ABSTRACT
Nature is a source of inspiration for engineering. Extensive investigations have been focused on integrating smart material technology into health monitoring systems. The development of new proceedings for fault identification, based on these ideas, will be proposed in this paper in order to prevent catastrophic failures and to increase in-service lifetime. Also, one important aspect in health monitoring that must be analyzed is the life expectation. In general, this demands knowledge of the structure model in great details, which not always is possible; in addition the dynamic systems frequently present non-linear characteristics. In this work the detection and location of the faults are accomplished in two stages. Initially the method of electric impedance is used to determine the location of the faults. Later on takes place the quantification of the faults in two ways, by using genetic algorithms or by using artificial neural network. Genetic algorithms (GA) are optimization processes founded on principles of natural evolution and selections. A GA takes an initial population of individuals and it applies artificial genetic operators about each generation. Neural network is a computational technique inspired by the neuronal structure of intelligent organisms. They can approach and to classify problems associated with non-linearities, if the patterns of input data represent the fault appropriately. These two methods are compared in this work with application for fault identification.

INTRODUCTION
Maintenance by using vibration signals inspection is classified as one of nondestructive technique for condition monitoring. The weakest point of maintenance inspection today is that has no general function for warning when incipient damage occurs in service [1]. To deal with these problems, this paper applies the concept of smart structure. The terms “intelligent material”, or “smart structure”, are fast becoming common phrases among the engineering community. These terms are used to describe a variety of modern advances in the word engineering. There is no agreement for the definition of these systems, however, the terms used in this work refer to structures with material components that are able to transform mechanical motion or force in electrical or magnetic fields, and vice versa. A list of materials employed in smart material system includes piezoelectric, electrostrictive and magnetostrictive elements, fiber optics, etc.

With the advances in actuator technology, particularly collocated sensor-actuators, and microcomputer processing, effective and lower cost nondestructive evaluation of large complex structures can be developed. To be effective, a health monitoring system must provide real-time and continuous structural health assessment [2]. Fault identification is characterized as an inverse problem.

The inverse problem consists in to determined the causes based on observation of their effects. In inverse problems the damage parameters (crack length and/or location) can be calculated through frequency variation. Otherwise, direct
problem involves the solution based on a complete description of their causes. The effects of fault in structure can be classified as linear or nonlinear. A linear fault situation is defined as the case in which the initially linear-elastic structure remains linear elastic after damage. Nonlinear fault is defined as the case in which the initially linear elastic structure behaves in a nonlinear manner after the fault has been introduced.

**Genetic Algorithms**

Genetic Algorithm (GA) is a technique based on Darwin’s evolution. An GA simulates an adaptation process taking an initial population of individuals and applying artificial genetic operators in each generation. In optimization conditions, each individual of the population is codified in a string or chromosomes, which it represents a possible solution for a certain problem, while the individuals adaptation is evaluated through a fitness function. Basically, to the individuals highly capable (better solutions) larger opportunities are given of if they reproduce, changing parts of genetic information, in a procedure of crossover. The operator of Mutation is used to change some genes in the chromosomes and to cause diversity in the population. The descent new population either can substitute the whole current population or to just substitute the individuals of smaller adjustment. This evaluation cycle, selection and generation, is repeated until that a satisfactory solution is found.

**Artificial Neural Networks**

Artificial Neural Network (ANN) is a computing technique that represent a mathematical model. This technique is inspired at neuronal structure of intelligent organism and it can acquire knowledge through experience. ANN can be used for resolution of a large range of problems found in several applied areas as: classification problem; identification system; fault diagnosis; analysis of signals and images; and optimal control. It, also, can approximate and to classify problems associated with nonlinearities. If the pattern of input data represent the fault appropriately, this formulation can be used with advantages, since, it can avoid the complexity introduced by model – based methods. Besides, the learning capacity of neural network is adapted to processes great number of input data, what is fundamental for applications in intelligent structures.

A general feedforward neural network topology takes the form of multilayer feedforward structure. The basic processing element is called neuron that consist of activity level, a set of input and output connection. The output of the neuron is determined as:

\[ y = f \left( \sum_{i=1}^{n} w_i x_i + b \right) \]  

(1)

where \( x_i \) are the input signals, \( w_i \) are the connection weighting, \( b \) is the bias value, and \( f \) is an activation function that may be a step, tanh, sigmoid function, etc. The estimation of parameters in nonlinear models is generally based on nonlinear optimization techniques, and the learning process consists of the adjustment of the weighting and bias value for a training data.

