DAMAGE DETECTION USING GLOBAL OPTIMIZATION AND PARAMETER IDENTIFICATION TECHNIQUES

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Abstract. *Many structures, during their useful life, are submitted to several types of static and dynamic loads. These loads and the structural deterioration process can cause different types of structural damages. Damage characterization and the knowledge of the changes in the material properties corresponding to these damages depend on the type of material and on the structural configuration. The thermal modeling of a damaged structure is done through boundary elements methods, providing numerical data to the inverse problem. Many techniques, such as genetic algorithms (GAs) and artificial neural networks (ANNs), have been used to localize and to identify damages in a structure and several algorithms have been implemented in the literature to characterize these damages. The GA is a global optimization technique that looks for a minimum difference between measured and computed potential values. On the other hand, the ANN is a technique of parameter identification, which simulates the non-linear behavior between internal potential values on the structure and the damage parameters. In this work, a comparison among the results obtained by these different techniques was performed and optimal results for the damage localization were obtained.*

Keywords*: damage detection, optimization, genetic algorithm, artificial neural network*

1. INTRODUCTION

The damage detection is an important branch of engineering where some measurements can be applied to guarantee the structural security. The life time of any structure can be predicted through the correct determination of the damage. The damage detection problem can be ranked as a problem of system identification or an inverse problem. The boundary element method (BEM) is used in the mathematic modeling of the direct problem. Parameter identification techniques and optimization techniques can be used to determine the unknown parameters of the damage. Several works have been developed to solve this type of problem. Among the parameter identification techniques, the artificial neural networks (ANN's) are very used. In the optimization techniques, the genetic algorithms (GA's) belong to the category of global optimization where the global optimum of the system has larger chances of being obtained.

In the works of Stravoulakis and Antes (1998), Liang and Hwu (2001), Burczynski and Beluch (2001), the BEM is used to model the direct mechanical problem numerically. Stravoulakis and Antes (1998) use the sequential quadratic programming (SQP) to determine the local optimum of the error (difference between the measured and the computed value) and the genetic algorithm (GA), to determine the global optimum of the same function. Liang and Hwu (2001) apply a backpropagation neural network for the on-line identification of holes or cracks in composite structures. Burczynski and Beluch (2001) use evolutionary algorithms at the identification of cracks and the problem is formulated as the minimization of the difference between the measured and computed values of displacements or stresses at selected boundary nodes. The work of Liu et al. (2002) proposes a method of inverse analysis using a backpropagation neural network and the computational mechanics, matching the of the finite element method with the boundary integral equation.

In this work, an example of heat flow through a simple conduction at a thin plate is investigated. The BEM is used to simulate the potential values on the external surface of the plate at given points. These potential values represent the distribution of temperatures on the plate. An assumption is made that the conduction of heat through possible internal holes in the plate is considered null (adiabatic holes). The use of thermal techniques shows that the distribution of temperatures on a plate changes due to the variations in the mechanical properties of the plate, what could be related to a determined damage. ANN's and AG's were used for the identification of the number of holes and its locations. The Matlab® was used for the development of the damage detection program.

2. GENETIC ALGORITHMS

The genetic algorithm (GA) is a search method based on the processes of natural evolution. This method works with a set of possible solutions for a given problem, composing the initial population. In this algorithm the problem variables are represented as genes in a chromosome, also denominated an individual. Starting from an initial population, the individuals with better adapted genetic characteristics have higher chances of surviving and reproducing.

According to Burczynski and Beluch (2001), the GA's are methods that do not depend on the choice of the initial point, increasing the chances of obtaining the optimum global of the system. So that the population is diversified and maintain certain acquired adaptation characteristics by the previous generations, the genetic operators (selection, crossover and mutation) can be used. These operators transform the population through successive generations, extending the search until arriving to a satisfactory result. Figure 1 shows how these genetic operators can be employed.

