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FAULT DETECTION USING PIEZELECTRIC DEVICES AND GENETIC ALGORITHMS

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ABSTRACT

Several studies have been accomplished in the area of identification of mechanical systems and there is a tendency of introducing artificial intelligence in projects of signal monitoring, which would allow automation in the process and characterization of faults, even for complex systems. The problem of variables identification or damage detection in mechanical systems is a class of inverse problem and, therefore, it doesn't present a unique solution. The inverse problem consists in determining the causes based on some observation of their effects and the damaged parameters (crack length and/or location) can be calculated in frequency domain. The proposed methodology in this paper works on frequency domain, and it uses in a first stage, the electric impedance method to determine the location of faults. Later in a second stage takes place the quantification of the faults intensity by using genetic algorithms. The paper concludes with an example of a structure in order to verify the proposed methodology.

INTRODUCTION

The impedance-based health monitoring technique has been applied to a wide variety of structures as a promising tool for real-time structural damage assessments. The basic concept of this technique is to monitor the variations in the structural mechanical impedance caused by the presence of damage [1]. Because structural mechanical impedance measurements can be difficult to obtain, the technique utilizes the electro-mechanically coupling property of piezoelectric materials (PZT). In this coupling property, the PZT's electrical impedance is directly related to the mechanical impedance, and will be also affected by the presence of damage.

In essence damage detection, localization and identification problems are inverse problems [2], since from the vibration response of the structure one seeks to obtain information about its condition (whether the structure is damaged, or not, what kind of defect is present, how big is the defect, etc…). Thus, given information about the vibration response of a structure (in the form of frequency response functions, or modal characteristics), the following inverse problems are addressed: Damage detection problem; damage localization problem and damage quantification problem.

Inverse problems and crack identification problems are of paramount importance for health monitoring and crack identification problems in critical applications in civil, aeronautical, nuclear, and general mechanical engineering. Crack identification problems are considered as output error minimization for appropriately parametrized mechanical models of structures with cracks in statics and dynamics. The inverse problems are formulated as output error minimization problems and they are theoretically studied as a believe optimization problem [3]. Beyond classical numerical optimization, computing tools (for exemplo genetic algorithms) are used for the numerical solution. Mathematical modeling and the numerical study of these problems require high knowledge in computational mechanics and applied optimization. Representative results of this work in progress include genetic algorithm optimization for fault quantification applied to beam structure.

Genetic Algorithm (GA) is a technique based on Darwin's evolution theory. An GA simulates an adaptation process taking an initial population of individuals and applying artificial genetic operators in each generation. Under optimization conditions, each individual of the population is codified as a string or chromosomes, which it represents a possible solution for a certain problem, while the individual 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, through a procedure of crossover. Mutation operator 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 [4].

ELECTRIC IMPEDANCE METHOD

Electric impedance method is a new smart health monitoring technique capable of on-line incipient damage detection in complex structures [5]. The basic concept of this impedance-based structural health monitoring technique is to monitor the variations in the structural mechanical impedance caused by the presence of damage. Since structural mechanical impedance measurements are difficult to obtain, this non-destructive evaluation technique utilizes the electromechanical coupling property of piezoelectric materials. This health monitoring method uses one PZT patch for both the actuating and sensing of the structure's response. A simple impedance model can describe the interaction of a PZT patch with the host structure.

The equation for the PZT connected on the structure can be analyzed in the Eq. 1 for the frequency dependent electrical admittance $Y(\omega)$ (inverse of impedance).

$$Y = i\omega a[\bar{\varepsilon}_{33}^{T}(1 - i\delta) - \frac{Z_S(\omega)}{Z_S(\omega) + Z_a(\omega)} d_{31}^2 Y_{11}^E] \qquad (1)$$

Variables Z_a and Z_s represent the PZT's and the structure's mechanical impedance, respectively. $\hat{Y}_{11}^E$ is the Young's modulus of the PZT at zero electric field, d_{31} is the piezoelectric coupling constant in an arbitrary x-direction at zero stress, $\bar{\varepsilon}_{33}^{T}$ is the dielectric constant at zero stress, δ represents the dielectric loss tangent of the PZT, and a is the geometric constant of the PZT. The Eq. 1 clearly indicates the direct relation of the mechanical impedance of the structure to the electrical impedance bonded onto this structure.