**Piezoelectric Elements**

Piezoelectric materials belong to a class of dielectrics that exhibit significant material deformations in response to an applied electric field as well as produce dielectric polarization in response to mechanical strains. In current technology, piezoelectric sensors and actuators can be created by poling an appropriate substrate through the application of a large electric field at high temperatures. Substrates for the process are chosen to have a crystalline, ceramic or polymeric lattice structure in which the atomic structure along at least one axis differs from that in the remaining coordinates; hence the material is anisotropic and typically orthotropic. Poling has the effect of partially aligning the polar axes of the domains to yield a macroscopic polarization, which facilitates the electromechanical coupling. As a result of this coupling the piezoelectric material will deform in response to an applied electric field, this gives the material its actuating properties. The sensing capability come from the converse effect in which the mechanical stresses in the material cause rotations of the partially aligned dipoles to generate an electric field. The figure 1 shows the piezoelectric effect [3].
Piezoelectric elements exhibit nonlinear hysteresis at high excitation levels, however, for common structural applications they can be approximated for linear. In this work we will use the linear constitutive relations for piezoelectric materials as given by [4].

\[
\begin{align*}
\{D\} &= \{\varepsilon\}^T \{S\} + \{\varepsilon\}^T \{E\} \\
\{T\} &= [c^E] \{S\} - [e^E] \{E\}
\end{align*}
\] (2)

where the superscript \((^S)\) means that the values are measured for constant strain, the superscript \((^E)\) means that the values are measured at constant electric field, \(\{T\}\) is the stress tensor \([N/m^2]\), \(\{D\}\) is the electric displacement vector \([C/m^2]\), \(\{S\}\) is the strain tensor \([m/m]\), \(\{E\}\) is the electric field \([V/m = N/C]\), \([c^E]\) is the elasticity tensor at constant electric field \([N/m^2]\), \([e^E]\) is the dielectric permittivity tensor \([N.m/V.m^2 = C/m^2]\) and \([\varepsilon^S]\) is the dielectric tensor at constant mechanical strain \([N.m/V.m]\). The letters in brackets indicate the variable unit ( SI system ) with N, m, V, and C denoting Newton, meter, Volts, and Coulomb, respectively.

If each element of the piezoelectric matrix \([e]\), is designed by \(e_{ij}\) where \(i\) corresponds to the row and \(j\) to the columns of the matrix, then \(e_{ij}\) corresponds to the stress developed in the \(j\)-th direction due to an electric field applied in the \(i\)-th direction. The piezoelectric strain constant \(d_{ij}\), relating the voltage applied in the \(i\)-th direction to a strain developed in \(j\)-th direction, are provided more often than the stress constants. However, the piezoelectric stress can be obtained from the strain constants, since the constitutive equation, also, can be written as [5].

\[
\{S\} = [s^E]^T \{T\} + [d^E]^T \{E\} \quad \text{(actuator equation)} \quad (4)
\]

\[
\{D\} = [d^T] \{T\} + [\varepsilon^T] \{E\} \quad \text{(sensor equation)} \quad (5)
\]

where \(\varepsilon^E\) is the dielectric tensor at constant stress.

Solution of the wave-equation for the PZT bar connected to the external mechanical point impedance of the structure lead to the following equation for the frequency-dependent electrical admittance, [6]

\[
Y = i\omega \sigma [\varepsilon^E_{33} (1 - i\delta) - \frac{Z_S(\omega)}{Z_S(\omega) + Z_a(\omega)} d_{33}^2 Y_{xx}] \quad (6)
\]

where \(Z_a\) and \(Z_S\) are the actuator and structure mechanical impedance respectively, \(Y_{xx}\) is the complex Young’s modulus of the PZT at zero electric field, \(d_{33}\) is the piezoelectric coupling constant in the \(x\)-direction at zero stress, \(\varepsilon_{33}^E\) is the constant at zero stress, \(\delta\) is the dielectric loss tangent of the PZT, and \(a\) is the geometric constant of the PZT.

