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Design of Optimal Layout of Active Sensing Diagnostic Network for Achieving Highest Damage Detection Capability in Structures

V. JANAPATI, K. LONKAR and F.-K. CHANG

ABSTRACT

An investigation is performed to develop a methodology for optimizing the layout of piezoelectric transducers based actuator-sensor network that will maximize the detection capability of a given SHM system for a hot spot in aerospace structures. The method utilizes a simulation tool for wave propagation as a basis to integrate pre-selected diagnostic algorithm with an optimization tool to maximize the probability of detection (POD) for a given damage size in a structure. The proposed method minimizes the number of actuators and sensors while maximizing POD through the selection of optimal location for each sensor and actuator. Fatigue cracks in metallic structures were studied in this investigation. This paper will highlight the method as well as some results for metallic structures.

INTRODUCTION

Extensive studies have been carried out recently for diagnostic algorithms for detecting damage in structures with built-in sensors and actuators. The detection capability of a given SHM system strongly depends on not only its algorithm, but also the sensor-actuator density, their distribution, and the hardware sensitivities (signal to noise ratio).

However, there have been limited studies on sensor network optimization [1-8] for SHM systems. Combinatorial optimization algorithms, particularly Tabu Search (TS), Simulated Annealing (SA), and Genetic Algorithm (GA) have been proposed for the optimization of the sensor network. Sensor network optimization methodology for passive SHM system has been well documented by Markmiller and Chang [3]. Guo et al. [4] implemented improved strategies for GA based technique to optimize sensor locations for truss structure. Gao and Rose [5] presented a GA-based technique which optimizes the sensor placement by minimizing miss-detection probability with the

Vishnuvardhan Janapati, Kuldeep Lonkar and Fu-Kuo Chang
Department of Aeronautics & Astronautics, Stanford University, CA-94305, USA

covariance matrix adaptation evolutionary strategy (CMAES). Das et al. [6] estimated the sensor certainty region through experimental data and used it to optimize sensor network by minimizing the overlap region. Guratzsch and Mahadevan [7] developed a probabilistic Finite Element Analysis based technique which includes model input uncertainty. It was used in optimizing the sensor network by maximizing the reliability of damage detection. Flynn and Todd [8] proposed an approach to optimize the sensor network by minimizing Bayes risk. This approach utilizes pulse-echo and pitch-catch data for damage detection.

In this study, we are proposing a model-assisted probability of detection (POD) based methodology to optimize an active sensing network to achieve highest POD. An efficient analytical tool is developed which is integrated with a spectral element method (SEM) based wave propagation simulation tool, Piezo Enabled Spectral Element Analysis (PESEA) [9].

Problem Statement

Given a geometry and material properties of a structure and a pre-selected diagnostic SHM system, it is desired to determine the optimal sensor network layout such that the POD is maximum for a given crack size '*a*' which may appear anywhere in a defined region.

METHOD OF APPROACH

In this study, an active sensing diagnostic algorithm (pitch-patch and pulse-echo) [10] is selected throughout the investigation for detecting damage in structures. For a given sensor network layout, the detectability depends on the sensitivity of scatter signal (difference between the baseline signal from the undamaged pristine structure and the current signal from the damaged structure) to exceed a predefined threshold. The distance is defined as damage detection distance (D^3). Unfortunately, D^3 strongly depends on the material properties, the geometry of the structure, the sensor-actuator layout, and the hardware and software. If the software and hardware are chosen, value of D^3 must be determined before the network is selected.

In this work, a model-assisted sensor network optimization technique is developed to calculate D^3 for the entire structure. A spectral element method based numerical tool is used to simulate ultrasonic wave propagation in structures to estimate D^3 profile. Once the D^3 profile is estimated, genetic algorithm (GA) [11] based optimization algorithm is implemented to optimize the sensor network by maximizing probability of detection of the network (POD_{net}) which is defined in the next section. A schematic of the sensor network optimization technique proposed in this work is shown in Figure 1.

