Anomaly Detection in Insulation of Switch-Disconnectors in Diesel Power Station Using ABNET, PSOM and MLP

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***Abstract* - This paper main goal is to detect insulation abnormality in switch-disconnectors installed in diesel power stations using thermographic images. It was used image processing techniques and pattern recognition by means of artificial neural network with supervised and adaptive training. In order to implement the anomaly detection system it was necessary to capture thermographic images of switch-disconnectors with and without dry band issues. A thermographer certified by ITC took the collected images used in this paper. The language of technical computing, MATLAB©, was used to make the preprocessing of all the collected images and it was also used for the training of an ABNET network, a PSOM network and a MLP network. Through the cross-validation method, the hit rate of the ABNET's network was 89%, the hit rate of the PSOM was 81.5% and for the MLP the hit rate was 92.6%. Results show evidence of the use of the ABNET network, since the MLP network has an architecture more complex. However, as new information such as temperature and humidity appears a MLP may become more attractive.**

***Index Terms* - Artificial neural networks, power systems, electromechanical devices, maintenance engineering, thermography**

I. INTRODUCTION

The growth of electricity demand in Brazil and the drought of rain caused the reduction of generation and even cause the paralysis of hydroelectric plants as the reservoir water levels reached the minimum operating level. In order to meet electricity demand, Brazil needed to change the type of dispatch between stand-by and continuous of Thermoelectric Plants Powered (TPP) by diesel [1].

Dispatched continuously, the electrical system in these regions suffer with the exposition of industrial pollution caused by exhaust gases from the burning of diesel oil. Thus, it is necessary to develop preventive maintenance techniques in order to preserve the reliability and availability of the electrical system [2].

Thus, thermography is a great supporter since the conditions of dry band at isolators can be recognized with the electrical system in full operation. The process to identify any abnormality starts with the isolation of the switch-disconnectors, allowing the continuity of electricity generation and proper maintenance can be performed on the equipment [3].

The use of thermographic images is one of the most effective techniques for predictive faults diagnosis of electrical components [4]. Thermographic inspection is used for finding heat problems before eventual failure of the system [4].

This study used artificial neural networks for automating the process of anomaly detection in insulation of switch-disconnectors. Among the neural networks was selected the neural network MLP for its great effectiveness in pattern classification. Also were selected ABNET and PSOM networks due to its low complexity architecture compared to the MLP.

This paper is organized as follows. Section II provides background information about the problem of dry band in switchgear [5]. Section III describes the ABNET network [6], PSOM network [7] and MLP network [8]. Section IV describes in detail how the requirements of these networks are used to isolation loss detection. Also the results of the evaluation are presented in Section IV. Section V argues a practical solution for implementing ABNET, PSOM and MLP networks using Raspberry PI 2 [9]. Finally, conclusions are provided in Section VI.

II. THERMAL GENERATION

A. Operating of Thermal Power Plants (Diesel Oil).

The low rainfall in the hydroelectric reservoirs in Brazil resulted in change at the energy scenario of the country, since the Thermoelectric Power Plants (TPP), which are designed to work in stand-by arrangements, began to operate in continuous regime. Fig. 1 shows this new scenario in the country (Reference: http://www.ons.org.br/historico/geracao_energia.aspx).

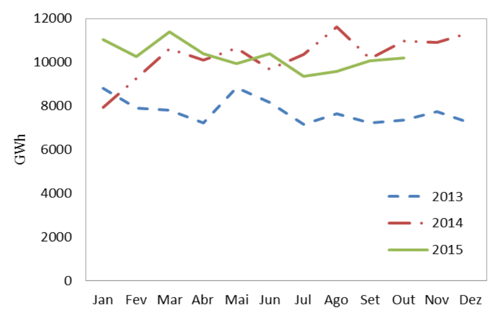

Fig. 1. Evolution of thermeletric generation in Brasil (GWh).

In face of changes in the energy matrix of the Brazilian electric sector and the increase in electrical energy demand, the power sector has demanded of electric utilities increasingly improved management, with high levels of reliability and low operating costs [10].