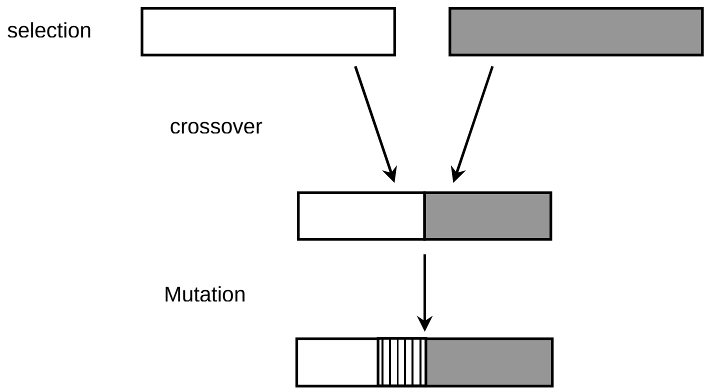

Figure 1. Genetic operators.

2.1. Genetic operators

- ***Selection*****:** is an artificial version of the natural selection process (Goldberg, 1989). In this operator type, the selection of the most able individuals of the current generation, which are chosen for the next generation, is made. The selection technique of the roulette type is the most divulged and used (Spall, 2003). Another technique is the uniform stochastic selection, where the individuals of the current generation are chosen in a random way for the reproduction. Associated to the selection process there is the elitism strategy that helps at the improvement of the GA convergence, where a certain number of individuals in each generation is passed directly to the next generation (Mitchell, 1999; Spall, 2003).
- ***Crossover*****:** is used to generate a new population through the recombination of solutions (chromosomes). A pair of individuals is divided at places randomly chosen and the genetic materials of these individuals are recombined, forming new individuals. These new individuals are again evaluated and, then, they receive a new value of individual aptitude. Among the crossover techniques there are the single, the scattered and the heuristic crossover.
- ***Mutation*****:** promotes a genetic diversity once the initial population can be insufficient of information to find the solution (Spall, 2003). With the use of this operator, a larger sweeping of the search space is made, avoiding that the GA converges for local minima. Techniques as uniform and Gaussian mutation can be used.

2.2. Parameters of the genetic algorithms

Several parameters of the GA influence in the behavior of the method. The most important parameters are: population size, generation number, crossover probability and mutation probability. The choice of the best configuration for the parameters is difficult and this choice depends on the realization of a great number of experiments and tests. The population size influences the global performance of the GA. This parameter indicates the number of chromosomes existing in each population, defining the search space of the problem. When this parameter is high, a biggest part of the search space of the problem is swept; nevertheless, a high computational cost is obtained to carry out many evaluations of the fitness function. On the other hand, when the population size is small, the algorithm performance decreases.

3. ARTIFICIAL NEURAL NETWORKS

The artificial neural networks (ANN's) are computational techniques that present a mathematic model to represent the human brain and to try to simulate the learning process of this brain. These ANN's are made by small unities called neurons. A biological neuron has several entrance ramifications known as dendrites (input terminals), a cellular body where the nucleus with the whole genetic information is located, and an axon (output terminal). The communication among neurons is made in the contact area among two neurons through the transmission of nervous pulses.

3.1. Model of an artificial neuron

The artificial neuron represents a simplified model of the biological neuron. According to Fig. 2, x_1 to x_n represent the n input terminals (dendrites), y_1 to y_m, the m output terminals, w_{1j} to w_{nj} are the weights in the inputs, representing the synapses (for a communication among neurons) among the neurons, and the threshold function represents the function in the output of the neuron. Every input sign is multiplied by a weight, indicating the influence of these signs in the output of the neuron. Then, a weighted sum is made, producing an activity level. If this level exceeds a given threshold, the information is passed for other neurons. In this case, the neuron is active.

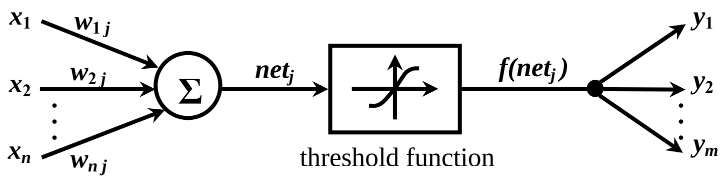

Figure 2. An artificial neuron structure (adapted of Chong & Zak, 2001).