For a given structure with an SHM system, there are three parameters which can affect D^3: (i) critical damage size '*a*', (ii) damage orientation, and (iii) environmental conditions. $ScNR_{aX}$ is defined as scatter to noise ratio and is given by Equation 1, where S_{aX} is the scatter amplitude due to a damage of size '*a*' for wave propagation distance '*X*', *N* is the amplitude of noise. $ScNR_{aX}$ is proportional to the damage size which means higher D^3 for higher damage sizes and vice-versa. Damage orientation also affects the scatter present in the signal by reflecting the propagating wave in different directions. When the temperature of the structure increases, wave dispersion and noise in the sensor signal increase which results in lower $ScNR_{aX}$ and lower D^3. Variations in the above three parameters is important and should be considered in designing an optimized sensor network for a given structure.

$$ScNR_{aX} = 20\log_{10}\left(\frac{S_{aX}}{N}\right) \tag{1}$$

$$if\ ScNR_{aX} > 10 \rightarrow D^3 = X \tag{2}$$

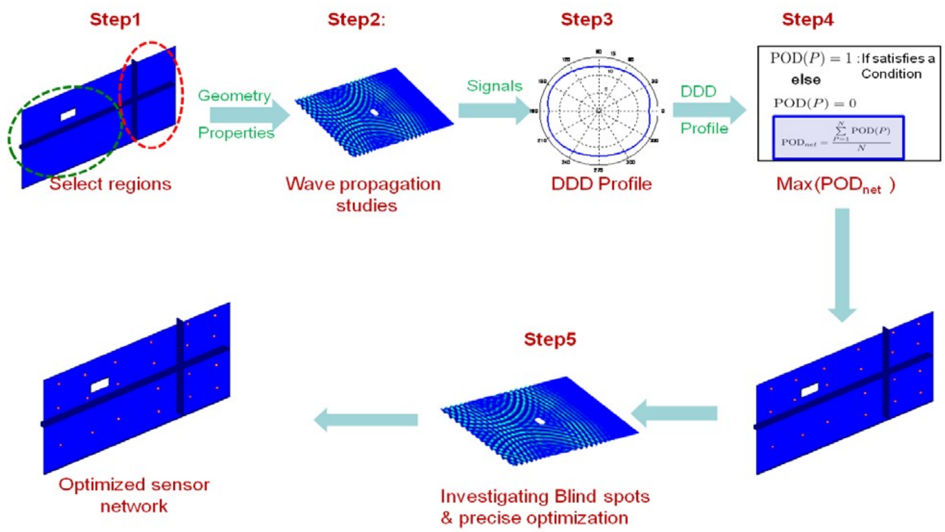

Figure 1. Schematic of the proposed approach for the sensor network optimization of SHM system.

SEM simulations to calculate D^3

In this study, spectral element method (SEM) based code is used to solve coupled equations of motion and Gauss's law to physically model piezoelectric transducers and simulate ultrasonic wave propagation in structures [9]. Attenuation in viscoelastic materials is implemented by introducing Rayleigh damping. Change in ambient temperature affects the sensor signal. This effect is incorporated in PESEA by varying the material properties of the structure, adhesive, and piezoelectric transducers with temperature [12]. PESEA can also be used to model ultrasonic wave propagation in complex structures with damage, such as crack in metallic structures and debond/delamination in composite structures. Crack in metallic structures is mode led by separating the nodes of appropriate neighboring elements to create a volume split. Debond/delamination is modeled by creating duplicate nodes and creating a volume split. Nodes in the area, where debond/delamination needs to be modeled are separated by small distance, like 5 µm.

In this study, simulations were carried out for an aluminium plate (10"× 23" × 2 mm) at different temperatures (25°C, 45°C, 65°C and 90°C) and crack orientations. In the simulations, 0.25" diameter and 10 mil thick lead zirconate titanate (PZT) elements were used to actuate 250 kHz ultrasonic Lamb waves and the propagating waves were sensed by sensor elements 2 to 6. Simulated sensor data were analysed to calculate D^3 profile through the estimation $ScNR_{aX}$ for different wave propagation distances and different environmental conditions. From Figure 2, D^3 can be estimated as 9.75".