**METHODOLOGY**

The proposed methodology can be divided in 2 parts. The first one determines the fault location through electric impedance technique. This method is based on high frequency ranges and local vibrations modes, therefore, the area of influence of each PSA is small. This technique can define with good accuracy the region of the fault. It is important to note that this method is not capable to supply the fault severity. The second part of this methodology supplies quantitative information of the fault. This phase can be done using Genetic Algorithms method, or Artificial Neural Network, or both methods in a simultaneous way, Figure 2.

The direct problem, which consists of the determination of the modal properties in function of the physical structural variations, has unique solution. However, the fault characterization is an inverse problem and, it does not present an unique solution. Any optimization method that desire to adjust the model will have great chance of failing for systems with medium level of complexity or greater. There exist various methods of model reduction or choice of variables that intends to overcome this difficulty. Among the more used the sensitivity analysis can be mentioned,
however, the fault can occur in positions where the variation of those parameters presents low sensitivity.

This paper deals with this problem, and the main advantage of the proposal methodology is that the method of electric impedance defines with accuracy the location of the fault. Then, it is possible to reduce, drastically, the number of variables that will be used in the optimization process.

![Diagram of the proposed methodology](image)

**Quantification using GA.**

The choice of the parameters that will be used to quantify the fault is accomplished after the location of the region of the fault. After the definition of these parameters, the adjustment of FRF measured (situation with defect) is done through the optimization technique using GA. When the difference among those curves is smaller than a specified value the process is finished. The difference among the system matrices without defect, M, K and C, and the matrices M *, K * and C * supplies the quantification of the defect. For the analyzed case was considered M* = M and C* = C.

**Quantification using ANN**

The proposal methodology scheme using ANN consists of two steps. In the first step the method of electric impedance is used to identify the fault location. The neural networks are trained for each specific fault using the impedance signals from the PZT - sensor. Therefore, in the second step the number of neural networks necessary is the same than the number of PZT.

The electric impedance is measured in high frequency, which guarantees great sensibility for local structural variations. The impedance signals must be processed and normalized in order to represent all conditions of faults that one wants to monitor. One of the largest advantages of this
method is that the variation of the signal is local and it doesn’t affect the others sensors (PZT). Therefore, simultaneous faults, that are difficulty identified for conventional methods, can be treated as if they happened independently.

**RESULTS**

This work accomplishes the numeric study of an aluminum beam with 30 millimeters of width, 5 mm of thickness and 500 mm of length. The beam is modeled by finite elements through the program "Smart Beam", available by the group of Intelligent Material Systems at DEM/FEIS. The beam was divided in twenty elements of type "BEAM", with two degrees of freedom per node, vertical displacement and rotation around the axis z. It is a clamped-free beam and the Frequency Response Function (FRF) of the system was considered for different situations of defects and loads.

The presented results consider the fault in the element five. The damage was simulated decreasing the inertia moment of area of this element to 90, 80, 70, 60, 50 and 40% of its initial value. Being like this, there are seven conditions for the system: the situation without fault and the other ones with six different types of faults, those conditions were denominated 1, 2, 3, 4, 5, 6 and 7, respectively. Figure 3 shows the beam with the element five highlighted, where the fault was simulated.

![Discretized beam with element five highlighted.](image)

Starting from the model in finite elements, the FRF was set up for the conditions of mentioned faults up to 2000Hz, where the appearance of the first seven natural frequencies can be verified.

**Results from Genetic Algorithm**

The simulations accomplished to quantify faults using GA can be divided in two stages: the first one, Case_1, was just left free to get variations the inertia moment of area of the element 5, considering the exact location of the fault. The second one, Case_2, considered that the technique of electric impedance located an area of three elements where the fault should be present. The inertia moment of area of the elements 4, 5 and 6 was left free to get variations. In each stage the parameters of GA were adjusted accomplishing several simulations. For each situation, GA was executed 15 times staying from the configurations without damage.

The objective function of GA used in this work is described below:

$$
a = \sqrt{\frac{\text{eig}(Kd06, Ms)}{2\pi}} \quad \text{at} = \sqrt{\frac{\text{eig}(K, Ms)}{2\pi}}
\quad av = a(34:40) \quad \text{atv} = at(34:40)

Fxe = \sum |av - atv|$$

where: $Kd06$ is the stiffness matrix with damage condition 7; $K$ is the matrix obtained by GA, $K = \text{alfa}$. $Ks$, $Ks$ is the stiffness matrix from the intact structure; and $Ms$ is the mass matrix from the intact structure. The GA consists of the objective function minimization, so, $E_c = 1/Fxe$.