The threshold function $f(.)$ can be of the threshold-type, or a sigmoid or a linear function. For a threshold-type, the output is set for one out of two possible levels, depending on the input level being bigger or smaller than a threshold value. For the sigmoid and linear functions, the output varies continuously with changes in the input, the linear function being a particular case in which the output is proportional to the total input.

3.2. Architecture of the artificial neural networks

An ANN is formed by the interconnected neurons whose inputs can be obtained from the outputs of other neurons or from input nodes. Different configurations of the artificial neuron can be made to develop different network topologies (Rao et al., 2005). The network topologies can be defined for the layer number, amount of neurons in the layers and the connection type among the neurons. Among the existent configurations, the ANN can be feedforward or feedback. At the feedforward neural networks, the neurons are interconnected in layers, but the flow of data only occurs in a direction (Chong and Zak, 2001). At the feedback neural networks, there is at least a feedback cycle, in other words, a neuron receives the information of neurons of the previous layer and of a subsequent layer.

The first layer at the network is the input layer, the last layer is the output layer and the layers between the input and output layer are the hidden layers. More complex problems can be implemented due to the use of the hidden layers; however the network learning becomes more difficult.

3.3. Training of an artificial neural network

The training is an iterative process of weight adjustment of an ANN. An ANN learns when a generalized solution for a class of problems is reached, in other words, when a given input leads to a target output. After the training, the ANN learns how to proceed for other input data in the problem domain. The training or learning algorithms differ in the manner how the weights are modified. When an external agent is used to indicate to the network an acceptable solution of the problem, the learning is said to be supervised. In this kind of training, the input and output vectors are known in the problem. The lack of the external agent leads to an unsupervised learning.

In this work a backpropagation neural network (BPN) is used, through a feedforward configuration and the backpropagation learning algorithm. The backpropagation algorithm carries out a supervised learning where the desired outputs are given as part of the training vector. In the training stage, this algorithm operates in a sequence of two steps. First, a sign is presented to the input layer of the network and this sign is propagated through the network until an answer is produced by the output layer. In the second step, the adaptation stage of the network is initiated. In this stage the obtained output is compared to the desired output for the input sign, producing a mistake. Finally, the mistake is passed back through the network for the weight adjustment among the layers to produce the correct output (Bigus, 1996). Details of the operation of this training algorithm can be verified in Lopes (2007).

4. DAMAGE DETECTION

In this work, a conduction problem is modeled, considering the heat flow due to the temperature distribution on the external surface of a thin plate. As assumption, the conduction of heat through possible internal holes in the plate is considered null (adiabatic holes). The BEM is used to simulate the potential values on the external surface of the plate and at given interior points.

To obtain the unknown parameters of the damage, such as location and size, through the GA, a functional can be defined as the difference between the measured values (in this work, simulated values) of the potential difference (between the plate without damage and the plate with damage) and the calculated values obtained from the damage detection program. This functional corresponds to the fitness function of the GA. The minimization of this fitness function allows the damage detection program to find the unknown parameters of the damage. The potential values are simulated through the BEM for the potential in 49 internal points of the plate, as shown at Fig.3. The functional formulation is shown at Eq. (1)

$$\mathbf{J}_j = \frac{1}{2}\sum_{i=1}^{n}\left(\mathbf{simulated}_i - \mathbf{calculated}_{ji}\right)^2 \tag{1}$$

being n the sensor number present in the plate; $\mathbf{simulated}_i$ the vector line of simulate values of the potential difference, representing the measured values in the plate for a determined damage; and, $\mathbf{calculated}_{ji}$ the vector of calculated values through the damage detection program for each individual j.

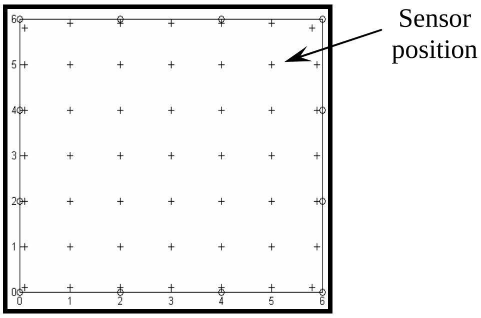

Figure 3. Sensor distribution for the GA.

