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A NOVEL ANN TRAINING APPROACH FOR SUPERVISED AND CONSTRUCTIVE LEARNING APPLIED TO FAULT CLASSIFICATION & SHORT-CIRCUIT ZONING IN RURAL PRIMARY DISTRIBUTION SYSTEMS

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In this paper, artificial neural networks (ANN) are proposed to classify and establish zoning faults (single-phase, bi-phase and tri-phase short circuits) in primary distribution systems. The proposed classification and zoning models are oriented toward the stochastic tracking of failures via emergency brigades. This work, instead of training a big ANN model, proposes to decompose the problem into two smaller ones in order to take advantage of the available previous knowledge and improved training. The classification model is based on an ANN with supervised learning (SL). The zoning representation is based on a simple binary perceptron with *constructive* learning (CL). In this article, the theoretical elements underpinning the proposal are detailed and justified. The performance of the proposed models is verified through various real primary network applications.

Key words: classification, zoning, faults, ANN, constructive learning, supervised learning.

1. INTRODUCTION

This article delves into the failures classification and zoning in distribution systems sited in rural areas, mountainous zones and wuthering heights (Los Andes of Chile). The emergency brigades are the key of the energy restoration process. This paper details theoretical solutions for classification and zoning of faults. These support the practical ideas of failure tracking via emergency brigades.

The distribution quality requirements resulting from deregulated electricity markets have led to improved methods of fault location in distribution systems so as to accelerate the restoration process. Failures and outages affect the reliability indexes. Distribution companies strive to improve the quality indices related to these phenomena with the purpose of becoming more competitive in current (free) markets of electricity. The distribution system failures cause disruptions of important processes, data losses, and a wide variety of insecurities and economic damages, among other things. About 80% of customer unavailability is caused by faults in distribution networks. Unfortunately, notwithstanding the experience in the use of algorithms developed for fault location in transmission systems, their operation is not satisfactory in distribution systems. The last is due to their topology and different operating principles: Non homogeneous feeders, multiple taps, many laterals, radial operation and available measuring equipments (only, the laterals indicate multiple possible locations of the fault in the power distribution system). As a result, it is not easy for the maintenance brigade to determine the real location of the fault, in a very long system, without delaying the restoration of service. Consequently, in distribution systems, a variety of approaches to fault location has been developed. Most of these methods infer the fault location, using data acquisition systems and information provided by protection devices. Their operation may be affected due to specific characteristics of a system. The implementation of a fault location expert system must consider the experience acquired both in terrain as in network operation. Among other important factors are the historical data, the number of failures, failure rates, failure types, environmental conditions, vegetation, vandalism, the interruption fault current measured by the recloser and the operating way of the brigades. Incorporating the experience of those who regularly labor in a distribution zone allows the integration of a large quantity of knowledge and the disposal of useless search paths of faults. Such paths only lead to misuse of resources and outsized brigade times. This experience involves, among other things, the recognition of the most common causes and patterns of failure, examples of which are trees, insulators and (high and low) levels of fault currents. The fault's location can even be found using a historic record of failures occurrences (location of schools, clinics, etc.). Nevertheless, in summary, the fault location in distribution systems is carried out without pre-established models of analytics to support an optimal search. Basically, only technical knowledge and experience of the brigade chief are present. The optimal design of a tracking strategy must deal with economic and human aspects. Resources are scarce and emergency brigades should not be implicated in searches without a practical sense. The proposed failures location strategy (via emergency brigades) has in consideration, among other things, that accessible equipment handling does not add costs to the process, nor does it involve specially trained staff. In other words, the investment will be minimal. In a more global context, the occurrence of short circuits in distribution networks has important effects on the daily life, the personal security and, from an economical point of view, even on the development of society. They are the most pervasive faults in the distribution power systems and they can cause significant economic damage and loss of lives. Consequently, it is absolutely necessary to develop a decision support system (DSS) [2, 3], which would prevent as much as possible, unforeseen failures from occurring or would help mitigate their effects. These objectives are unattainable without the effective application of information, communication and power-switchgear technologies and computer models. This paper proposes a novel solution for assisting distribution system operators (utility's brigades) in their decision making activities. With the help of present-day technologies, the proposed system can be considered a viable solution for faults management.