Damage in the structure reflects in changes of parameters such as mass, stiffness, or damping. Assuming that the PZT's parameters remain constant, any changes in the mechanical impedance Z_S change the overall admittance. Previous experiments in the laboratories have shown that the real part of the overall impedance contains sufficient information about the structure, and is more reactive to damage, than the magnitude or the imaginary part. Therefore, all impedance analyses are confined to the real part of the complex impedance.

EVOLUTIONARY COMPUTATION

The search methods and optimization, usually, are classified as techniques based on calculation, search aleatory and enumeration. The methods guided by search aleatory are set in technical enumeration. However they are used for additional information to guide the search.

Nowadays, Evolutionary Computation (EC) is constituted as an alternative to the conventional techniques in search and optimization. CE includes a growing number of methodologies, of which the most important are [6]: Genetic Algorithms, Evolutionary Programming, Evolutionary Strategies, Genetic Programming and Systems Classifiers.

Genetics Algorithms

Genetic Algorithms have been invented by Holland (1975) and is used for a wide variety of problems such as structural analysis, machine learning, cellular manufacturing, combinatorial optimization and game playing. Genetic Algorithm (GA) is a technique based on Darwin's evolution. As GA simulates an adaptation process taking an initial population of individuals and applying to them artificial genetic operators for each generation. Under optimization conditions, each individual of population is codified in a string of chromosomes, which represents a possible solution for a certain problem, while the individuals adaptation is evaluated through a fitness function.

Basically, for individuals highly capable (better solutions) larger opportunities are given of if they reproduce, changing parts of their genetic information, in a procedure of crossover. The mutation operator is used to change some genes in the chromosomes and to cause diversity in the population. The descending 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.

The terminology for genetic algorithms is [7]: *Population*, the collection of individuals represented by chromosomes that make up the possible solutions to the problem being solved. *Chromosome*, the encoding of the parameters for a solution to some objective function we are trying to optimize for. Each individual in the population of possible solutions is encoded into its own, distinct chromosome. The encoding can vary from a simple binary bit string or integer array to elaborate data structures. *Individual*, is a single member of the genetic algorithm population. It is one of the solutions to the objective function. Specific values of the decision variables are coded within the chromosome of the individual. The individual may contain additional information such as its fitness value, the generation number in which it was produced, and other statistics and facts about its identity and fitness. *Gene*, represents a parameter of the objective function. The parameter's locus in the chromosome can be comprised of one or more bits in a binary representation or one or more characters in a higher-level alphabet. The alleles of the gene are all the allowable values of the parameter that can be expressed in the encoding of its locus in the chromosome. *Fitness*, the value of fitness assigned to an individual in the genetic algorithm population. It is the value obtained from the fitness function (objective function) when the individual’s values for the decision variables are used. *Fitness Function*, provides a measure of fitness for a chromosome when applied to the problem to be solved. An evaluation function takes a chromosome as an input, decodes it into its natural representation, applies it to the problem and returns a number or a list of numbers that is a measure of the chromosome's performance on the problem to be solved. The interaction of a chromosome with an evaluation function provides a measure of fitness that the genetic algorithms use when carrying out reproduction. *Generation*, the collection of individuals in a population at one instant of time, or one cycle of the genetic algorithm. Members of the population are selected to be parents to produce offspring via crossover and mutation. The offspring are placed in another population making up the next generation. This selecting parent is repeated, from one population generation to create a population for the next generation, until the stopping criteria for the genetic algorithm has been met.

Genetic operations

In order to improve the current population, genetic algorithms commonly use three different genetic operations. These are *selection*, *crossover*, and *mutation*. Both selection and crossover can be viewed as operations that force the population to converge. They do this by promoting genetic qualities that are already present in the population. Conversely, mutation promotes diversity within the population. In general, selection is a fitness preserving operation, crossover attempts to use current positive attributes to enhance fitness, and mutation introduces new qualities in an attempt to increase fitness.

Roulette Wheel selection: This means that the chance of an individual being chosen is proportional to its fitness, Fig. 1. Individuals are not removed from the source population, so those with a high fitness will be chosen more frequently than those with a low fitness.

