A complex Neural Classifier for the Fault Prognosis and Diagnosis of Overhead Electrical Lines

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Abstract. The technique proposed in this work is finalized to the non-intrusive monitoring of high voltage electrical networks. In order to develop a prognostic method capable of avoiding failures on overhead transmission grids, the connection joints between two sections of the line are considered. The method is based on the use of Frequency Response Analysis (FRA) and machine learning, represented by a neural classifier based on a Multi-Valued Neuron (MVN) neural network. The procedure can be considered as a smart measurement block, where a single measure is used by a neural classifier to extract information able to diagnose an electrical system. This means that the method shown in this paper can be developed and adapted to solve many different problems in the world of industry, such as the management of the most worn electrical devices. In this sense, the maintenance organization plays a fundamental role and the prognostic approach allows the reduction of the recovery times by locating critical components. This monitoring system increases the global availability of the electrical grid in which it is used and, from a practical point of view, it can be used by network operators to obtain online control of operating conditions.

1. Introduction
The method described in this paper had been developed to face a specific class of malfunctions and failures which can occur in the electric power transmission lines, in particular high voltage and very high voltage ones (over 30 kV and over 120 kV). It is usual to assume a system non well working when it is interested by an anomalous behaviour, that is some of the components of the equivalent model are deviating out of nominal values, beyond an accepted tolerance margin. For this reason, the first step of the procedure must be the correct identification of a lumped equivalent model [1]. Identifying the deviations from nominal values, before than they lead to a breaking, can be considered a “prognosis” operated over the whole system. At present, most of the approaches to the identification of failures are in some way inspective and local to the region of possible fault (conducted by human operators, drones, thermal imaging cameras), require to move over a large territorial area, and present problems in safety management. An alternative way to face a problem of diagnosis is to go through investigations (measurements) carried out far from the points where the failure occurs. In this work, to locate the failures on transmission lines the study of the frequency response will be used [2]. An electrical transmission line is a succession of conductor wires and junction points (joints in proximity of pylons), consequently it can be considered, from a circuital point of view, like a succession of identical blocks. Over this equivalent circuit the measurements done at different frequencies can be simulated and analysed. The responses associated to these measurements will largely depend on the parameters of joints and conductors. The conductors normally used in high voltage networks are called
ACSR (Aluminium Conductor Steel Reinforced): the internal part is made of steel and it guarantees high mechanical resistance while the external cover is made of aluminium and it guarantees high electrical conductivity [1][3][4]. The π-model used here has two longitudinal parameters and two shunt parameters that depend on the physical characteristics of the conductor [5][6]. The equivalent lumped circuit representing the joint region has been developed in order to complete the equivalent model. It includes the behaviour of the line components that connect two different sections of the same phase. The model of joint has been developed using the solder joint model reported in [7]. The solder joint is typically used in low power analog circuits, however its form is similar to the one of bolted joint in the overhead lines [8]. Finally, the network elementary section is created through a cascade connection of the joint equivalent circuit and that of the conductor.

The main factors considered for monitoring the state of health of lines are two: the oxidation and the partial breakage of the joints [7]. They can alter the characteristics of the materials and therefore modify the electrical parameters belonging to the model [9][10]. In the approach presented here the conductors’ joints along the line are taken into account, while the line conductors are assumed as well working parts, inside their tolerance range. The whole method is structured in several blocks that will be described in next section and is based on the relationship between frequency response and joint conditions; this is achieved through a machine learning approach.

2. Line and joint model

The fundamental section used for the test in this work is composed by the connection of the joint circuit with the conductor [1][4].

The first part of the equivalent circuit shown in figure 1 refers to the ACSR and depends on its characteristic parameters ($R_l$, $C_l$, $L_l$, $G_l$) and on its length ($\Delta \lambda_l$). In the joint part of the model the elements are in relation with three geometrical characteristics: $\Delta \lambda$ is the length of the junction region, $d$ is the width of the junction region and $H$ is the height of the junction region [7][8][11].

$$R_{sj} = \frac{\rho H}{2\delta(\Delta \lambda + d - 2\delta)}$$

(1)

Figure 1. Lumped circuit single section of the line.

Figure 2. (a) Physical structure of the joint (b) Breaking mechanism.