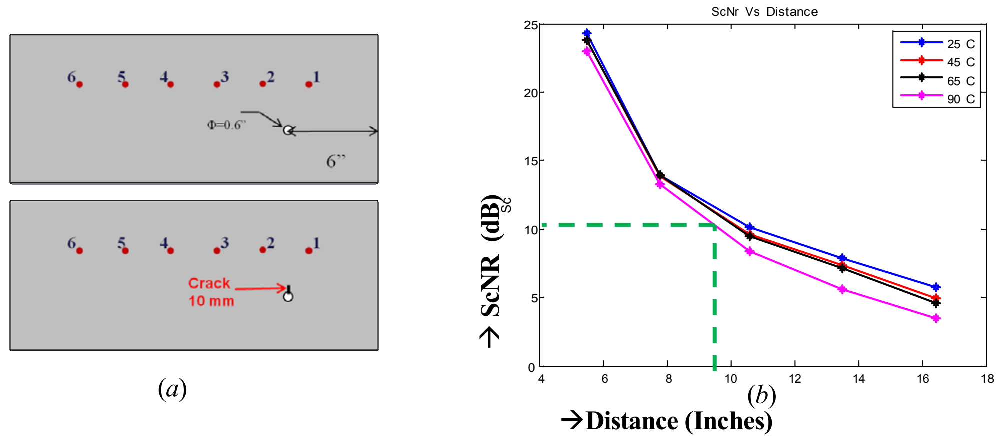

Figure 2. (a) Schematic of aluminum plate (with and without crack) attached with PZT elements, (b) and Scatter to Noise Ratio ($ScNR_{aX}$) for different wave propagation distances under varying temperature conditions.

Probability of Detection of Sensor Network (POD_{net})

POD_{net} is defined as the overall network *POD* of the monitoring system in detecting damage anywhere in the structure. In general, POD_{net} should be 100% for a given monitoring system. In this work, total structure is discretized into a grid of points based on the required resolution in X and Y directions and it is assumed that the detectability of a point is either '0' or '1' based on the following criterion.

$$POD_a(P)\begin{cases} =1 & if \sum_{a=1}^{m}\sum_{s=1}^{n} D_{\min} \le D(a,s,P) \le D^3 \\ =0 & otherwise \end{cases} \quad (3)$$

Where, *P* is index of a point in the grid, *a, s* are indices of actuator and sensor respectively, *m*, *n* are numbers of actuator and sensors respectively. D_{min} is minimum distance between any actuator and sensor (this is required due to the signals' crosstalk). *D(a,s,P)* is the summation of distance from actuator '*a*' to point '*P*' and from point '*P*' to sensor '*s*'.

Genetic Algorithm (GA) based optimization tool

Evolutionary computation techniques such as GA [11] are search algorithms based on the mechanics of natural selection. They are robust, conceptually simple and very efficient in finding a near global optimum. The GA based inverse method of reconstruction starts with a population of randomly guessed candidate solutions (initially three sensor locations parameter sets) where each candidate solution corresponds to the location of sensors. For each candidate solution, POD_{net} is evaluated using the objective function (Equation 4). Candidate solutions which have high POD_{net} value can be placed in the selection process to go to the next generation while the rest of them are discarded. Typically, this process needs to be carried out several hundred times to achieve the maximum POD_{net} value required for the given application. Once the maximum POD_{net} reaches/exceeds the required POD_{net} specified in the requirement, then the optimization process stops its evolution. If the maximum POD_{net} in a generation doesn't reach required POD_{net}, then one more sensor is added and the evolution process starts all over again and this process is repeated until required POD_{net} is achieved. The objective function (POD_{net}) to be maximized during this process is given by the following equation, where *P* is index of the point and *N* is total number of points in the grid.

$$POD_{net} = \frac{\sum_{P=1}^{N} POD_a(P)}{N} \tag{4}$$

Effect of System and Environmental Parameters on *POD_{net}*

POD_{net} of a structure varies with variations in the sensor placement, the number of sensors, D^3 profile and the temperature. Hence, it is important to keep these parameters in mind while designing a sensor network for a given structure. In the following illustrations, 18”×15”×0.078” thick aluminum plate and 250 kHz wave frequency were considered.