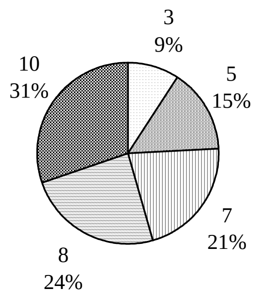

Figure 1. Roulette Wheel Selection.

Crossover: A reproduction operator, which forms a new chromosome by combining parts of each one of two parent chromosomes. The simplest form is single-point crossover, in which an arbitrary point in the chromosome is picked. All the information from Parent A is copied from the start up to the crossover point, then all the information from Parent B is copied from the crossover point to the end of the chromosome. The new chromosome thus gets the head of one parent's chromosome combined with the tail of the other. Variations exist which use more than one crossover point, or combine information from parents in other ways.

The crossover operation is the most important genetic operation. This operation is used to create new individuals by combining the qualities of 2 or more genes, Fig. 2.

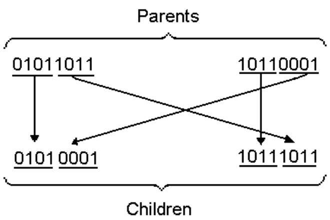

Figure 2. The crossover operation.

Mutation: A reproduction operator, which forms a new chromosome by doing (usually small) alterations to the values of bits.

The general genetic algorithm uses several simple operations in order to simulate evolution. The goal of the genetic algorithm is to come up with a "good", but not necessarily optimal solution to the problem.

METHODOLOGY

Nature is a source of inspiration for engineering. 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, or prognosis of the life remains of the mechanical system in normal work condition. 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 by using genetic algorithms. Genetic algorithms (GA) are optimization processes founded on principles of natural evolution and selection. A GA takes an initial population of individuals and then applies artificial genetic operators them, generation after generation.

This method is based on high frequency ranges and local vibrations modes, therefore, the area of influence of each PZT 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 optimization, Figure 3.

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 a unique solution. Any optimization method that is supposed 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 proposed 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.

The damage quantification problems are approached using the Frequency Response Functions (FRF) measured for a number of DOF's (Degree of Freedom) and for a number of frequencies. The FRF's are measured for the case of a healthy structure and for the structure under test. The method works and it uses the differences between the measured values and the reference values (measures accomplished in the structure without fault). After the damage quantification the finite element method is used to model the tested structure. The fundamental stiffness of the obtained damaged substructures is identified by minimizing an objective function of the corresponding stiffness differences of the healthy structure and the structure under test. The stiffness decrease in the finite elements is considered as an indication for the presence of damage. Accordingly, the damage is localized further down to the damaged finite elements of the structure. The stiffness decrease also gives a measure for the extent of the damage - that is directly proportional to the stiffness decrease.