The interruption of electric energy is a phenomenon that profoundly affects the development of human society. From the disasters theory point of view, it is one of the most widespread disasters. If areas where the faults occur can be predicted, the fault risk management should be much easier. Using mathematical simulations and models of faults scenarios, it could be able to prevent and to investigate the problems that arise during and after the occurrence of the failure. Here, short-circuits classification and zoning are modeled via ANN in the context of decision support systems oriented to fault tracking by means of utility emergency brigades. As a result, this paper describes original ideas referring to the fault effects mitigation. Its main objectives are a) designing a fault classification and zoning tool, b) developing an information system by using combined ANN mathematical models and switchgear technologies, in order to estimate the affected areas and c) developing zoning scenarios, using an on-line computational system, in order to support the emergency brigades to find a fault.

The proposal is sited in the domain of disaster management, based on and contributing to the applied DSS theory. However, because of its complexity, the problem of disaster automatic management (DAM), in a (classic and) intelligent manner cannot be easily solved [12]. The paper points out certain considerations regarding the current situation of fault tracking and switchgear technologies on providing online support for decision making. In short, the article identifies (and attacks) the problem of faults classification and zoning, as a problem embedded in the DAM, DSS, ANN and stochastic faults tracking theories [16] via emergency brigades. For the latter, this paper presents a detailed proposal, some applications and their solutions.

Different techniques to help the process of finding faults have been reported in the most important technical literature. In the IEEE Std C37.114-2004 [4], traditional forms of fault detection, since 1933, are detailed:

I. Group 1. a) Observant technologies, i.e., a large number of integrated measuring devices [1], b) Artificial intelligence techniques including: neural networks [5, 14, 15] and immune optimization algorithms [6], c) Impedance methods, methods based on travelling waves, frequency components methods and hybrid methods [9].

II. Group 2. a) Reliability indices [11], b) Methods of a statistical nature using finite samples (in order to extract characteristic patterns of the recorded signals by the measuring equipment during a fault) [10, 11, 12].

The main goal for finding faults in rural distribution systems is to propose a working protocol for the minimization of the average restoration time of the emergency brigades. It consists of three stages: i) *discrimination*, ii) *zoning* and iii) *tracking* of electric faults. The *discrimination* takes advantage of the capacities that switches or reclosers, installed in principal distribution substation (PDS), have in order to solve this task. The *zoning* uses only the PDS recorded data to construct the "short-circuit current ranges" of fault locations. Consequently, the problem of zoning is recognized as a databases construction and management dilemma. The *tracking* is an optimization stochastic process which uses the *failure probability*, the *inspection time* and the *transit time* of each line, used by emergency brigades, to minimize the time taken in finding the fault. Then, a general strategy provides a plan of action (protocol) to emergency brigades and reduces significantly the time and mileage used to find the point where the failure occurred. In this context, the *discrimination* and *zoning* methods, here proposed, consider the network topology, the involved geographical and environmental characteristics and the fault technical knowledge. In this paper, ANN´s are proposed to classify and establish zoning faults (single-phase, bi-phase and tri-phase short circuits) in primary distribution systems. The classification and zoning models, oriented toward a stochastic tracking by emergency brigades, are based on an ANN with SL and a CL simple binary perceptron, respectively. Rather than using complex ANN learning techniques and big ANN models for classification and zoning, as in [16, 5] this work breaks down the problem into two smaller ones which take advantage of the available previous knowledge. The data, for the supervised training, are spurious and unbalanced. The electro-technical theory on electric power systems is used for the constructive training. In this article,_the theoretical elements are detailed. The performance of the models is verified through medium voltage real primary networks applications.

2. PROPOSED MODELS

Nowadays, the non-urban electric power distribution systems are demanding a considerable updating and significant improvement of the fault-tracking supervision and restoration strategies. In particular, the development of techniques, tools and methodologies that allow refining the *anomalies tracking processes*, via emergency brigades, has been a pattern in all power distribution segments. The adoption of such practices is more and more essential for driving favorable indices related to power quality and reliability.