The ANN's simulate the non-linear behavior between the measured potential values in the plate and the hole parameters (location and size). In ANN's, information regarding the potential difference in the plate are supplied in the input of the network, and the data, amount, location and size (radius) of the hole, are supplied in the output. Holes of different sizes and at different places can be part of the data supplied to the net. Having defined the input and output data, the next step is to build the network and, then, this network can be trained. Finally, the network can be tested for other potential difference data, obtaining as answer, the amount, location and size of the hole. For the assembly of the input data of the network, initially 25 internal points were considered. These internal points represent the sensors on the plate. After, the number of sensor was decreased to 15, 9 and 5, respectively. In the present work, the sensors were uniformly distributed on the plate and no positioning study of the sensors was performed. The distribution of the sensors on the plate, for each case, is shown at Fig. 4(a), Fig. 4(b), Fig. 4(c) and Fig. 4(d).

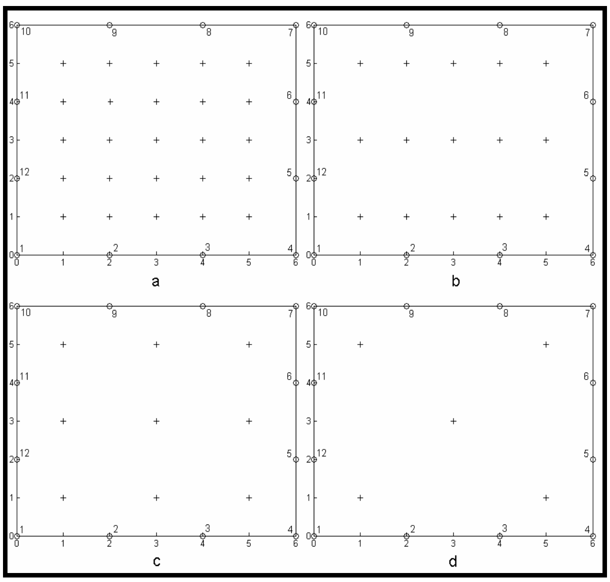

Figure 4. Sensor distribution for the ANN: (a) 25, (b) 15, (c) 9 and (d) 5.

4.1. Chromosome configuration of the genetic algorithm

To solve the damage detection problem, an initial population is supplied to the GA. The chromosome that represents an individual of the population can be made according to the vector presented in Eq. (2):

$$c = \begin{bmatrix} g_1 & g_2 & g_3 & g_4 & \cdots & g_{n+3} \end{bmatrix} \tag{2}$$

where:
g_1 – first gene representing the *x* position of the hole center;
g_2 – second gene representing the *y* position of the hole center;
g_3 – third gene representing the hole radius;
$g_4 \;\cdots\; g_{n+3}$ – fourth gene and the subsequent genes representing the measures of the potential difference between the plate without hole and the plate with hole.

When the plate presents two holes, the assembly for the chromosome obeys the following structure: gene 1 represents the hole number in the plate, genes 2 and 3 represent the coordinates of the first hole, genes 4 and 5 represent the coordinates of the second hole, genes 6 and 7 represent the radius of the first hole and second hole, respectively, and the genes starting from gene 8 represent the measures of the potential difference at the plate in study.

4.2. Configuration of the input data for the artificial neural network

The potential values in the plate are obtained through the BEM for the potential problem, considering nine different hole positions. Considering a single hole with a radius equal to 0,15 *cm* at each position (0.5;0.5) *cm*, (0.5;3) *cm*, (0.5;5.5) *cm*, (3;0.5) *cm*, (3;3) *cm*, (3;5.5) *cm*, (5.5;0.5) *cm*, (5.5;3) *cm* e (5.5;5.5) *cm*, the normalized values of the potential difference were found. Then, other hole of radius equal to 0.05 *cm* was also analyzed in each mentioned position. If the number of holes in the plate is two, the stored data are the values of the normalized potential difference, the hole number, the parameters of the first hole and the parameters of the second hole.