The Thermoelectric Power Plants (TPP) fueled by diesel oil are composed of several units (diesel generators). The number of components can reach 500 generating units. The pursuit of 100% effective availability is desired by the National System Operator (ONS). Interruptions in the power supply of the TPP affect the availability of indicators and reduce the revenue of companies, and may result in costly fines.

In the diesel engine, fuel oil burning is not complete, resulting in gases and particulate waste that is directed through the engine exhaust, resulting in black smoke coming out of the engines, when they are triggered [2].

Thus, continuous operation of the TPP powered diesel exposes the insulating structures of power plants to extreme operating conditions, as the high rate of industrial pollution, corresponding to suspended particles and electrical discharge that the switch-disconnectors are exposed.

B. The Insulation in Switch-Disconnectors.

The non-ceramic insulators, after prolonged exposure to the intense electrical discharges and industrial pollution, suffer the degradation of the insulation surface and hydrophobicity. Thus, it is necessary to develop a rigorous maintenance plan. The cleaning of insulators like first option presents the best solution, but it is costly, because the time required for cleaning and the labor involved would affect directly on the availability of generation [5].

The accumulation of industrial pollution on insulators and especially in connecting rods of a switch-disconnector dramatically reduces the insulation capacity of the equipment, thus affecting the conditions of non-reliability of the generation system. Over time with the industrial pollution accumulates it is possible to observe the creation of dry bands and arise of partial discharges. The increase of humidity may generate a phase-to-ground discharge causing the automatic shutdown of the generating system [5].

In TPP powered by diesel oil, the pollution with greater contribution is that generated by burning diesel oil [11]. The insulating structure when wet and dirty has contaminants that influence the current flow on an insulator. In contrast, inert components also have their contribution because they are formed by a portion of material, which does not dissolve and form a surface layer on the insulator, where the conductive components are deposited [5].

The loss of insulation occurs when moisture dissolves the surface layer composed of inert components, which allows circulation of a current. The current flow causes heating by Joule effect and this humidity evaporates leaving a saturated solution. The surface layer starts to dry at the locations with most energy circulation, which makes the zero conductivity in this region. Therefore, the current search for other ways until the wetness evaporates, causing the dry band failure [5].

The development of dry band generate a potential difference applied to the point, because the resistance is very high and occurs the interruption of the current, an electrical arc can break the dielectric strength of the air creating a bridge between the extremes of dry band.

The thermographic inspection identifies problems caused by thermal anomalies, due to the relationship between the current and the increase in resistance of the components [12]. In this sense, the use of thermal imaging identifies the existence of dry band, enabling preventive maintenance before the automatic shutdown caused by a phase-to-earth. Fig. 2 shows a thermal image of a disconnector used in TPP average tension with high strength on a rod.

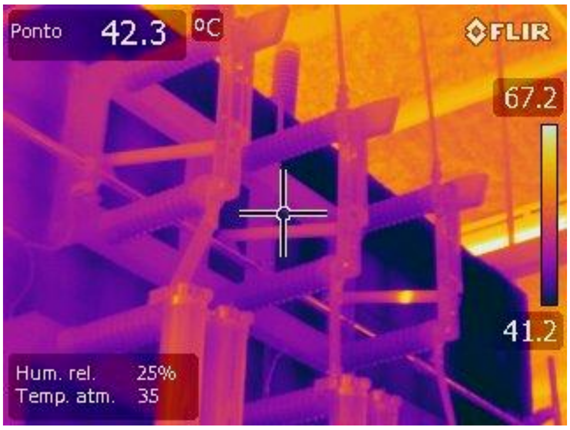

Fig. 2. Thermographic image of a switch-disconnector used in TPP in medium voltage and that has a high resistance in a connecting rod.

The Fig. 2 shows problems caused by thermal anomalies at a switch-disconnector used in TPP in medium voltage.