In Chilean electric power distribution systems, most consumers belong to 12, 13.2/13.8, 15 and 23 kV classes. In these segments, the occurrence of faults is very large, caused mainly by climatic alterations, such as storms, winds and periods of droughts, which submit the distribution systems a variety of harmful consequences. These inconveniences make the non-urban electric power restoration very slow and difficult, due to the systems own particular configurations and environmental conditions. Generally, for the distribution systems, the faults *zoning* is usually anticipated through information provided by consumers and the accumulated technical experience. These data address the emergency brigades to the supposed faulted places. If the initial estimative is incorrect, then the emergency brigades should investigate new places. This “inelegant” procedure (accompanied by stressing techniques) is repeated until the exact location of the fault is found. This article is inspired in an efficient classification and well-organized zoning of electrical anomalies that reduce (to emergency brigades) the fault tracking time and improve (to distributors) the rates of reliability. In order to address this challenge, this work proposes a neural structure to classify and another one for zoning failures of rural primary distribution systems. Classification and zoning are the first and most sensitive strategies for the tracking and the location of an anomaly via emergency brigades. The fault classification is based on a supervised-learning-ANN, while the short-circuit zoning is based on a constructive-learning-ANN. Essential data for the proposed tasks are a)Topology, components and parameters of the network, b) Levels of normal operation currents, including sudden load changes, c) Interruption fault currents in the SW (main switch or recloser of the principal power substation)

2.1. Classification model

The tracking zone depends strongly on failure type affecting the distribution system. Consequently, the failure type classification is vital (for emergency brigades) to efficiently explore (tracking) an anomaly. In this paper the fault classification concept is concerned by a) Data acquisition (I-current vector) and b) Detection of faulted phases (y- binary vector). In few words, the proposed structure operates using only data acquisition obtained from the power or principal distribution substation. The vector-data is composed of three phase signals of current. The ground current is computed using the registered data. These digitalized data are processed and their main characteristics, representing each type of fault, are established. The transient recognition segment classifies the disturbance as a normal load alteration or fault occurrence. The detection of faulted phases determines the involved phases in a short circuit and the type of failure.

The neural network model. The proposed short circuit classification uses a binary output ANN with supervised learning. Its structure is shown in Fig. 1.

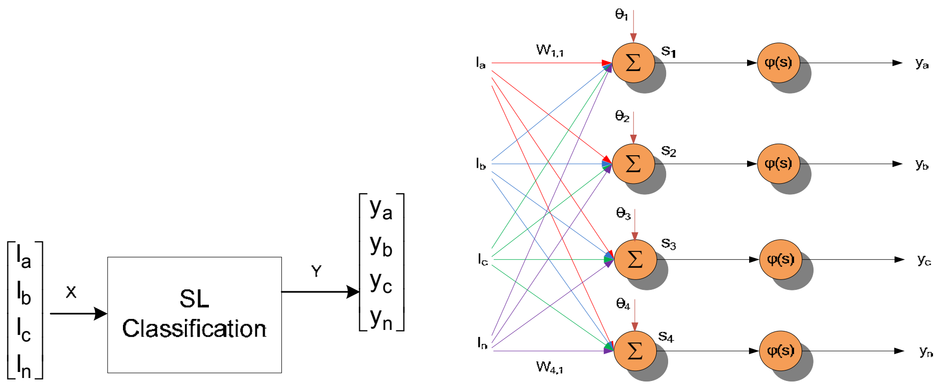

Fig. 1 – a) Classification block diagram; b) classification topology.

The ANN system input vector, contains the interruption short-circuit currents (I_a, I_b, I_c) and the residual current (I_n) values. This is:

$$X = I_{abcn} = \begin{bmatrix} I_a \\ I_b \\ I_c \\ I_n \end{bmatrix}. \tag{1}$$

The interruption and residual currents are read, by the emergency brigades, from the main switch located at the head of the feeder.

Regarding Fig. 1, the transfer function φ (s) is the step function (2). It assigns to the output y given by equation (3). If the phase is faulted then y = 1 and 0 otherwise.

$$\varphi(s) = \begin{cases} 1 & \text{if } \; s \geq 0 \\ 0 & \text{if } \; s < 0, \end{cases} \tag{2}$$

Where $s = W^{t} X + \theta$ is the activation function, W^t is the transpose of the weight vector W and θ the threshold parameter.

$$y = \varphi(s). \tag{3}$$

The faulted phase is recognized by one of the four neurons. For example, if the fault current vector is (for a real data of a "noised"-single-phase short-circuit in phase

b) $X^{\mathrm{T}} = [4 \;\; 109 \;\; 17 \;\; 98]^{\mathrm{T}}$, the corresponding output vector will be $y^{Y} = [\; 0 \;\; 1 \;\; 0 \;\; 1]^{\mathrm{T}}$.