In the Case_1 the variables used in GA were: size of the population = 8; maximum number of generations = 12; and rate of selection = 0.09. Table 1 shows the results obtained. The ideal value of $\text{alfa}$ is 0.4, that means decreasing of 60% in the inertia moment of area on element 5.

In the Case_2 the parameters were: size of the population = 80; number maximum of generations = 100 and rate of selection = 0.09. Table 1 shows the results obtained in the accomplished simulations. In this case, the variation on elements 4, 5 and 6 were represented by $\text{alfa}_1$, $\text{alfa}_2$ and $\text{alfa}_3$, respectively. The ideal values for these parameters are: $\text{alfa}_1 = 1.0$, $\text{alfa}_2 = 0.4$, and $\text{alfa}_3 = 1.0$, considering that doesn’t have fault in elements 4 and 6, and the damage condition 7 on element 5.
The error showed in Table 1 considers the sum of the errors on the seven first natural frequencies considered. It was considered the average on 15 simulations.

Table 1. Values of \( \alpha, \alpha_1, \alpha_2 \) and \( \alpha_3 \).

<table>
<thead>
<tr>
<th>Case_1</th>
<th>Case_2</th>
</tr>
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<tbody>
<tr>
<td>Run</td>
<td>alfa</td>
</tr>
<tr>
<td>1</td>
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</tr>
<tr>
<td>2</td>
<td>0.3835</td>
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<td>3</td>
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<td>7</td>
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<td>8</td>
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<td>9</td>
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</tr>
<tr>
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<td>Average</td>
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<td>Error (%)</td>
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</tbody>
</table>

**Results from Neural Network**

The quantification of the fault, also, was done by a ANN. For this configuration, it was used the backpropagation algorithm, one hidden layer, and the sigmoid activation function. The number of neurons in the hidden layer varied depending of the input pattern.

ANN's training is strongly depending of the input data. If it is representative, it will have great chance to converge. In this sense, three training types were used differentiating the input pattern, in the first one were used the logarithm of the absolute value of FRF up to 2000Hz with an increment of 0.5Hz, in the second one were used the values of the first seven natural frequencies, and finally the percent variation of those natural frequencies. This variation is obtained through Equation 8.

\[
\Delta F(i) = \frac{F_{\text{without fault}}(i) - F_{\text{fault}}(i)}{F_{\text{without fault}}(i)} \times 100; \quad i = 1, 2, \ldots, 7 \quad (8)
\]

where:

- \( F_{\text{without fault}} \) = natural frequency without damage.
- \( F_{\text{fault}} \) = natural frequency with fault.

In the training process, the value 0 (zero) was attributed to the intact structure, while the value 1 (one) corresponds to the pattern with the maximum fault. Thus, if net had success in the training process, the output value should be between the limits 0 and 1, and this result indicates the fault severity.

Of the three used training types what presented better results was the percentage variations of the natural frequencies, in agreement with Equation 8. Figure 4 shows the result of the net using as input data the frequency variations with the numbers of neurons in the hidden layer varying from 1 to 7. The configuration with 5 neurons in the hidden layer showed better generalization capability.

**CONCLUSION**

The combined application of electric impedance techniques and GA can offer a robust and efficient criterion for identification of structural damages. Because, in the first stage of this methodology, the fault location can be determined with accuracy, the set of parameters for the optimization process is drastically reduced. The advantages of GA associated with the small number of variables to adjust make one to believe in the potentiality of the method.

The training of the net is very sensitive to the input data. The frequency percentages presented better results when compared with the training using the FRF curves or using raw values of natural frequencies. Figure 4 showed that the net presented better generalization capability with five neurons in the hidden layer. Once intermediate values of faults obtained in this curve presented larger likeness with the real damage behavior.
In this work it was possible to compare two optimization techniques with different characteristics. In the first one it is necessary to know the mathematical model of the structure (GA), and the other one (ANN) is a non model-based technique. Both techniques showed good results for problems of fault quantification, with the possibility of combined use to verify the results. One of the main advantage of this methodology it is the application for simultaneous damage conditions.

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