III. ARTIFICIAL NEURAL NETWORKS

The development of Artificial Neural Networks (ANN) came up with the observation that the human brain processes information differently of the observed in a conventional computer. From a formal point of view, the ANN is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use [8].

In this paper it was modeled an ANN for the detection of dry band failure conditions in the insulators of switch-disconnectors of TPP using the language of technical computing, MATLAB (Academic Research License`s number 70.820). Three ANN models were used in this paper: ABNET (Antibody NETwork) [6], PSOM (Non Parametric Self-Organizing Map) [7] and MLP (Multilayer Perceptron) [8]. The complexity of an ABNET network and PSOM network are much lower than a MLP network.

A. Multilayer Perceptron (MLP)

Over forty-five years, Minsky and Papert (1969) demonstrated that a Single Perceptron (SP) is unable to represent or approximate efficiently various functions such as, for example, the XOR logic function [13]. However, [14] proposes the use of a SP for representing the nonlinearity $f(R)$ relatively complicated from the point of view of its mathematical equation as published in [14]. On the other hand, the story reveals the development of new structures that were capable of representing and approximating the functions that were missed by the structure developed by [15].

Between these structures, there is the ANN known by Multilayer Perceptron (MLP) [16] rigorously demonstrated that only a single hidden layer is sufficient to approximate continuous functions by an ANN. Other researchers have also contributed in this direction [17]. However, using the backpropagation algorithm for training the MLP networks that minimize the mean squared error, eventually contribute to the solution of many problems and not only for the approximation of functions [8]. Thus, this paper is using a MLP network with a single layer for abnormality detection in isolating switch-disconnectors installed in TPP using pattern classification. The network nodes respond to the input by hyperbolic tangent activation function (bipolar sigmoid).

The main function of the learning process through the backpropagation training algorithm is to encode an input-output mapping by adjusting the synaptic weights of the MLP network.

The multilayer perceptron is trained in a supervised manner in two stages. The first stage is represented by the signal propagation that part of the input and moves on toward the output. The other stage is the back-propagation of the error that consists of comparing the response obtained by the network and the desired response, and this difference is used in the reverse way to update the network weights. Thus, at the training of a MLP, it is expected that the network be well trained in order to learn enough information about the past to generalize the future.

B. ABNET Network

The ABNET network (Antibody NETwork) is a competitive Boolean neural network based on principles of the immune system of recognition and response to microorganisms and molecules that cannot be observed by sensory mechanisms [6].

Briefly, the ABNET network is based on growth processes (insertion of new classes at the network output), pruning (removing pre-established classes in the output) and updating weights. Thus, the network can identify the presence of redundant patterns.

In order to process a pattern recognition by a network application ABNET binary input data is required. The applications presented in [6] efficiently demonstrated that a network ABNET has low complexity in its architecture and is capable to solve problems of pattern recognition of binary inputs. Fig. 3 shows a schematic pruning and growth of the network ABNET that must be implemented by the training algorithm [6].

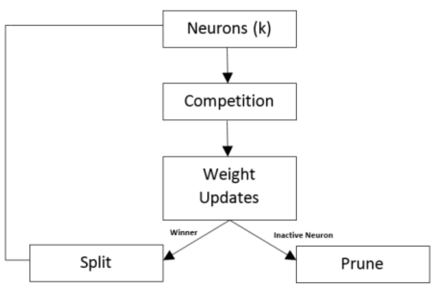

Fig. 3. Main steps of the ABNET learning algorithm [5].

C. PSOM Network

The PSOM network (Non Parametric Self-Organizing Map) is a non-parametric architecture network that presents some changes in the training algorithm for self-organizing maps (SOM), originally proposed by Kohonen [8].

The PSOM network, as well as ABNET, has a training algorithm based on a pruning procedure, whose ultimate goal is the reduction of the dimension of the topological map generated.

Fig. 4 shows a comparison of typical architectures for SOM (two-dimensional structure) and PSOM (dimensional structure), with the neighboring node *j*, *NEj* (*Nc*) published in [7].