In general, the proposed neural network classifies the type of failure, for any distribution system. Its classification looks like a binary vector $y^{\mathrm{T}} = [y_a \;\; y_b \;\; y_c \;\; y_n]^{\mathrm{T}}$.

Learning

The learning rule is provided by a proper training set (sample) of network behavior (4), where X_t is an input and y_t is the corresponding output (target) to the network

$$\{X_1, y_1\},\ \{X_2, y_2\}\ \ldots\ \{X_t, y_t\}\ \ldots\ \{X_M, y_M\}. \tag{4}$$

The sample size is called M. As the inputs are applied to the ANN, the network outputs are compared to the targets. The learning, according to Fig. 1, is then used to adjust the weights and biases in order to move the networks outputs closer to the targets. The objective is reducing the error $\boldsymbol{e}$ given by (5). There $\mathbf{y}_{\text{target}}$ is the target vector and $\mathbf{y}$ is the neuron response.

$$e = y_t - y \,. \tag{5}$$

The training set requires of **M** short circuit interruption currents vectors (mono-phase, bi-phase and tri-phase failures, with and without fault resistance, non grounded and grounded) and the **M,** corresponding, targets vectors. The training process should converge in k finite iterations, if the classes are lineally separable [13]. For the prior, a realistic test system can be used or even better, historical values of real networks.

2.2. Model of zoning

The model of zoning defines the “geographical” strip where the fault can be found. For the prior, an artificial neural network based on a constructive learning binary perceptron (CLBP-ANN) is used. The output information of each neuron is associated with the fail/non-fail state of the distribution system bus. It is activated when the measurement of short-circuit current belongs to a foretold interval of failure. Given the status of the problem, the zoning ANN may exhibit one or more active neurons. In general, the components of the input vector represent excitation signals for the ANN. Each component of the synaptic weight vector w_i represents a measure of the connection intensity between the associative entry units and the i^{th}-artificial neuron. Polarization or threshold of activation (inhibition) to the i^{th} neuron is defined as θ_i. As a result, i is referred to the i^{th} bus of the distribution network (Fig. 3). The transfer function is denoted as f(s) while the neuron output is called B_i. In this application, each bus of the distribution system is associated to a neuron as shown in Fig. 2.

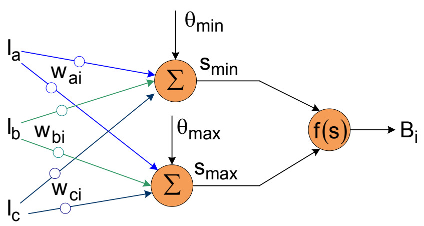

Fig. 2 – Basic neural model for zoning.

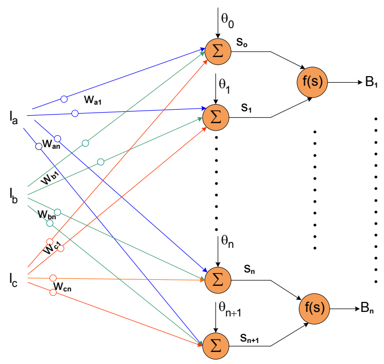

Fig. 3 – Topology of the neural network for zoning.

The neural network is composed of as many neurons as system buses. The neuron input vector I_{sc} and the vector of weights w_i are defined by (5) and (6), respectively

$$I_{sc} = \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix}. \tag{5}$$

$$W_i = \begin{bmatrix} w_{ai} \\ w_{bi} \\ w_{ci} \end{bmatrix}. \tag{6}$$

The input vector, vector of weights and thresholds are all real values. Propagation rule is the weighted sum of the dot product of weight vector by the input vector, see (7). The transfer function $f(s)$ is given by (8) and the output of each neuron B_i is given by (9)

$$s_i = \sum_{x=a,b,c} I_{xi} w_{xi} - \theta_i , \tag{7}$$

$$f(s) = \begin{cases} 1 & \text{if} \quad s = 1 \\ 0 & \text{otherwise} \end{cases}, \tag{8}$$

$$B_i = \begin{cases} 1 \ = B_{i-on} & \text{if } f(s) = 1 \\ 0 \ = B_{i-off} & \text{otherwise.} \end{cases} \tag{9}$$

The neural network model. The topology of the neural network is a neurological structure where each CLBP has learned (*constructively*) to recognize the faulted place.

