The application of Genetic Algorithm for sensor placement of PZT wafers towards the application in structural health monitoring

Zainab M Ismail, Mohammad Ali H Fakih, Samir A Mustapha, and Hussein A Tarhini

1 Department of Mechanical Engineering, Maroun Semaan Faculty of Engineering and Architecture, American University of Beirut, Beirut, Lebanon

sm154@aub.edu.lb (Samir A Mustapha)

2 Department of Industrial Engineering and Management, Maroun Semaan Faculty of Engineering and Architecture, American University of Beirut, Beirut, Lebanon

Abstract

The optimization of the number and location of piezoelectric (PZT) wafers, used in sensor networks for continuous monitoring of structures, is not completely well developed. This paper presents an effective method based on genetic algorithm for network optimization of piezoelectric wafers, towards the application in the field of structural health monitoring. The proposed objective function is to maximize the coverage of the monitored area, represented by a set of control points, while using the least possible number of sensors. In the optimum solution, each control point should be covered by a user-defined number of sensing paths, defined as the coverage level. During the optimization process, any location on the plate is considered as a potential position for a PZT wafer.

A MATLAB code was developed to implement the algorithm, and selected simulation cases have been executed to demonstrate the efficiency of the proposed optimization algorithm. The algorithm provides the flexibility of changing a wide range of problem parameters such as the number of piezoelectric wafers, their coverage range, the required coverage level and the number of control points. The tractability of the model proposed was improved by feeding the solver an initial solution that made the branch and bound technique less extensive.

Keywords: Sensor network, optimization, Genetic Algorithm, piezoelectric, non-convex surfaces, structural health monitoring

1. Introduction

Implementation of continuous structural monitoring systems in aerospace, mechanical and civil structures would form a major establishment in the field of damage detection and assessment. Continuous monitoring requires the constant collection of data from sensors that are embedded within the structure. The number of sensors needed to cover a structure and their placement is associated with many challenges, i.e., they depend on the type of data collected (vibration, strain, etc.) and the approach adopted for data analysis.
Various metaheuristic algorithms exist in literature with many common foundations (1). They implement a form of stochastic optimization, so that the solution found is dependent on the set of random variables generated (2). In combinatorial optimization, by searching over a large set of feasible solutions, metaheuristics can often find good solutions with less computational effort than iterative methods or simple heuristics (2). As such, they are useful approaches for optimization problems. Padula and Kincaid (1) have described several combinatorial optimization methods like Tabu Search (TS), Simulated Annealing (SA), and Genetic Algorithm (GA) for actuator/sensor placement.

An effective method based on genetic algorithms (GAs) has been presented by Jin et al. (3) to minimize the total distance between the sensors, of a wireless sensor network, and the sink (data collector). This would allow for an energy efficient and a longer living sensor network. Optimization was achieved by dividing the sensor network into clusters, each having a cluster-head responsible of collecting the data from all the nodes within the cluster. Later on, cluster-heads will transmit the compressed data to the sink. The authors have used the GA-based approach to determine both the number and locations of the cluster-heads, to minimize the communication distance within the sensor network. In addition, they have proposed an improved genetic algorithm, in which a two-gene-bit crossover and a two-gene-bit mutation are applied on the parent strings. Heinzelman (4), Tillett (5), and Ostrovsky (6) have also worked earlier on minimizing the communication distance for a predetermined number of cluster-heads. Mallardo et al. (7) have presented a passive sensing algorithm based on GA and ANN techniques, to optimize sensor-positions for impact detection on composite structures. The optimization process took into consideration the uncertainty due to environmental conditions and the possibility of malfunctioning of one or more sensors.

In this study, a novel model for PZT-wafer-placement optimization was developed. The objective function of the algorithm was to maximize the coverage of the monitored area, to a predefined level of coverage. The model takes into account several practical constraints such as the attenuation and the coverage of the excited wave. Since GA was proven to be effective in sensor optimization problems (2, 8, 9), it was adopted in this study and further validated on plates of different shapes with non-convex surfaces.

2. Methodology

The proposed optimization algorithm evolves by measuring the coverage on a finite number of control points and maximizing the number of covered points. The coverage level \( n \), which is a parameter chosen according to the user’s requirements, is defined as the number of sensing paths required to cover a control point in order to be considered as covered. Huang and Tseng (10) stated that an accurate damage localization requires the coverage of three sensing paths \( n = 3 \), according to triangulation protocols. A sensing path (defined by any pair of PZTs) covers a control point if it lies within a given distance from the centerline of the path. This distance is referred to as the path coverage \( z \) and was set to 40 mm based on literature (11, 12). Other constraints included the plate’s geometry, the number of available PZT wafers \( N \), the minimum distance between each two PZTs \( d_{\text{min}} = 40 \) mm to avoid having multiple PZTs at the same location, and the minimum angle between two sensing paths \( \alpha_{\text{min}} = 10^\circ \) to ensure that the sensing paths are not collinear. Further, a maximum
spacing between the actuator-sensor pair was defined to account for the attenuation in
the wave signal, in this case it was set to be less than $d_{\text{effective}} = 600$ mm. The
geometry of the plate was defined as a polygon having a certain number of vertices. The
sensor locations were assumed to be continuous variables, as opposed to Thiene et al.
(13) in which finite possible locations, for the PZT wafers, were predefined. For clarity,
a sketch illustrating the model constraints and terminology is presented in Figure 1.