5. RESULTS AND DISCUSSIONS

5.1. Analysis of the results obtained from the genetic algorithm

In this topic, the results obtained by the damage detection program are analyzed for a problem of heat flow in a thin plate. Initially, a plate without damage and with the dimensions (6×6) *cm*, Fig. 5, was simulated through the boundary element method (BEM). The boundary of the plate was discretized into 12 elements and the value of the potential was evaluated at 49 internal points. The contour conditions for the problem are represented in this figure, where q represents the heat flow and u represents the temperature at the boundary. Then, a plate with a central hole of radius 0.06 *cm*, with the same dimensions and boundary conditions, was also simulated, and the obtained results for the potential were compared with the plate without damage.

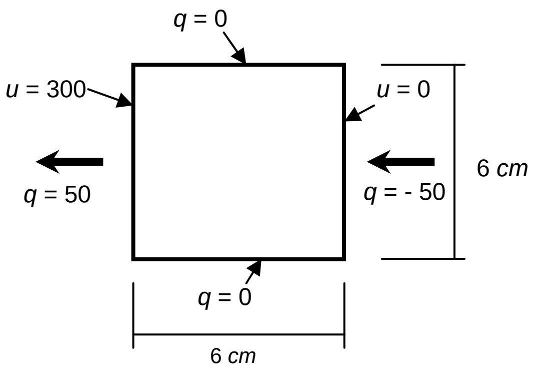

Figure 5. Boundary conditions of a square plate.

The stopping criterion of the GA was configured for the generation number equal to 75. The other parameters of the GA, for the first simulation, were configured as:

- Initial population size: 330 individuals;

- Crossover probability: 0.8;
- Mutation probability: 0.2;
- Elitism: 2;
- Crossover function: heuristic;
- Mutation function: Gaussian.

For the program that detects a hole, the chromosome configuration presented in item 4.1 was used to form the initial population of GA. Through the potential-BEM code, the potential values at 49 internal points were obtained for the plate without damage and for the plate with damage. Initially for one hole, the radius considered in the problem was 15 *cm*, 0.03 *cm* e 0.09 *cm*. For each one of these radius, the coordinate x of the hole center was varied of 0.5 *cm* to 5.0 *cm* and the coordinate y of the hole center was varied of 0.5 *cm* to 5.5 *cm*, both coordinates with a step size of 0.5 *cm*. Then, 110 different positions for each radius in the plate were simulated and the respective values of the potential difference were stored for a-posteriori processing. In the program that runs the GA, the values of the potential difference were normalized, taking in consideration the largest value of this difference. Finally, the initial population with 330 individuals can be formed. As the potential values near the right border (temperature equal to zero) of the plate are close to zero, the potential difference is used instead of the direct use of the potential value.

The discretization of the plate is showed at Fig. 6 and the result found by the damage detection program for a hole in the position (3;3) *cm* and radius equal to 0.06 *cm*. The program was run only 5 times, because there was no significant difference when this value was increased. The real position of the hole is represented in continuous line and the results found by the GA in non continuous lines.

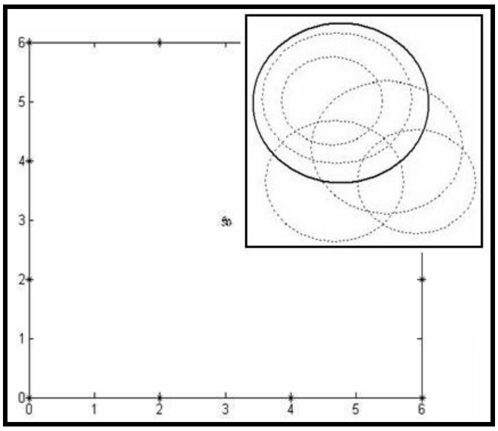

Figure 6. Real and simulated hole for the first simulation.

The results for the second simulation are shown at Fig. 7, where the elitism value is changed from 2 to 10, in other words, guaranteeing that 10 individuals survive in the next generation. In Fig. 7, one can verify that the holes are concentric, and a small uncertainty exists in the value of the hole position. Also, the radius is not much sensitive to the variation of the GA parameters, presenting a significant uncertainty. The average time to run the two examples in a computer with a clock of 3.0 GHz was about 100 s, with a difference of 5%.