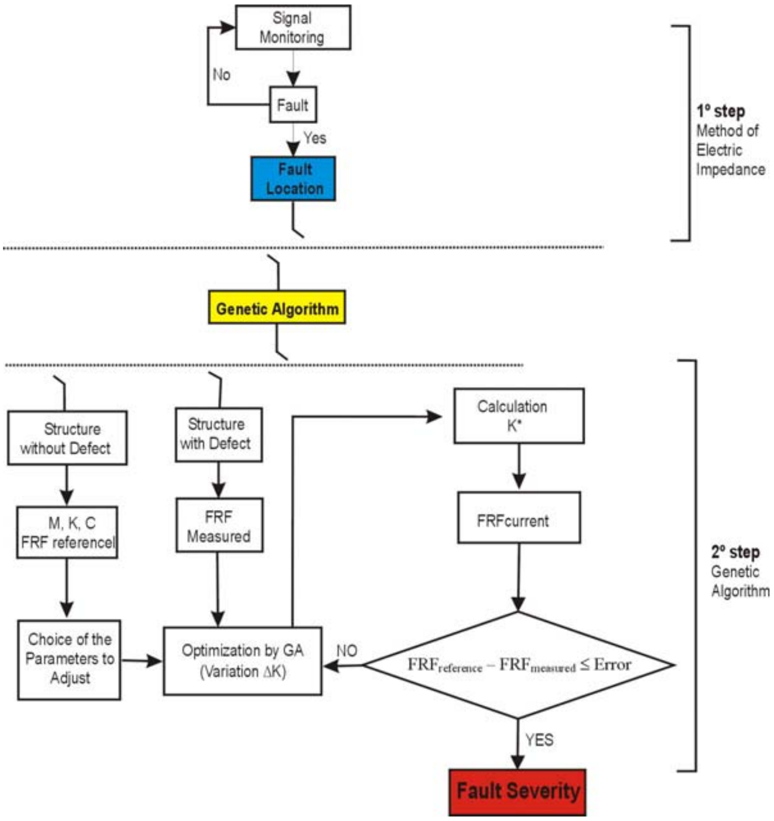

Figure 3. Chart of the proposed methodology

The choice of parameters that will be used to quantify the fault is accomplished after the finding of the fault region. After the definition of these parameters, the adjustment of FRFmeasured (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 fault. For the analyzed case it was considered M* = M and C* = C.

RESULTS

Summary of how variables were implemented in GA.

1. Code: Binary;
2. To generate initial population: Aleatory;
3. Objective function: minimize the FRF;
4. Selection type: implemented the type “Roulette”;
5. Crossing: implemented the types with one point and two points;
6. Mutation: implemented the uniform type;
7. Stopping criteria: if one of the stop approaches is satisfied the process it is concluded. In otherwise to return to the step 3.

The fault detection in a structure is accomplished through the variation of the curve Function of the Response in Frequency, FRF. The fault simulated in this work consists of a traverse cut to the beam, with width b and depth a. To simulate the defect, it is considered the variation of the moment of inertia I of the element, where, the width of the fault is maintained constant, and the same of the element. In the equation 2 it is possible to observe as the stiffness, K, obtained through the method of finite elements is influenced by the variation of the moment of inertia I.

$$\mathrm{I} \rightarrow K = K\left(\frac{E.\mathrm{I}}{L^3}\cdot[.....]\right) \rightarrow\ f = f(K,M) \qquad (2)$$

In Fig. 4 it is possible to notice how the depth of the fault influences in the reduction of the inertia moment.

The objective function of GA used in this work is described below. The GA consists of the objective function minimization, so, *Ec = 1/Fxe.*

$$f_m = f_{reference}(1:7) \qquad f_{aj} = f_{mensured}(1:7)$$

$$Fxe = \sum \left| f_m - f_{aj} \right| \qquad (3)$$

where $f_{reference}(1:7)$ and $f_{mensured}(1:7)$ refers the first seven natural frequencies of the structure.

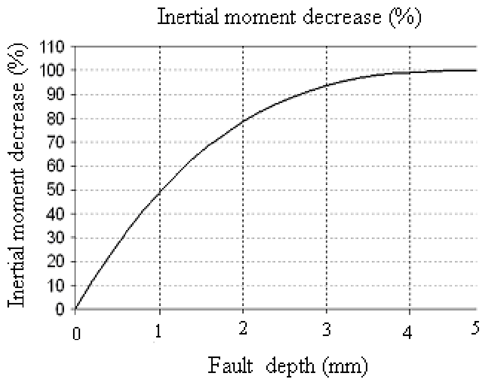

Figure 4. Analysis of the influence of the fault introduced in the structure.

The numerical application is carried out on an aluminum beam with 25 millimeters of width, 5 mm of thickness and 500 mm of length, Fig. 5. The beam is modeled by finite elements through the program "SmartSys", which includes the electromechanical coupling of the piezoelectric sensors/actuators. 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 beam and the Frequency Response Function (FRF) of the system was considered for different situations of defects and loads.

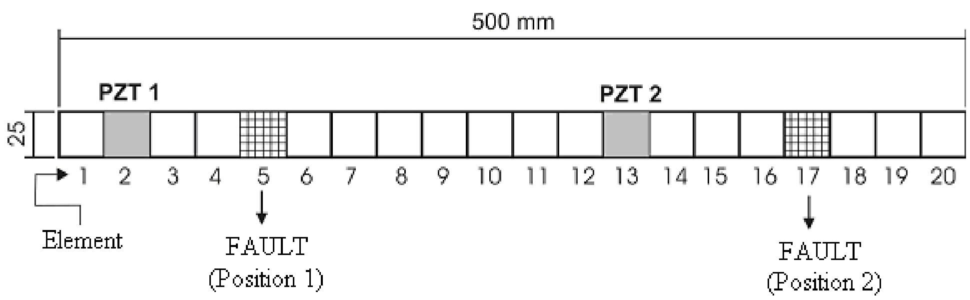

Figure 5. Discretized beam with element fifth and seventeenth highlighted.