Therefore, the parameters representative of the joint region are three: the resistance $R_{sj}$, the inductance $L_{sj}$ and the capacitance $C_{sj}$. 

$$R_{sj} = \frac{\rho H}{2\delta(\Delta \lambda + d - 2\delta)}$$

(1)
The skin effect, which reduces the effective conductive section of the cable, is taken into account, making the value of $R_{sj}$ variable with the frequency. The depth of penetration of the current at the frequency $f$, called $\delta$, is:

$$\delta = \frac{1}{\sqrt{\pi f \mu_0 \mu_r \sigma}}$$

(3)

The mechanisms of oxidation and partial breaking can modify the electrical parameters of joint [7][11]. The conductivity of the joint material $\sigma$ decreases with the increasing oxidation and this means that the resistance $R_{sj}$ exceeds its nominal value. The situation of partial breakage represents the last phase of the oxidation process and it produces the variation of each joint parameter. In detail, the variation of $L_{sj}$ is assumed to be associated to the partial breakage, while $C_{sj}$ variation is low and not influent.

$$L_{sj} = \frac{\mu_0 \mu_r H}{2\pi} \left[ \ln \left( \frac{2H}{\Delta \lambda + d} \right) + 0.5 \right]$$

(2)

The formulas (4), (5) and (6) are obtained by considering a typical breaking mechanism of solder joints. The breaking parameters are two: $x$, the width of the crack, and $h$ the height of the crack.

$$R_{sj} = \begin{cases} \rho \frac{H-h}{2\delta(\Delta \lambda + d - 2\delta)} & (d-x) \geq 2\delta \\ \rho \frac{H-h}{2\delta(\Delta \lambda + d - 2\delta)} & (d-x) < 2\delta \end{cases}$$

(4)

$$L_{sj} = \frac{\mu_0 \mu_r (H-h)}{2\pi} \left[ \ln \left( \frac{2(H-h)}{\Delta \lambda + d} \right) + 0.5 \right]$$

(5)

$$C_{sj} = \varepsilon \varepsilon_r \frac{x \Delta \lambda}{h}$$

(6)

3. Outlines of Method

The transmission line under exam can include several joints and the main objective of the whole procedure is to locate which one of the joints included in the section is in critical conditions. This can be done by elaborating the frequency response. In other words, the inputs of diagnosis evaluator are electrical quantities (voltages, currents, powers), measured at different values of frequency. Taking into account that the frequency response is strictly tied to the transfer function of the electrical network, it is also depending on the electrical parameters, which can vary according to the failures mechanisms.

The state of a junction region is categorized in three different classes:

- nominal (regular working) condition;
- soft failure (state of oxidation);
- hard failure (breakage of the element).

In nominal condition the parameters of the joint are inside the tolerance, in soft fault condition some parameter values can go outside the tolerance range, without yet compromising the operations, while finally the hard fault is an extremely significant variation. From an operational point of view, the oxidation of the joint structure corresponds to the soft fault condition while its damage represents the hard fault condition.

The system set up for the problem classification is a complex neural network which receives the measurements of the frequency response as inputs. Summarizing, the main steps of the method are the following:

- simulation of the whole system;
- analysis of testability;
• selection of frequencies;
• classification of the state of joint.

3.1. Simulation of the line/joint

The repeated simulations of the circuit under test allow to train the learning machine aimed to the classification of the anomalies. Due to the high number of simulations usually required to this aim, and the substantially linear nature of the modeled lines, a symbolic simulator has been chosen. The best suited to this aim appeared to be SapWin© (Symbolic Analysis Program for Windows) [12]. It is a simulation software for linear lumped electric/electronics circuit, powerful and freely available [13]. It provides the response of a circuit in symbolic form. This simplifies the task of performing simulations in a reasonably quick time. In figure 3 a generic screenshot of the program is shown with a simulation of the line section.

![Figure 3. Lumped circuit single section of the line.](image)

3.2. Testability analysis

In a problem of parametric identification, a preliminary study called “solvability analysis” is needed in order to have, without any ambiguity, the maximum number of components that can be assumed variables simultaneously, given one or more test points [14][15]. The testability index T is used for this reason and it can be at most equal to the maximum number of parameters NP. If T is less than NP, there is one or more sets of electrical components that cannot be considered unknown at the same time, called ambiguity groups [16][17]. The testability analysis is here executed by the program LINFTA [14], analysing the equivalent circuit of the overhead line, where only the joint parameters are considered variables.
3.3. Frequency set selection
The values of the measurement frequencies are obtained by means of a technique able to reduce the error due to tolerances and noise, as demonstrated in [18].

3.4. Classification tool
The tool for the classification of fault and anomalous conditions has been selected in the category of “complex-valued” based neural networks. It is a multilayer neural network with multi-valued neurons (MLMVNN). The algorithm is mathematically demonstrated in [19], and it presents the advantage to be derivative free. This choice was done for a couple of reasons: the great performance of this NN as classifier, also with respect to SVM (the best one apart this) and for the possibility to be directly applied to “complex” signals, calculated in magnitude and phase, like in the case of frequency response.