The process of recognizing patterns in a PSOM network allows the use of non-binary input values, which makes it somewhat more advantageous that the network ABNET image recognition in colorful images. The PSOM network has a low architecture when compared with the MLP network. This is possible because of the pruning process of training algorithm of ABNET and PSOM networks that promote the removal of units that are not representative [6] [7].

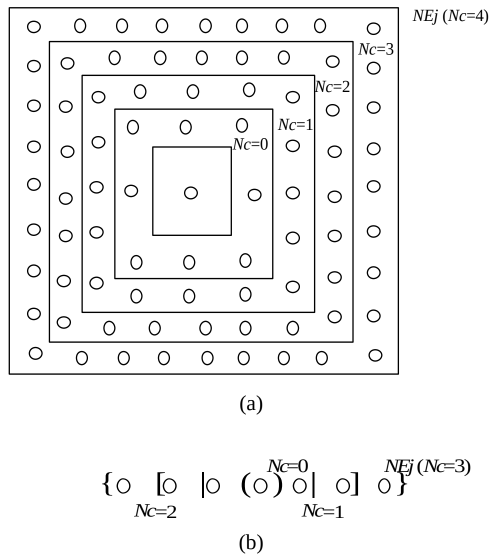

Fig. 4. Typical architectures with neighboring node *j*, *NEj* (*Nc*) [6], (a) two-dimensional structure (SOM) and (b) one-dimensional structure (PSOM).

D. Cross Validation

The cross-validation process is a standard statistical tool that serves as a guide for the proper training of an ANN [18] [19]. Thus, the data set is divided into two groups [8]: (1) Estimation Group (EG) represented for about 80% of the samples; and (2) Test Group (TG), represented by approximately 20% of the samples. After training the ABNET and MLP networks, both of them are tested using images of the TG. To prevent “memorization”, networks are trained through epochs. It gives the name of epoch to the random presentation of EG standards in training.

E. Pattern Recognition

The spectrum division of image analysis techniques is divided into three areas: (1) low-level processing; (2) intermediate level processing; and (3) high-level processing. The high-level processing is used in this paper where pattern recognition involves the recognition and the interpretation [20].

An ANN performs pattern recognition process as the inputs are being repeatedly presented with the relevant category to which they belong. Thus, each group of network inputs is trained to be able to provide an output.

After this pattern recognition, in the training phase occurs the testing stage where inputs are presented to the network that has sufficient information to recognize the class to which that group of images belong.

The pattern recognition performed by a neural network is naturally statistical with the patterns being represented as a point in a multidimensional space dimension, divided into regions associated with a particular class [8].

The complexity of the architecture of a neural network in which an image is used as shown in Fig. 2 (resolution 320 x 240 pixels) tends to be high. Seeking the way of optimization, a great advantage can be gained including a pre-processing stage of the images followed by the modeling of ANN [21]. Thus, most applications using neural networks requires that a pattern of input data undergo pre-processing in order to obtain the expected result with the lowest possible complex architecture.

IV. Propose of an ABNET Network, a PSOM Network and a MLP network for the Detection of Isolation Loss

A. *Image Bank*

In the case under study, it was collected a group of 100 images of 320 x 240 pixels. To reduce the complexity of the networks that would be implemented, the images passed through a pre-processing where samples of specific points of the switch-disconnector were extracted, indicating the presence or absence of dry band and reflection.

After collecting images, a thermographer certified by Infrared Training Center (ITC), generated an image bank for representation of 3 (three) patterns classes, namely: (1) images with dry band on the switch-disconnectors (C1 class); (2) no dry band images (C2 class); and (3) images with no dry band and with reflection problems (false-positive class) (C3 class). Thus, it was created an image bank formed by 135 (one hundred thirty-five) 16 x 16 pixel images, with 45 (forty-five) images for each class. Samples of the EG image bank and TG image bank, used for the network training through cross-validation, are shown in Fig. 5.

The MLP used the complete image bank with the three (3) classes. However, the ABNET network used only the C1 and C2 classes. In the case of ABNET network, sample images also went through a binarization process using the Otsu's method [22].