The proposed constructive *learning*

In most ANN applications, the neuron training (in order to get the desired output) starts with random initial weights and polarizations. These are improved (based on the example), using optimization techniques as the least-squares. In this proposed model the optimization process is implicit in the laws of electric network physics. That is, the learning phase is based on the minimal losses operation of electrical distribution systems. The reader can read on this aspect in [11, 12]. As a result, it can be written (10):

$$w_{ai} I_{ai} + w_{bi} I_{bi} + w_{ci} I_{ci} - \theta_i = s_i . \tag{10}$$

Then, assuming identical synaptic weights, the i^{th}-CLBP neuronal weights are guaranteed by the following constructive completion (11)

$$w_i = \frac{\theta_i}{\sum_i I_{abc}}, \tag{11}$$

where $\sum_i I_{abc}$ is the sum of the i^{th} – predicted fault currents and θ_i the i^{th} – thresholds.

Consequently the θ_{min} or θ_{max} (see Fig. 2) for each bus of the network can be calculated by

$$\theta_{i\text{-}bias} = w_i * \left(I_a + I_b + I_c\right) * \left(1 \pm \varepsilon_i\right), \tag{12}$$

where $\theta_{i\text{-bias}}$ is $\theta_{\min}$ or $\theta_{\max}$. $\left(I_a + I_b + I_c\right)$ contains the measured real disruption currents.

The characteristic factor ε_i depends on the expected historical variability of $\theta_{i\text{-bias}}$, i.e., the neural network learns to associate the different levels of failures currents (for various environmental, climatic, geographical conditions, among others) with each bus of the system. By this approach the distribution network area under failure is identified.

In summary, the zoning work is synthesized in the following steps:

1. Training the proposed ANN via constructive learning.
2. Read the fault current from SW.
3. An input vector of failure currents feed the trained ANN.
4. Each CLBP analyzes its arriving information.
5. A perceptron is activated when $\theta_{i\text{-bias}}$ is contained in the interval [$\theta_{\max}$, $\theta_{\min}$].
6. Various perceptron units can be activated revealing the buses under failure.
7. The zoning of failure is obtained from the buses associated with the activated perceptrons. On this subsystem, the anomaly is tracked and, consequently, the restoration is carried out. The process of failure classification and tracking zoning of the anomaly is shown in Fig. 4.

3. APPLICATIONS

The real system chosen to implement the proposed model is the "Comuy - Mahuidanche" network, from FRONTEL S. A. Utility, Chile. This network is a radial feeder with a low degree of protection. The system has been modeled (compacted by the utility) with 21 nodes. It provides electricity to rural areas with hard access. Electric cables not always follow the outline of the public road. The lines pass through rough terrain and its inspection paths are rarely paved. This network is composed of 20 sections of line (Fig. 5). The feeder voltage is 23 kV. For the training process, mono-phase, bi-phase and tri-phase interruption currents were considered. In general, in order to perform the calculations of learning, identification and zoning, Matlab® and ETAP® tools were used. The neural network training (for identification) was conducted with a sample of 924 (single-phase, bi-phase, tri-phase) short-circuit current values. For validation and test, a sample of 252 values of currents of fault was used. The accepted criterion of performance was 1 %. However, the model identified 100% of failures.

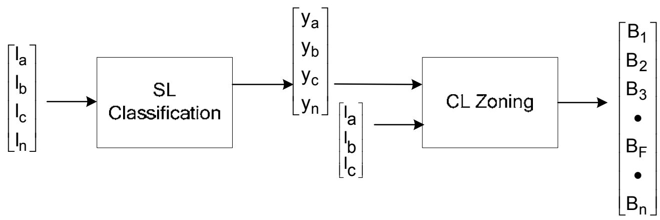

Fig. 4 – Basic classification and zoning failure process.