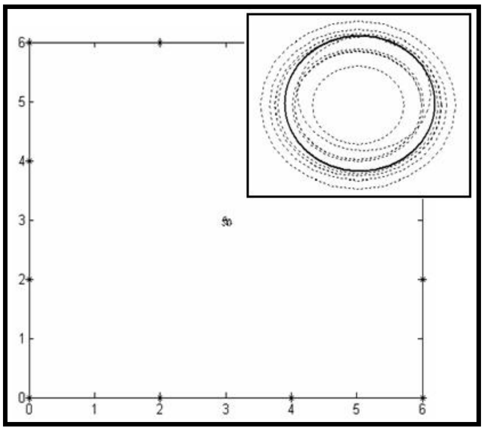

Figure 7. Real and simulated hole for the second simulation.

A hole in the position (4;5) *cm* and radius equal to 0.06 *cm* was considered in the third simulation. The program was run 5 times and the average time was of 119.8 s. The results found for the hole parameters (xc - coordinated *x*; yc - coordinated *y*; r - radius), with 99.7% of confidence (medium value more or less three times the standard deviation), for the three previous examples are presented in Tab. 1:

Table 1. Results obtained by the GA.

Parameters	**Simulation 1**	**Simulation 2**	**Simulation 3**
xc [cm]	3.014 ± 0.074	3.000 ± 0.005	3.965 ± 0.124
yc [cm]	2.971 ± 0.091	3.001 ± 0.010	5.002 ± 0.089
r [cm]	0.042 ± 0.021	0.061 ± 0.038	0.006 ± 0.021

The developed program finds an occurrence area of the damage, what can be verified by the presented results. In the GA, there is a small mutation presence and a crossover function that is different for each run of the algorithm, in other words, there is an associated occurrence probability. Besides, little information is supplied to GA, being necessary to improve the input data of the algorithm.

For the program that detects up to two holes, the initial population formation took into consideration the 330 individuals representing a hole in the plate and other 330 individuals representing two holes, totaling 660 individuals. For the individual formation with two holes, while a hole of radius 0.03 *cm* at the position (3;3) *cm* was kept fixed, a hole of radius 0.15 *cm* swept the plate as done for a hole. For the second individual set, the radius values were inverted, in other words, in the position (3;3) *cm* there was a hole of radius 0.15 *cm* and for the position that varied, a hole of radius 0.03 *cm*. For the third individual set, both the holes had a radius of 0.03 *cm*.

The values of the potential difference were normalized with relationship to the largest value of the potential difference, completing the formation of the initial population of GA. Finally, the formation of the chromosome was made as explained in item 4.1. The results obtained from this program for the detection of a hole in the plate were similar to the results already presented. However, there was difficulty in detecting two holes in the plate. Perhaps, the values of the radius were very small and, moreover, there was lack of consistent information supplied by the BEM. Finally, the chromosome codification of the GA should be the most random to consider all possible solutions of the problem.

5.2. Analysis of the results obtained from the artificial neural network

Considering the same problem of heat flow from the previous item, initially the presence of a single hole in the structure was studied. Then, the influence in the results was verified when the number of sensor at the plate was decreased. However, no study regarding the sensor positioning was accomplished in this work. As well as the input data, the values used to test the network were assembled following the sensor distribution scheme at the plate presented in the Chapter 4. A hole of radius 0.10 *cm* in each position ((1;1) *cm*, (2;4) *cm*, (3;3) *cm*, (4;2) *cm* and (5;5) *cm*) was considered to test the network. The best choice for the parameters of the backpropagation neural network (BPN) was:

- Neuron number in the input layer: 50;
- Neuron number in the hidden layer: 4;
- Neuron number in the output layer: 4;
- Threshold function in the input and hidden layers: tan-sigmoid transfer function (tansig);
- Threshold function in the output layer: linear transfer function (purelin);
- Training function: gradient descent with momentum and adaptive learning rate (traingdx);
- Error goal: 1×10^{-5};
- Number of epochs: 5000;
- Learning rate: 0.05.