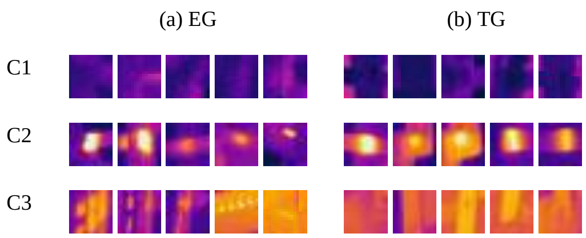

Fig. 5. Samples of the Image Bank (a) Estimation Group (EG) and (b) Test Group (TG).

B. *Proposal of ABNET Network*

Pursuing the lowest complexity of the ANN architecture, the bank of binarized images was used in the training of the ABNET network. The ABNET network started with 256 (two hundred fifty-six) inputs and 1 (one) neuron in the output layer.

The Fig. 6 shows the growth of the network trained in function of the number of iterations performed. Note that ABNET network converged to a network with three (3) neurons in the output layer, and there has been no inputs connection to one of these neurons. Thus, the ABNET network converged your training to two effective outputs, represented by C1 and C2 classes.

The Fig. 7 shows the final structure of the ABNET network so that 72 (seventy-two) patterns for the EG were used for training the network representing the classes C1 and C2. The representation of ABNET network in Fig. 7 is very peculiar: a simple network with 256 (two hundred fifty-six) inputs and only 2 (two) neurons in the output layer, as mentioned above.

The TG composed of 18 (eighteen) images were shown to ABNET network, which led to the hit rate of 89% (eighty-nine percent) in the network-testing phase.

Importantly, the ABNET network is a network with binary representation. Therefore, the network is extremely sensitive to variations of any binarization process, such as Otsu method [22] that is used in this paper. Thus, for a good implementation to detect issues of dry band failure by an ABNET network, it suggests a good collection of thermographic images, avoiding images with reflection, which often depends on the conditions in the field.

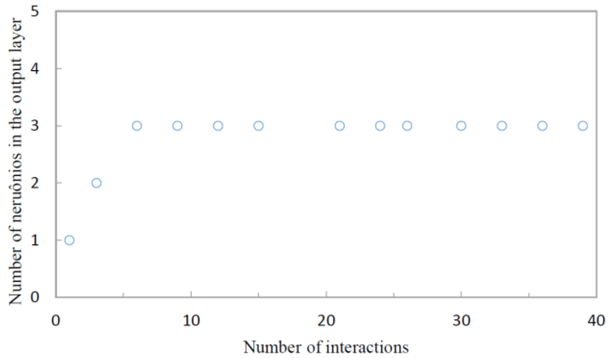

Fig. 6. Growth of the ABNET Network in training stage.

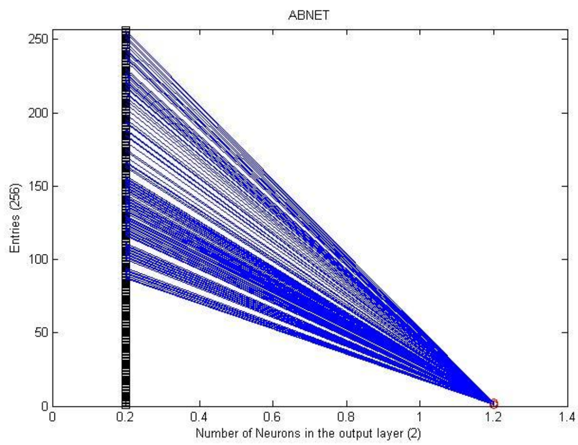

Fig. 7. Representation of the ABNET Network for anomaly detections at isolation in switch-disconnectors in TPP.

C. Proposal for PSOM Network

In order to minimize the complexity of the ANN architecture and the convergence training algorithm of the PSOM network, it was used only 3 (three) representative samples of 16 x 16 pixels (256 entries) for each class (C1, C2 and C3).

