Reliable Structural Failure Detection in Eye Bolts using Reflectometry Signals

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Abstract—Eye bolts are critical elements of the electrical power distribution systems and structural failures on such devices can lead to service interruption, financial losses and hazard to civilians. Due to their installation routine is costly, time-consuming and ineffective, because it depends on the de-energization of the circuit, disassembly and visual inspection of the bolts. In this paper, a new approach for detecting structural failures on eye bolts is proposed. An intelligent system based on an artificial neural network is used to process the reflectometry signals measured in order to detect the condition of the eye bolt automatically. The high accuracy in the experimental results suggests that the method proposed can improve the efficiency of the preventive maintenance routine performed on eye bolts, and, consequently, increase the reliability of the power distribution systems.

Keywords— network parameters, fault detection, transmission lines, artificial neural networks, eye bolts, reflectometry.

I. INTRODUCTION

Electric power cables are fastened to high-voltage insulators on poles and towers through lifting eye bolts. Over time, the effects of weather and the friction caused by mechanical stress make these bolts lose their desired physical characteristics. Additionally, these structures can undergo corrosion processes that lead to the degradation of the metallic material, causing the weakening of mechanical properties such as strength, elasticity and ductility. For voltages below 69 kV, in which concrete poles are commonly used, it is difficult to evaluate the state of the eye bolt. As a result, in the event of rupture, power supply interruption is generally observed, along with financial losses and endangering of people's lives, since a substantial portion of such distribution systems is found in urban perimeters. A typical eye bolt installation is shown in Fig.1.

The common method of assessing the condition of eye bolts it is through visual inspection. However, as a considerable part of its structure is hidden inside the pole, the system must be completely de-energized and disassembled for evaluation of the eye bolts. Such procedure is not very effective, has high costs, involving a time-consuming process and does not effectively map the condition of all the bolts, because their verification occurs randomly, due to the difficulties listed.

This work proposes a new maintenance methodology, using a microwave device, coupled to the eye bolt without the need to disassemble the system, in some cases, the proposed inspection can be performed even with the system energized. The bolt failure detection is made automatically with the aid of a machine learning technique which analyses the signal measured and returns transparently to the operator the structural condition of the bolt. With such a strategy, it can be shown that it is possible to determine the condition of the eye bolt with high accuracy and efficiency.

II. METHODOLOGY

The proposed fault detection system is based on the principle of electromagnetic wave propagation in transmission lines, formed by two parallel conductors with different diameters [1]-[2] and reflectometry theory [2]-[6]. The return loss signal acquired is then passed through an artificial neural network (ANN) classifier specially trained in the task of detecting failures on the eye bolts.

A. Microwave Eye Bolt Adapter Connector

To conduct the signal along the eye bolt, a reference conductor is required parallel to it, forming a bifilar transmission line. Thus, a microwave adapter device called eye connector is required to insert the signals into the transmission line formed by the conductors. This matched connector adapts a standard N-connector from the vector network analyser (VNA) to the eye bolt with low losses. The VNA used is a portable model Keysight Fieldfox N9952A [7], intended to provide a real measurement environment.

The special eye connector was designed in a cylindrical shape in order to be naturally threaded at the end of the bolt. The central pin of the N-female connector that receives the
VNA cable makes electrical contact with the lifting eye bolt through the cylindrical surface of the eye connector. There is a Teflon board to insulate the cylindrical body and the external part of the N connector, which receives the reference rod. The description of the main components of the special eye bolt connector are exhibited in Fig.2.

In this way, once the electromagnetic wave injected into the system reaches a discontinuity in the structure, part of the incident wave is reflected and another part is transmitted throughout the transmission line, changing the return loss characteristics observed in contrast to the faultless eye bolt case. This makes it possible to differentiate an intact bolt from the faulty one.

Based on the simulation results, the frequency range was chosen due to the following aspects: observance of multiple points of resonance; low relative shift between measurements and simulation; robustness and low complexity to design the experimental setup. The range of frequencies from 200 MHz to 700 MHz, was adopted, once it fulfilled well such constraints.

Through the analysis of the results of the simulations, presented in Fig.5, it can be observed that the differences caused in the return loss responses by the failures are subtle, which suggests using some sort of machine learning tool to identify whether or not there is a fault in the eye bolts. Thereby, a failure detector was proposed, provided by an artificial neural network trained with a set of return loss signals measured from intact and faulty eye bolt samples.

**B. Simulations**

The measurement setup was modelled by the tool ANSYS High Frequency Structure Simulator (HFSS) software [8]. A series of electromagnetic simulations were performed, designed to predict the general behaviour of the return loss for the complete measurement system. Each bolt is simulated using the computational model. The configuration of such bolts is shown in Fig. 4.

C. **ANN-based Classifier**

The techniques and applications of artificial neural networks have been constantly improved and demonstrate accuracy comparable or better than humans in several recognition tasks [9]. ANNs has already been used in microwave applications such as modelling [10]-[12], design of devices [13], calibration [14], and fault detection [15].

ANNs are able to learn how to distinguish among different classes of data based just on the examples previously presented to it, without the need for any physical model. Through a learning process, ANNs can capture underlying characteristics.
of data and to establish the relationships between input and output parameters with a great capacity of generalization. Such characteristics are used to design an ANN-based system which is able to detect failures on anchor bolts through the analysis of the measured return loss responses.