The influence of the reduction of the sensor number in the results found by the ANN for a hole in the position (3;3) *cm* and of radius equal to 0.10 *cm* can be analyzed at Tab.2. At Tab.3, the results for a hole in the position (4;2) *cm* and of same radius that the previous hole are presented. The problem domain is reduced when there is a decrease of the sensor number on the plate. The obtained results depend on the distribution of the sensor on the plate and of the quality of the input data.

Table 2. Influence of the reduction of the sensor number for a central hole.

real				**Simulated**		
Sensors number	***xc***	***yc***	***r***	***xc***	***yc***	***r***
25	3	3	0.10	3.0035	3.0003	0.0992
15	3	3	0.10	2.9949	2.9977	0.1009
9	3	3	0.10	2.9998	2.9973	0.1002
5	3	3	0.10	3.0010	2.9959	0.1000

Table 3. Influence of the reduction of the sensor number for a non-central hole.

real				**simulated**		
Sensors number	***xc***	***yc***	***r***	***xc***	***yc***	***r***
25	4	2	0.10	3,4568	0,5676	0,0994
15	4	2	0.10	2,1225	0,5135	0,0994
9	4	2	0.10	2,4224	0,4355	0,0224
5	4	2	0.10	1,4138	0,9774	0,1000

Figure 8 shows the results obtained for a hole of radius 0.10 *cm* in each position ((1;1) *cm*, (2;4) *cm*, (3;3) *cm*, (4;2) *cm* and (5;5) *cm*), only considering 5 sensor on the plate and, whose distribution is presented in item 4.

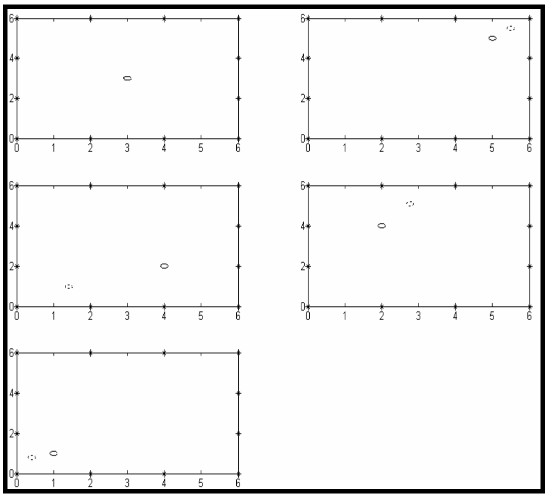

Figure 8. Results obtained by the ANN for 5 sensors.

In the simulated examples that follow, the input data in the damage detection program needed to be modified, allowing the ANN to detect until a hole. The attention was at the detection of more than a hole and how to perform this detection, this way, 25 sensors were considered on the plate and a reduction in the sensor number was not done. The Fig. 9(a) shows the outputs of the damage detection program for a hole in the position (3;3) *cm* and radius of 0.10 *cm*. At the Fig. 9(b), is presented another hole in the position (4;2) *cm* and of same radius that the previous example. At the Fig. 9(c), are presented two holes in the positions (1;3) *cm* and (5;3) *cm*, both of them with a radius of 0.10 *cm*. Another simulate example was two holes in the plate, one hole in the position (1;1) *cm* and radius 0.15 *cm* and other hole in the position (3;3) *cm* and radius 0.10 *cm*, according to Fig. 9(d). Finally, at Fig. 9(e) are two holes in a plate, one hole in the position (5;5) *cm* and radius 0.15 *cm* and other hole in the position (3;3) *cm* and radius 0.10 *cm*.