A pre-processing of the images was necessary for modify color images (3 x 16 x 16) from image bank to represent them in grayscale (1 x 16 x 16). It was used values between -1.0 and +1.0 to represent images of C1 and C2, and values between -0.5 and +0.5 were used to represent the images of C3 class. The use of this range for C3 occurred due to the similarity of this class with the class C2.

The PSOM network trained began with an initial number of 15 clusters (neighborhood *Nc* = 4, see Fig. 4) and during the network training occurred the pruning process of neurons. Finally, the PSOM network converged to a configuration with three (3) clusters, representing each of the C1, C2 and C3.

Fig. 8 shows the mapping of the three outputs by PSOM network after performing the pruning process during training and convergence of PSOM network.

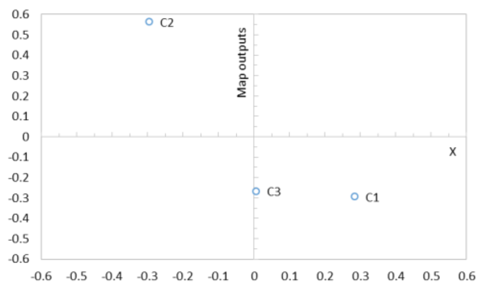

Fig. 8. Representation of PSOM network outputs after training for anomaly detection in isolating of switch-disconnectors in TPP.

After training the PSOM network, the weight matrix connecting the 256 (two hundred fifty-six) inputs to 3 (three) entries was obtained. It was presented 27 (twenty seven) samples of TG patterns for the PSOM network classification, and the hit rate was 81.5% (eighty-one point five percent). Fig. 9 shows the structure of the trained PSOM network.

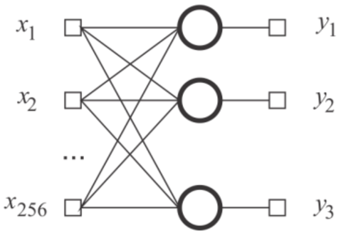

Fig. 9. Representation of the PSOM Network for anomaly detections at isolation in switch-disconnectors in TPP.

D. Proposal for MLP Network

MLP networks can be used to solve pattern classification problems [8]. Thus, Fig. 10 shows the structure of the trained MLP. As can be seen, in addition of 256 (two hundred fifty-six) entries, there is three new entries compared with the ABNET network and PSOM network. The three new entries are: (1) an entry to represent the highest temperature at a point of the input pattern; (2) an entry to represent the ambient humidity in the image collection stage; and (3) the representation of bias. The three additional inputs were used in order to increase the accuracy of the neural network to classify the selected standards.

Using a learning rate $\alpha = 0.01$ and a time equal to $\mu = 0.1$, the MLP network architecture was obtained in the training phase to randomly display 135 (one hundred and thirty-five) training standards of the C1, C2 and C3 (EG).

Fig. 11 shows the minimum number of neurons in the hidden layer at the convergence of the backpropagation training algorithm of a MLP with mean square error equal to 2 x 10^{-2} and maximum number of training epochs equal to 200,000 times. Thus, the minimum architecture of trained MLP for anomaly detection in switch-disconnectors in TPP requires 6 (six) neurons in the hidden layer.

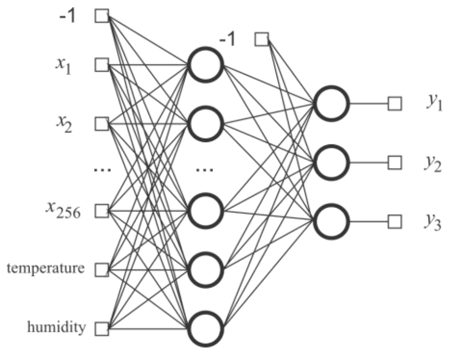

Fig. 10. MLP network representation for anomaly detection in isolation in switch-disconnectors in TPP.