Figure 1. A sketch illustrating the optimization model constraints and terminology

The fitness function, to be maximized, was defined as the percentage of covered control
points. Since the problem is a non-convex problem with binary variables, it is
impossible to check whether the solution is a local or a global optimum. Thus, to reduce
the probability of being stuck on a bad local maximum, a code that generates a
preliminary solution and feeds it into the optimization algorithm was developed. The
preliminary solution distributes, uniformly, the available number of sensors along the
edges of the plate geometry. The algorithm runs automatically for multiple times,
through which it changes the number of sensors and calculates the corresponding
coverage, until it reaches the predefined desired coverage (in this study it was set to
95% of the control points) with the least possible number of sensors.

2.1 Parameter notation

$K$ : Set of control points
$(x_k, y_k)$ : Coordinates of control point $k$
$N$ : Number of PZT wafers to be placed
$n$ : Coverage level
$d_{\min}$ : Minimum distance between each two PZTs
$d_{\text{effective}}$ : Maximum spacing between the actuator-sensor pair
$\alpha_{\min}$ : Minimum angle between two sensing paths
$z$ : Path coverage
2.2 Decision variables

The definitions and equations of the current and the following sections are valid ∀:

\[ k \in K; \quad i, j, i_1, j_1, i_2, j_2 \in N; \quad i < j; \quad i_1 < j_1; \quad i_2 < j_2. \]

\((x_i, y_i)\): Optimized coordinates of PZT wafer \(i\)

\[ C_k = \begin{cases} 1 & \text{if control point } k \text{ is covered} \\ 0 & \text{otherwise} \end{cases} \]

\[ C_{ijk} = \begin{cases} 1 & \text{if control point } k \text{ is covered by PZT wafer line } (i, j) \\ 0 & \text{otherwise} \end{cases} \]

\[ d_{ij} = \text{Distance between PZT wafer } i \text{ and PZT wafer } j \]

\[ d_{ijk} = \text{Distance between PZT wafer line } (i, j) \text{ and control point } k \]

\[ d_{ik} = \text{Distance between PZT wafer } i \text{ and control point } k \]

2.3 Model

\[
\max \sum_{k \in K} C_k 
\]

(1)

\[
d_{ij}^2 = (x_i - x_j)^2 + (y_i - y_j)^2
\]

(2)

\[
d_{ik}^2 = (x_i - x_k)^2 + (y_i - y_k)^2
\]

(3)

\[
d_{ijk} = \frac{|(y_j - x_i)x_k - (x_j - x_i)x_k + x_j x_k - y_j x_k|}{\sqrt{(y_j - x_i)^2 + (x_j - x_i)^2}}
\]

(4)

\[ C_{ijk} = 0 \text{ if } d_{ijk} > z \]

(5)

\[ C_{ijk} = 0 \text{ if } d_{ik} > d_{ij} \]

(6)

\[ C_{ijk} = 0 \text{ if } d_{jk} > d_{ij} \]

(7)

\[ C_{ijk} = 0 \text{ if } d_{ij} > d_{effective} \]

(8)

\[ C_k = 0 \text{ if } \sum_{i \in I} \sum_{j \in J} C_{ijk} < n \]

(9)
The objective function is to maximize the number of covered control points as shown in equation (1). Equations (2) and (3) calculate the distance between two PZT wafers and the distance between a PZT wafer and a control point $k$, respectively. Equation (4) calculates the distance between the sensing path $(i,j)$ and the control point $k$. In equation (5), for a specific control point $k$ to be covered by a path, $d_{ijk}$ must be less than the path coverage distance $z$. Equations (6) and (7) represent the triangular inequality equations between an actuator-sensor pair and a control point. These equations ensure that the control points covered must fall within the range of the sensing path. Equation (8) disregards all paths longer than $d_{\text{effective}}$. Equation (9) describes the required coverage level for all control points. Equation (10) summarizes the minimum angle constraint ($\alpha_{\text{min}}$) which is the angle between each pair of paths. Equation (11) makes sure that the PZT wafers are separated by a distance $\geq d_{\text{min}}$. Equation (12) defines the plates’ geometry.