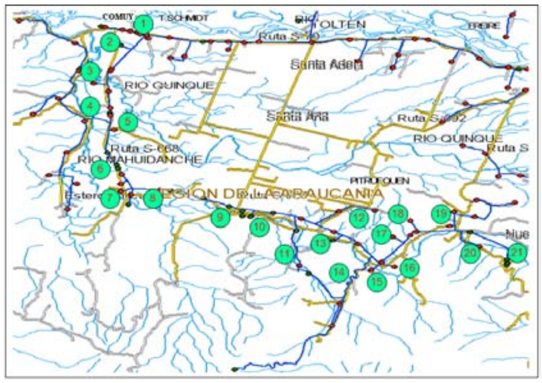

Fig. 5 – Feeder *Comuy* - *Mahuidanche*.

3.1. Case: Single-phase short-circuit

The information known, provided by FRONTEL-SAESA electric utility, is: a) A single-phase short-circuit took place phase in phase b on line 17; b) the input vector **I,** collected by the brigade leader, was $I^{\mathrm{T}}_{abcn} = [12 \ \ 92 \ \ 16 \ \ 88]^{\mathrm{T}}$

a) The output of identification failure module, trained as detailed in section 2.1, gives $y^{\mathrm{T}} = [0 \ \ 1 \ \ 0 \ \ 1]^{\mathrm{T}}$. It confirms the information provided by FRONTEL-SAESA electric utility.

b) The input vector enters to the module of zoning which, trained as detailed in section 2.2, casts the nodes as part of the area of failure, i.e.,

Table 1

Output bus

B_{on}	1	1	1	1	1	1	1	1
Bus	11	12	13	14	15	16	17	18

All the above process is synthesized in Fig. 6. The Comuy-Mahuidanche distribution subsystem, or tracking zone of faults, is shown in Fig. 7. For this contingency the original zone of tracking composed by 20 sections of lines is reduced to 7.

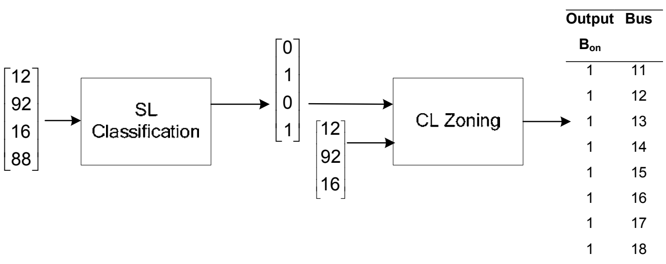

Fig. 6 – Classification and zoning for Case 1.
A single-phase short-circuit of 92 A.

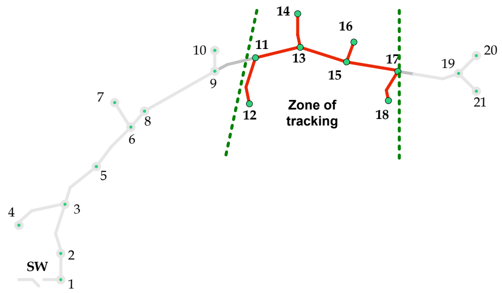

Fig. 7 – Zone of tracking for the single-phase short circuit (92 A in phase b).

Evidently, this zone reduction will imply a decreased time of restoration, a reduced energy not supplied and a significant decline in the emergency brigades' inspection times. Line 17, where actually the anomaly was produced, is present in the tracking area. Reviewing the complete feeder means to go on 32.35 km of line, through a complex territory not necessarily bordering the road. In the case of a failure, this fact maintains the unavailability of the system for a longer time. However, the zoning reduces significantly (to 13.3 km) the power cables to inspect; this is a 41.1% of the total kilometers of the system, reducing significantly the tracking process and thus the customer unavailability. Earlier fault detection avoids the electricity company to pay fines for customers without electricity. Fault resistances or grounding influence the actual anomaly location. This is directly linked to different causes, as the conditions of the terrain, the hour in which the fault occurred, climatic conditions, the cause of failure, among others. As a result, the zoning process is essential in order to search the faulted line.