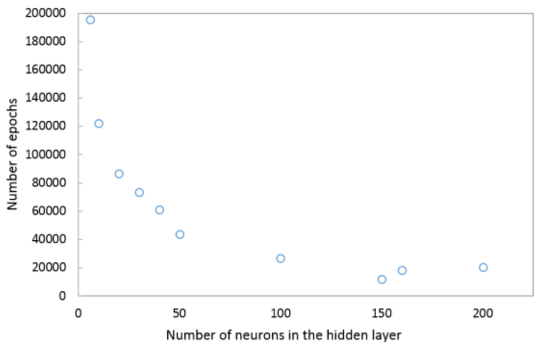

Fig. 11. Number of neurons in the hidden layer versus number of epochs for the MLP network trained.

After training the MLP, 27 (twenty and seven) samples of the TG's bank were presented to the network, yielding a 92.6% (ninety-two point six percent) hit rate, i.e., only two images with dry band failure were classified as images with reflection.

Thus, it can be seen the potential of a MLP have in relation to ABNET and PSOM network. In addition, the MLP network is sensitive to variation problems in capturing images, such as reflection problems reported and represented by class C3. Moreover, have two new entries for future training of a MLP network using a new database sensitive images to fluctuations in temperature and humidity.

Therefore, MLP network is presented as a solution with great potential to detect abnormalities in the insulation switch-disconnectors installed in TPP. However, all networks also have their workspace as will be shown in the next section.

V. Practical Solution for Implementation of ABNET, PSOM and MLP Networks Using Raspberry Pi 2

The ABNET network architecture has only 256 (two hundred fifty-six) connections against 1,575 (one thousand five hundred seventy-five) of the MLP network connections. Tab. 1 shows these numbers in terms of complexity of each trained network. Note that ABNET network is much simpler than the MLP because it has binary representation.

The complexity of the trained ABNET network architecture is equal to 256 (two hundred fifty-six) connections. At the PSOM network, the necessary number of connections is equal to 768 (seven hundred sixty-eight). And for the MLP, the number of connections is equal to 1.575 (one thousand five hundred seventy-five). Tab. 1 shows the number of connections for each trained network as well as a comparison to the complexity of RNA and their respective binary representation. So it can be checked that ABNET network is much simpler than the PSOM and MLP networks, but ABNET still having a binary representation. The PSOM network also has a relatively simple architecture, but has a non-binary representation. The MLP has a more complex architecture compared to the ABNET and the PSOM networks and has a non-binary representation. Therefore, the architecture of a network ABNET stands out as the RNA with lower complexity.

TABLE I
Network Complexity to Solve the Anomaly Detection in Insulation of Switch-Disconnectors Problem

RNA	**Number of Connections**	**Architecture complexity**	**Binary representation**
ABNET	256	Low	Yes
PSOM	768	Low	No
MLP	1,575	High	No

A practical solution to implement ABNET networks, PSOM and MLP can be performed using Raspberry Pi 2 [9]. This technology uses a low-cost personal computer that serves as a perfect alternative to promote interconnection with one thermal imaging camera through an automatic identification process of malfunction in switch-disconnectors of TPP. Since the process can be patented, the authors do not suggest a block diagram to show the process.

VI. Conclusion

Through this study it was concluded that the MLP and PSON networks are a good alternative for detecting abnormality in switch-disconnectors in TPP, since the recognition of color images standards provides a level representation. However, ABNET network is much simpler besides requiring a good image capture and pre-processing of images using Otsu's binarization process.

Through cross-validation, the hit rate for the classification of ABNET network patterns was 89% (eighty-nine percent).The hit rate for the classification of PSOM network patterns was 81.5% (eighty-seven point four percent). And for the MLP, the hit ratio was 92.6% (ninety-two point six percent). Results show evidence for use of ABNET and PSOM network, since the MLP network is more complex. However, as new information, such as temperature and humidity, can be obtained, the MLP may become more attractive.

The main gain in the use of ABNET, PSOM and MLP networks is that they can assist in anomaly detection in insulation of switch-disconnectors in TPP, advance triggering preventive maintenance cleanings of switch-disconnectors, adding more revenue for the TPP to stop a single generator model.

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