GA was used to implement the proposed model. A typical GA requires a genetic representation of the solution domain, and a fitness function to evaluate it. Once these elements are defined, a GA proceeds to initialize a population of solutions and then improve it through repetitive application of the mutation, crossover, inversion and selection operators. The built-in MATLAB GA function was used with the intermediate crossover function and adaptive feasible mutation. A population size of 200 was used in each generation to reduce the chance of getting a local optimum. “Rank” scaling function was used to give a scaled fitness value for each single individual in the population. The scaled fitness value of an individual is what defines its probability to be selected as a parent, using the “Stochastic uniform” selection function. The selected parents are used to form a second generation population of solutions, through a combination of genetic operators including crossover and mutation. Five percent of the population, with the best fitness values, are chosen to pass to the next generation without undergoing crossover and mutation operations (elitist selection). New parents are selected for each new child, and the process continues until a new population of solutions of appropriate size is generated. In the next generation, the average fitness should have increased, since the best organisms from the first generation were mostly selected for breeding, along with a small proportion of less fit solutions. Less fit solutions could be also produced due to random mutation and crossover between good individuals. However, these solutions ensure genetic diversity within the genetic pool of the parents, and therefore ensure the genetic diversity of the subsequent generation of children. The algorithm terminates when a maximum number of generations has been produced, a satisfactory fitness level has been reached for the population, or the highest
ranking solution’s fitness has reached a plateau such that successive iterations no longer produce better results. The mutation probability, crossover probability and population size parameters should be tuned to find reasonable settings for the problem under study. A very small mutation rate may lead to a genetic drift (which is non-ergodic in nature), and a very high rate may lead to the loss of good individuals from the population. When the crossover rate is too high, a premature convergence of the genetic algorithm may result. A crossover rate of 0.8 was taken in this study.

3. Results and discussion

The model was validated on a square-shaped panel containing two circular holes, as well as on a T-shaped panel. As mentioned earlier, the level of coverage (\(m\)) is a user defined attribute that can be controlled to achieve any level of coverage, at the cost of longer computational time and higher number of sensors. Level 3 (\(m = 3\)) optimization was chosen, in this case, for demonstration on the non-convex plates. Figure 2 shows the monitored geometries with sufficient number of control points randomly distributed to cover the plates, in addition to the preliminary solution of the PZT wafers and the covered control points. During the optimization process, the selected number of sensors is the minimum \(N\) giving a coverage of at least 95%.

Starting with the square panel, the optimization algorithm led to a minimum number of \(N = 13\) sensors required to achieve a coverage of 95%. However, the coverage of the preliminary solution was below 84% for the same number of sensors. For the T-shaped panel, the preliminary coverage was 84%, while it was found to be 96.47% for the optimized solution, for a minimized \(N = 12\) sensors. The covered and uncovered zones for the optimized solutions are shown in Figure 3. The number of sensing paths lying in the neighborhood of a point is not the only indicator of its coverage. However, the angle between each pair of paths and the path length play a main role while calculating the coverage of each point. Figure 4 (a) and Figure 4 (b) show the variation in coverage percentage with the number of sensors for the square panel and the T-shaped panel, respectively. It was shown that once a decent coverage is achieved (about 95%), any additional sensors may not contribute in a significant improvement in the coverage. Noteworthy coverage improvement was achieved between the initial preliminary solutions and the optimized ones. This indicates the high efficiency of the proposed optimization approach.
To check the repeatability of the results, based on the proposed optimization process, a fixed set of number of sensors ($N$), known to give an optimized coverage percentage of above 80%, was chosen for the two different test panels. The optimized sensor network of each value of $N$ (from the chosen set) was computed 10 times, separately. Figure 5 shows the mean coverage percentage, of the two panels, with error bars showing the variation among the 10 trials. Once $N$ becomes sufficient to yield an optimized coverage percentage of above 90%, high stability in the percentage coverage is noticed, with a maximum standard deviation of 2.3%.
Figure 5. Histograms of the mean coverage percentage with error bars (of the 10 trials) for different numbers of sensors: (a) square panel and (b) T-shaped panel

4. Conclusions

A novel approach for PZT-wafer-network placement, based on genetic algorithm, has been presented in this paper. The proposed objective function was to maximize the coverage of the monitored area, represented by a set of control points, while using the least possible number of sensors. Simulation results were presented for two cases, a square panel with geometrical discontinuity and a T-shaped panel. The results showed a major improvement in the coverage level between the preliminary and optimized solutions. A coverage of 95.25% was achieved on the square panel, while a coverage of 96.47% was obtained for the T-shaped panel, based on the minimized number of sensors. The repeatability of the results was demonstrated and the variations in the solutions were minimal. Future work will include experimental validation, as well as applying the approach on structures that are in service.

Acknowledgements

We acknowledge the support from CNRS for their award #103085. We would also like to acknowledge the financial support of the University Research Board at the American University of Beirut for their awards #103008 and 103371.

References and footnotes