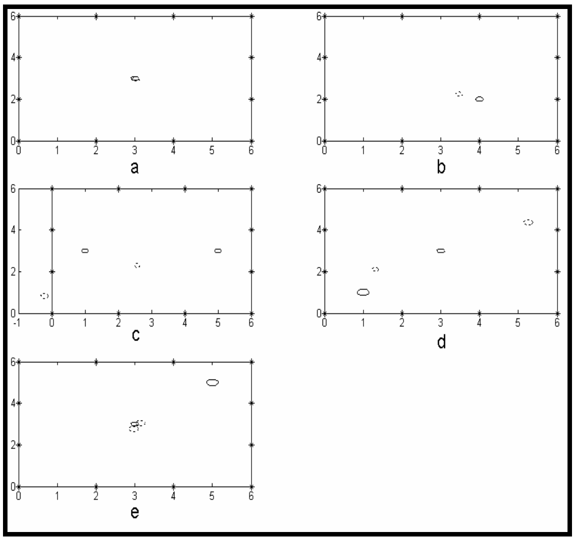

Figure 9. Results for until two holes in the plate.

The detection of more a hole presented great difficulties. As was already mentioned, great part of this difficulty is due to the bad quality of the input data of the damage detection program. Finally, the results depend on the quality of the input data of the ANN and of the appropriate choice of the configuration parameters of this network. To continue with the detection of more than a hole in the plate through the ANN, the direct problem (data obtained from the BEM) should be gotten better. New loadings on the plate and a new BEM should be considered, allowing to identify circular and elliptic holes, and also cracks, in the structures.

6. CONCLUSIONS AND FUTURE WORK

6.1. Conclusions

In this work two numerical techniques for damage detection were used, one through the method of global optimization based on an heuristic, the genetic algorithm (GA), and other technique through a parameter identification procedure, the artificial neural networks (ANN's). In this work, a heat flow problem was investigated, and the boundary element method (BEM) for the potential was used as the code for the direct problem. The BEM for the potential supplies the necessary information (potential values at internal points of the plate) to the damage detection program.

For the damage detection problem using GA, it was verified that this algorithm is a hard technique, because this technique needs to analyze several times the problem for the best configuration choice of the parameters. Moreover, the GA also presents a high computational cost due to the several evaluations of the fitness function. The damage detection program using GA finds an occurrence area of the hole; however, the program presents difficulty in finding the value of the radius of the hole.

An advantage of the parameter identification techniques in relation to the techniques of global optimization is that for the first ones, the damage detection problem can be solved more quickly. In comparison with the GA, the damage detection program solved through the ANN presented better results as the determination of the radius size; however, the ANN presented difficulties in finding the exact area of the occurrence of the damage. Possibly, this fact was due to training problems of the network; in other words, the problem was due to the choice of the configuration parameters of the network and the choice of the input and output data.

Finally, the GA was found to be useful in locating the occurrence area of the hole while the ANN was useful to find the size of this hole. Taking into account the advantages of each technique, a hybrid approach could be considered for future work. In this approach type, the GA could be used to find the occurrence area of the damage, and then the ANN could find the exact size of this damage, reducing the search time for the optimum result. An important observation is that very small holes are difficult to observe by the damage detection program, mainly when these holes are close to the borders of the plate.

6.1. Prespectives for future work

Several approaches for future work on this matter could be considered, such as:

- Study about sensor positioning on the plate, seeking to reduce the number of sensors;
- Substitution of the potential variable at the BEM by its derivative (i.e., gradient components), because the derivative is more sensitive to the changes in the information supplied to the problem;

- Use of BEM for the elasticity problem, where the variable is the displacement and the derivative is the deformation;
- Use of a hybrid approach, considering the advantages of each technique; in other words, the use of the GA to find the occurrence area of the hole and the use of the ANN to find the exact size of this hole;
- Use of the Kalman filter (KF) as the identification procedure for the damage detection problem;
- Comparison among the results obtained by the three techniques, GA, KF and ANN's;
- Modifications in the damage detection problem to allow the identification of elliptic holes and cracks. For the detection of cracks in the structure, the use of BEM for the fracture mechanics is necessary;
- Use of other methods of global optimization, such as taboo search, ant colony, and differential evolution, for the comparison among the results obtained.

7. ACKNOWLEDGEMENTS

The authors would like to acknowledge the financial support from the Brazilian agencies CNPq – Conselho Nacional de Desenvolvimento Científico e Tecnológico, and FAPEMIG – Fundação de Amparo à Pesquisa do Estado de Minas Gerais.

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9. RESPONSIBILITY NOTICE