An artificial neural network can be seen as a circuit with a set of highly interconnected elements linked with modifiable interconnection weights [16]. The basic elements of an ANN are the artificial neurons, in direct analogy with the biological neurons from which they were initially inspired. Artificial neurons essentially compute a weighted sum of the input vector components and convert this value into outputs through an activation function, which is intended to introduce nonlinearity and increase the capacity of the ANN to model nonlinear systems [17],[18]. The output $y$ of a single neuron with $m$ inputs and an activation function $\varphi$ can be given by eq. (1), where $x_i$ represents the $i^{th}$ component of the input vector $x$ and $w_i$ is the respective weight associated to it [19].

$$y(x, w) = \varphi(\sum_{i=0}^{m} (w_i \cdot x_i))$$

(1)

A feedforward (FF) neural network architecture, also known as MLP – Multi-Layered Perceptron, was used in this work. In this type of ANN, the outputs of the neurons of some layer $l$ are the inputs of the neurons of the next layer $l + 1$, therefore, information flows straight through the network from the input to the output, without loops, as shown in Fig.6.

![Basic structure of a feedforward artificial neural network.](image)

Fig. 6. Basic structure of a feedforward artificial neural network.

The knowledge of an ANN is stored in the weights that interconnects the neurons. The exact values of such weights are defined through a learning process that is usually made by a supervised training algorithm, based on the repeated presentation of a set of previously labeled data to the ANN. Considering a dataset with $N$ labeled elements and an ANN with $k$ weights, the general objective of the training process is to find the set of weights $w^*$ which minimizes the cost function eq. (2), where $t(x_j)$ is the target output desired for some input $x_j$, $y(x_j)$ is the overall output of the ANN for some input $x_j$, and $\lambda$ is some positive number called regularization penalty term, introduced to control and avoid the excessive growth of their own values [20]. Such strategy improves the generalization capacity and avoids the overfitting of the ANN model.

$$w^* = \arg\min_w \left( \sum_{j=0}^{N} (t(x_j) - y(x_j))^2 + \lambda \sum_{i=1}^{k} w_i^2 \right)$$

(2)

For the system proposed in this work, each input vector $x$ is made of a measured response of the return loss acquired from some eye bolt. Such a vector has dimension 1001, due to the maximum resolution of the VNA and is composed by samples of the return loss equally spaced in frequency from 2 MHz to 1 GHz. The target output $t$, in its turn, has a binary representation, being 0 for the intact bolt and 1 for the faulty one.

### III. RESULTS AND DISCUSSION

Fig. 7 presents the measurement results and its visual analysis shows that the variations in the signals for faulty and intact bolts are small and distributed along the entire signal. Such result reinforces the proposition that an artificial neural network tool is required to determine the condition of the bolt accurately.

![Measured return loss responses for the eye bolts in Fig. 4.](image)

An extensive set of measurements were performed and a labeled database was built from a set of 320 signals acquired from measurements made in 7 different eye bolts in wet and dry conditions, as shown in Table 1. The same bolt was measured several times in order to provide the ANN enough information about those signal variations due to normal errors inherent to the measurement process, such as imperfect connections and noise, that must be ignored by the classifier.

| Eye Bolts | EB0 | EB1 | EB2 | EB3 | EB4 | EB5 | EB6 |
|-----------|-----|-----|-----|-----|-----|-----|-----|
| Measurements (Dry) | 100 | 20 | 20 | 20 | 20 | 20 | 20 |
| Measurements (Wet) | 40 | 10 | 10 | 10 | 10 | 10 | 10 |

Such database was used to train and test the ANN on the task of detecting failure on the bolts. From the dataset, at each iteration, 80% of the signals were randomly chosen and used to train the ANN, whereas the remaining 20% were reserved to test the performance of the system.

Principal component analysis (PCA) was implemented on the input vectors from the database in order to avoid overfitting, reduce the dimensionality of the signals and speed up the learning process of the ANNs [16]. For the specific case of return loss responses assessed in this work, it was observed that
considering just 64 principal components was enough to retain 99% of the variance of the original signal.

An ANN set up with an accuracy of 99.7% in the task of detecting failures on the anchor bolts was achieved through a set of exhaustive simulations. The hyperparameters of such ANN are presented on Table 2.

Table 2. Set of hyperparameters of the ANN used to detect failures in the anchor bolts.

| Hyperparameter          | Value                      |
|-------------------------|----------------------------|
| Type of ANN             | FF - MLP                   |
| Number of input units   | 64                         |
| Number of hidden units  | 32                         |
| Number of output units  | 1                          |
| Activation function (hidden units) | ReLU [18]          |
| Activation function (output units) | Sigmoid [18]         |
| Penalty term (λ)        | 0.8                        |
| Number of epochs        | 120                        |
| Optimization algorithm  | Adam [21]                  |
| Batch size              | 16                         |
| Loss function           | Binary Cross-Entropy [22]  |
| Training set size       | 236 measured samples       |
| Test set size           | 64 measured samples        |
| Metric                  | Accuracy (%)               |
| Performance achieved (accuracy) | 99.7%                    |

IV. CONCLUSION

In this paper, a new methodology to detect structural failures in eye bolts from the analysis of return loss by an artificial neural network is described. Simulations performed in a high-fidelity simulator validate the design of a special connector used to apply high-frequency signals into the transmission line formed by the eye bolt and the reference rod.

Due to the complexity of the signals acquired, a binary ANN classifier based on a multi-layered perceptron architecture is developed. Such a machine learning tool was trained in the task of detecting faults in the eye bolts, through the presentation of examples from a database made up by measurements carried out in physical bolts with different configurations of failure.

In the experiments realized on the test setup, the system obtained an average accuracy of 99.7% in such a task, which suggests that the proposed methodology is able to diagnose the eye bolt field conditions in a real environment.

Future work includes improving the detection system, embedding the classifier in a single compact device, and to execute additional field measurements in order to verify the performance of the system in a real operation condition.

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