The Multi-Valued Neuron with discrete activation gives as output:

\[
P(z) = e^{iz} = e^{i2\pi j/k}, \text{ if } 2\pi j/k \leq \text{Arg } z < 2\pi (j + 1)/k
\]  

(\( z = w_0 + w_1x_1 + \ldots + w_nx_n \) is the weighted sum of inputs and \( k \) is the number of classes in the classification problem). The continuous activation function is:

\[
P(z) = e^{i\text{Arg } z} = z|z|
\]  

where \( z \) is the weighted sum and \( \text{Arg}(z) \) is the argument of the complex number \( z \).

The learning algorithm, modified and improved in [20] [21], has been generalized to any number of output neurons and hidden layers and finally adapted to the soft margin concept to implement a classifier [22]. It was found from (11) (here the complex QR decomposition is used) the weights of the whole learning set (\( M \) learning samples). The adjustment quantities \( \Delta w_0^{(h)}, \Delta w_1^{(h)}, \ldots, \Delta w_n^{(h)} \) applied to the weights, are calculated by the \( M \) errors \( \delta^{(j)}, j = 1, \ldots, M \) , and they are equal to the weighted sum:

\[
\Delta w_0^{(h)} + \Delta w_1^{(h)} x_1^{(j)} + \ldots + \Delta w_n^{(h)} x_n^{(j)} = \delta_j^{(h)} \quad j = 1, \ldots, M
\]  

where \( x_1^{(j)}, \ldots, x_n^{(j)} \) are the inputs for the \( j \)th learning sample and \( \Delta w_0^{(h)}, \Delta w_1^{(h)}, \ldots, \Delta w_n^{(h)} \) are the corrections applied to the weights. Equation (11) can be considered as an algebraic system of \( M \) linear equations in \( n+1 \) unknowns \( \Delta w_0^{(h)}, \Delta w_1^{(h)}, \ldots, \Delta w_n^{(h)} \) and written in the vector form:

\[
\mathbf{X} \left( \Delta \mathbf{w}^{(h)} \right) = \delta^{(h)}
\]  

where \( x_i^{(j)} \) is the \( i \)th input of the \( h \)th hidden neuron from the \( j \)th learning sample, \( \Delta \mathbf{w}^{(h)} \) is the vector of corrections applied to the weights of the \( h \)th hidden neuron, and \( \delta^{(h)} \) is the errors vector, calculated over the set of samples. System (10) is overdetermined for almost all practical applications (i.e. the one presented here), every time that number of samples is much larger than the input dimension, that is \( M \gg n + 1 \). In these practical cases, a least squares method can be adopted, to find

\[
\hat{\Delta} \mathbf{w}^{(h)} = \arg \min_{\Delta \mathbf{w}^{(h)}} \| \mathbf{X} (\Delta \mathbf{w}^{(h)}) - \delta^{(h)} \|^2
\]  

\[
\hat{\Delta} \mathbf{w}^{(h)} = X^* \delta^{(h)}
\]  

(11) where \( X^* = (X^T X)^{-1} X^T \) is the pseudo-inverse of matrix \( X \) taken from (12) and \( X^T \) is the conjugate-transposed of matrix \( X \). After \( \hat{\Delta} \mathbf{w}^{(h)} \) was found from (11) (here the complex QR decomposition is used) the weights of the \( h \)th hidden neuron can be corrected by the following expressions:
\[
\vec{w}_t^{(b)} = w_t^{(b)} + \Delta w_t^{(b)}; \quad i = 0, 1, \ldots, n
\]  

After that all hidden neurons have been corrected in this way, the same procedure is applied to adjust the weights of output neurons. The described approach provides a powerful classifier [23].

4. Application and discussion
The main objective of the developed procedure is the non-intrusive evaluation of the health state of the junction regions in the overhead electrical transmission lines. Several operative situations in presence of 3, 4 and 5 junctions have been tested. The specific measurement done is that of the input current, which can be therefore seen as an “input admittance” test-point, which is also the most suitable in a real-world operative configuration. Another important preliminary aspect is that the testability for this family of analog equivalent circuits is always maximal when we consider as potentially variable just the joint equivalent parameters (i.e. in the case of 3 joints, each one with 3 parameters, \( T = 9 \) and so on). This result guarantees that, at least potentially, the network function is invertible with respect to any parameter, and therefore all the fault classes are recognizable. Of course, this does not mean that all the anomalous situations can actually be recognized, but that at least there is no ambiguity between each other; in other words it is a necessary (but not sufficient) pre-condition to face the problem.

