7 | 2.8944 | 6.7600 |
| | 8 | 2.8887 | 7.2711 |
| | 9 | 3.7397 | 8.6022 |
| | 10 | 2.8021 | 10.0606 |
| 7.7749 | 1 | 7.7902 | 0.9801 |
| | 2 | 7.7523 | 2.0141 |
| | 3 | 7.7726 | 3.0021 |
| | 4 | 7.6078 | 3.9452 |
| | 5 | 7.1515 | 5.0252 |
| | 6 | 7.7869 | 6.0418 |
| | 7 | 7.7647 | 7.1110 |
| | 8 | 7.4338 | 8.0044 |
| | 9 | 7.8057 | 9.0520 |
| | 10 | 7.7647 | 9.9779 |

TABLE 2
Results for sample test using capacitance $C' = 3\times10^{-10}$F and a goal of 0.1.

| SIMULATION INPUT DATA | | ANN OUTPUT | | EVALUATION |
|---|---|---|---|---|
| C $(10^{-10})$ F | $\ell$ | C $(10^{-10})$ F | $\ell$ | |
| 3.0000 | 1 | 2.5061 | 0.9455 | VERY GOOD |
| | 2 | 1.6236 | 1.7084 | VERY GOOD |
| | 3 | 7.3484 | 3.8889 | GOOD |
| | 4 | 6.1924 | 5.0980 | GOOD |
| | 5 | 3.7849 | 3.5580 | REASONABLE |
| | 6 | 9.6529 | 5.6725 | VERY GOOD |
| | 7 | 4.6261 | 6.1948 | GOOD |
| | 8 | 5.8131 | 5.4770 | BAD |
| | 9 | 3.9266 | 9.7598 | GOOD |
| | 10 | 3.4943 | 7.3896 | BAD |

For each result, it was attributed a grade according to the proximity of the input of ANN. A “Very Good” grade for the location if the rounded parameter was equal to the input value. “Good” if the rounded parameter was equal to an integer immediately down or up. “Reasonable” if the rounded parameter was equal to two units immediately down or up and “Bad” for the other cases.

The capacitance values in almost every case was near to the data input, this shows that the parameter C well represents the insulation condition of the TL.

## 9. Conclusion

This work shows a methodology of detection, fault location and provides variables of insulation condition of

TL using as primordial idea the harmonic decomposition of the leakage current of a TL. An ANN and a mathematical model were used as a tool. The validation of the model was based in the theory of gaussian closed surfaces

The results presented were considered satisfactory for fault location and for determining the value of capacitance that creates that fault. With these two parameters, it is possible to analyze the insulation condition of a TL in a particular stretch.

The ANN was successfully tested with data acquired in other days. There is a tenuous limit between a fault situation and the normal condition of operation, because there are uncountable situations of faults and normal conditions.

There is no data available (recorded data) of capacitance values for failure, fault or normal conditions for a TL. It is a problem that makes the fault classification much more difficult.

The results were considered good and applicable. It is important to say that the proposed methodology is a prototype and that further researches are necessary to conclusively provide a predictive maintenance. However, this paper shows a real possibility of prediction and fault location for a TL using an idea conceptually different and innovative.

## 10. Acknowledgment

The authors would like to thank ELETRONORTE for providing several equipment, including the Power Sentinel 1133A analyzer.

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