Initially, it is done a test to evaluate the need and importance of the first stage of the proposed methodology. The fault in the 5th element of the structure was accomplished altering in 20% it's inertia moment. In this first stage all elements were considered in the optimization process. Meaning that we let free to be changed all inertia moments of the elements. The Tab. 1 shows the medium data obtained after 3 executions of the genetic algorithm. The accurate data (or ideals) for the inertia moments are: element five equal to 0.8000 and others 1.0000.

Table 1. Data obtained for optimization considering all elements.

Element	1	2	3	4	5
I (m^4)	0.6950	0.6100	0.9261	0.7073	0.9326

Element	6	7	8	9	10
I (m^4)	0.9818	0.9472	0.5859	0.9560	0.9560

Element	11	12	13	14	15
I (m^4)	0.9114	0.8528	0.9906	0.8944	0.7367
Element	16	17	18	19	20
I (m^4)	0.9724	0.9994	0.8217	0.7202	0.9443

In the previous situation it was considered a fault in the 5th element of the structure and with adjustment possibility in every inertia moment of the structure. We can observe that the algorithm didn't converge to the ideal situation, that is to say, it didn't get to detect that the fault was in the element 5.

When we used the electric impedance technique to accomplish the structure monitoring, an area where is located the fault is found and with that the search space is reduced.

The presented results consider the fault in the fifth and seventeenth elements, simultaneously. The damage was simulated decreasing the area inertia moment of 20% on fifth element and 15% on seventeenth element. Figure 5 shows this elements as well as the PZT positions. Starting from the model in finite elements, the FRF was set up for the conditions of mentioned faults up to 2000 Hz, where the appearance of the first seven natural frequencies can be verified beam with the element five and seven.

The variables used in GA were: size of the population = 80; maximum number of generations = 80; crossover probability = 0.90 (90%); and mutation probability = 0.05 (5%).

Table 2 shows the results obtained from the accomplished simulations. In this case, the variation on elements 4, 5, 16 and 17 were represented by I^4, I^5, I^{16} and I^{17}, respectively. The ideal values of these parameters to be found by GA are: $I^4 = 1.0$, $I^5 = 0.8$, $I^{16} = 1.0$ and $I^{17} = 0.85$. The error considers the sum of the errors on the seven first natural frequencies considered. It was considered the average on 15 runs.

Table 2. Results obtaed by using GA.

Run	1	2	3	4	5	6	7	8	9	10	**Average**	**Standard deviation**
Generation	80	80	80	80	80	80	80	80	80	80		
I^4 (m^4)	1.000	0.998	0.999	1.000	0.992	1.000	1.000	0.999	0.995	0.999	0.9982	0.00266
I^5 (m^4)	0.799	0.806	0.804	0.800	0.802	0.801	0.800	0.813	0.814	0.804	0.8043	0.00531
I^{16} (m^4)	1.000	0.991	0.996	0.999	0.987	0.999	1.000	0.987	0.988	0.997	0.9944	0.00554
I^{17} (m^4)	0.850	0.845	0.851	0.850	0.846	0.851	0.850	0.851	0.853	0.850	0.8497	0.00241

CONCLUSION

Contrary to most model-based Non Destructive Evaluation (NDE) techniques, which rely on the lower order global modes, an approach utilizing high frequency structural excitation was developed. This technique would be more useful in identifying and tracking small defects, in the sense that damage is a local phenomena.

Another advantage of this methodology is that multiple damage, in several different locations, can be also analyzed. It is almost an impossible task to optimize by GA for all possible combination of multiple damages, in different areas, if global frequency response functions are utilized. However, in this method, the limited sensing area of each PZT sensor helps to isolate the effect of damage on the signature from other far field changes. Thus, the fault in a remote location has only minor influence to the other PZT sensors, and each PZT sensor reflects only the changes occurred in near field.

It was proposed a combined damage detection methodology using electrical impedance technique, and an optimization procedure. GA was applied to quantify the fault, however, any other Structure Health Monitoring (SHM) algorithm that considers nonlinearities should be applied in it. Impedance technique gives clear information about the damage location, and therefore, it is used to select a small subset of parameters. The amount of damage is, then, described by values of parameter variation on the model design level.

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.

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