3.2. Case 2: Non grounded bi-phase short circuit

The input vector **I**, the output of identification failure module, enters to the module of zoning which casts the nodes as part of the area of failure, are detailed in Fig. 8. The classification module categorizes the input information as a non-grounded two-phase short circuit (Fig. 8). The zoning module concentrates the fault lines tracking between nodes 5 to 8 (Fig. 9). According to the company report, the failure was a non-grounded bi-phase and took place on the line between nodes 5 and 6. The prior indicates that both the classification of the fault and zoning were successful. The latter, because the line section where effectively the anomaly occurred is in the field of fault tracking. On the other hand, the territory of fault tracking had been reduced to a 13.3 % of the total kilometers (Fig. 9), i.e., 4.3 km of line. Of course, once again this will reduce significantly the tracking time and thus the customer unavailability. Consequently, the information provided by FRONTEL-SAESA electric utility, about the localization of fault, is confirmed.

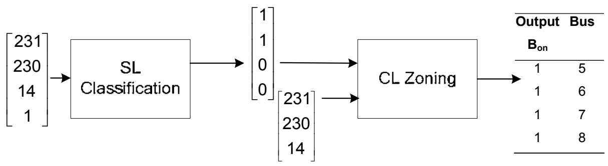

Fig. 8 – Case 2, Classification and zoning. A non-grounded. two-phase fault (between a&b phases).

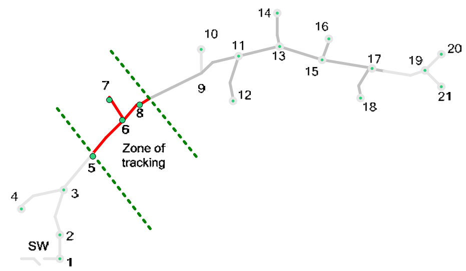

Fig. 9 – Tracking area for the non-grounded two-phase fault (between a&b phases).

3.3. Case 3: Three-phase short-circuit

The classification module announced a three-phase short circuit (Fig. 10). The zoning module restricts the fault tracking area to the lines around the buses 16 to 21 (Figs. 10 and 11). The failure, according to the company report, was a three-phase one and was found on the line tracking area between bus 17 and 19. Results show that both the fault classification and the definition of the fault tracking area were successful. The fault tracking territory has been reduced to 6 line sections, equivalent to 6.9 km of line. The prior represents a 21.2% of the total tracking area (Fig. 11). Thus, the cost of damage to the client will decrease significantly.

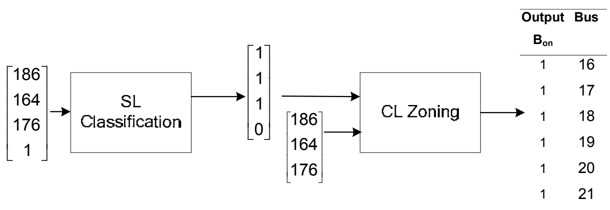

Fig. 10 – Classification and zoning processes for the three-phase short-circuit.

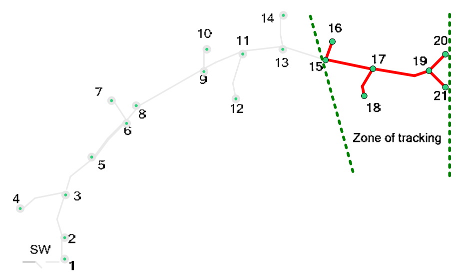

Fig. 11 – Tracking zoning for the three-phase short-circuit.

4. CONCLUSIONS

In this paper, artificial neural networks (ANN), to classify and establish zoning faults (single-phase, bi-phase and tri-phase short circuits) in primary distribution systems, have been presented. The proposed classification and zoning models are oriented toward the stochastic tracking of failures via emergency brigades.

Robust ANN based models have been proposed for classification and zoning of a failure in electric distribution systems. The results are contrasted with real cases that taking place in field.

The combination of a constructive and supervised learning has proved to be an efficient learning strategy solution for this type of task.

The model for zoning shows good results, i.e., it reduces to 41%, 13% and 21% the area to track for single-phase, bi-phase and tri-phase short circuits, respectively. In all cases significant reductions in the fault tracking zone definition are also achieved.

Constructive learning shows an excellent performance for this problem. In general, the proposed neural network successfully classifies the 100% of failures, for any distribution system.

The proposed methodology based on ANN models provides a good decision making tool to organize the emergency work-team to find faults, improving continuity supply rates, capitalizing the installed maneuver equipment and taking account of the distributed sources of generation.

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