In order to train the whole system, a dataset is needed. Matlab\textsuperscript{®} program allows the training matrix to be obtained using the symbolic form of the transfer functions outputted by SapWin\textsuperscript{©}. A certain number of combinations are generated, depending on the number of joints. Taking into account that each joint can fall in three different health states: healthy, oxidized and broken, then if the line includes \( ng \) joints there are \( 3^{ng} \) possible combinations. In each possible combination are included a number of repeated simulations done with a random variation of line parameters inside a \( \pm 10\% \) tolerance and joint parameters randomly varying inside the range relative to the 3 possible conditions (uniform probability distribution).

As last step, the classification of joint status allows to locate the most critical point of the line. The complex MVN neural network described in section 3.4 is used as classifier. Each junction region corresponds to a couple of complex neurons in the output layer of the neural network, the first one to classify the oxidation state, the second one to classify the breakage, as reported in figure 4. The hidden layer of the network contains 120 neurons for \( ng = 3 \), 180 for \( ng = 4 \), 220 for \( ng = 5 \) (heuristically obtained testing the network with number of neurons increasing till the best option). The learning time on a last generation PC is just few minutes. Three tables of results are presented here. The table 1 shows the result for a section of line constituted by three pylons (thus 3 joints), the table 2 shows the result for a section of line constituted by four pylons (4 joints). Table 3 shows the result for a section of line constituted by four pylons (5 joints). The used measure is the current input, fixed the voltage (i.e. input admittance). The total generated samples (by SapWin and Matlab) are 10000; and a \( k \)-fold cross-validation approach is used with \( k = 5 \). A tolerance range of \( \pm 10\% \) with respect to the nominal values is used to define the electrical parameters belonging to the \( \pi \)-models. In this way it is possible to consider the influence of environmental conditions and load current on the conductor status. As regard the Oxidation and Breaking states of the joints, two different fault classes are created based on the formulas shown in section 2. During the simulations, each electrical component of the joints is randomly chosen in these categories.
The results are very good for the first two situations, with a natural decreasing of the classification quality in case of four joints with respect to three, but still more than acceptable. The results for a further increase of number of joints, brings instead to significant degradation of results, starting from five joints up, as evident in table 3. This can, in some way and at this stage of method development, constitute the superior threshold for accepting quality of the result. It should finally be noted a very good ability of generalization, with test results sometimes even better than training ones.

**Table 1.** Results of classification of three sections.

| Joint | Train Oxidation | Train Breaking | Test Oxidation | Test Breaking |
|-------|-----------------|----------------|----------------|---------------|
| Joint 1 | 0.9810 | 0.9799 | 0.9778 | 0.9815 |
| Joint 2 | 0.9910 | 0.9800 | 0.9500 | 0.9889 |
| Joint 3 | 0.9540 | 0.9815 | 0.9300 | 0.9889 |

**Table 2.** Results of classification of four sections.

| Joint | Train Oxidation | Train Breaking | Test Oxidation | Test Breaking |
|-------|-----------------|----------------|----------------|---------------|
| Joint 1 | 0.9780 | 0.9822 | 0.9660 | 0.9858 |
| Joint 2 | 0.9500 | 0.9850 | 0.9272 | 0.9741 |
| Joint 3 | 0.9450 | 0.9800 | 0.9309 | 0.9809 |
| Joint 4 | 0.9300 | 0.9900 | 0.9000 | 0.9846 |
Table 3. Results of classification of five sections.

| Joint   | Oxidation | Breaking | Oxidation | Breaking |
|---------|-----------|----------|-----------|----------|
| Joint 1 | 0.9550    | 0.9314   | 0.9430    | 0.9259   |
| Joint 2 | 0.6780    | 0.7700   | 0.6597    | 0.7626   |
| Joint 3 | 0.7700    | 0.8300   | 0.7356    | 0.8267   |
| Joint 4 | 0.7652    | 0.9000   | 0.7652    | 0.8942   |
| Joint 5 | 0.6450    | 0.7205   | 0.6298    | 0.7019   |

5. Conclusion

In this work, a method has been developed to locate the malfunctions due to anomalies in junction points of an overhead power transmission line. In this way it is possible to adopt specific maintenance works when malfunctions occur and increase the mean time to failure of the whole transmission line. The providers of electrical energy have shown a marked interest for this kind of applications and the future developments of the method will refine the approach to a specific operational situation. The simulation results demonstrate the possibility of classifying the state of health of the joints and preventing critical failures. For this reason, the prognostic method shown in this paper represents an optimal basis for the development of an intelligent monitoring system that operates in real time on overhead transmission lines.

6. References

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