Effect of sensor placement on POD_{net}

In order to show the importance of the sensor placement on overall detectability, two sensor network configurations (original and modified) with six element sensor network were considered. Modified configuration was the same as the original configuration except the location of one sensor which was changed slightly. POD_{net} of sensor network was calculated for the original and the modified configurations. Figure 3 shows the effect of sensor placement on the POD_{net}. It can be observed that optimized sensor placement influences the overall damage detectability.

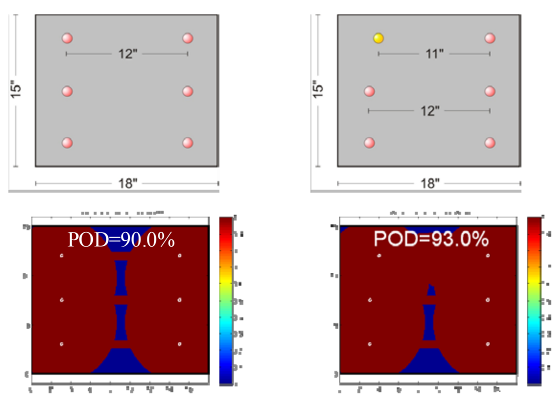

Figure 3. Effect of sensor placement on the PODnet.

Effect of varying number of sensors and D^3 *profile*

For a given structure, POD_{net} can be improved by increasing the number of sensors. Figure 4 shows that increasing the number of sensors from 4 to 6 increases

POD_{net} from 48% to 75% which is a huge improvement. Similarly, increasing the D^3 improves the detection capability which is evident from Figure 4 (b). For a given monitoring system, D^3 can be improved by using more sensitive sensors, better data acquisition and data analysis software, and using optimum signal parameters such as the actuation frequency, the number of cycles in the input signal.

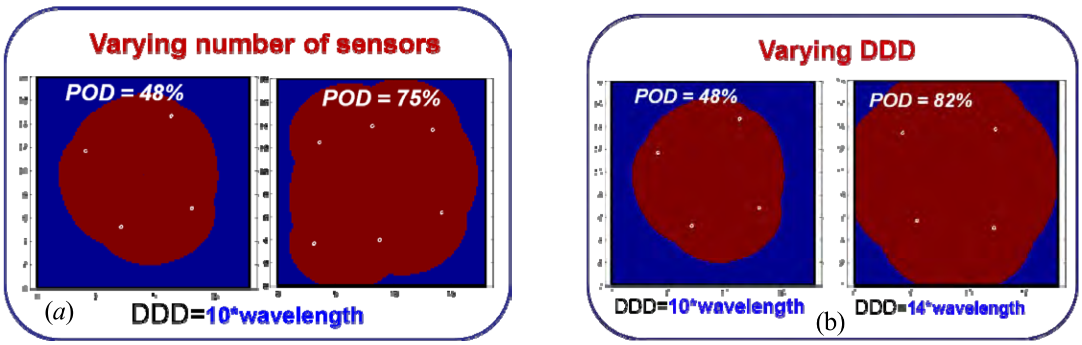

Figure 4. (a) Effect of number of sensors on POD_{net}, (b) Effect of varying DDD on POD_{net}

Effect of temperature on POD_{net}

SEM based wave propagation model was used to simulate the sensor signals when the sample is at 25°C, 40°C and 55°C temperatures. The simulated sensor data were analyzed to estimate D^3 profile, which was used to calculate POD_{net}. It was observed that D^3 decreases with increase in temperature as noise in the signal increases. From Figure 5, it can be seen that POD_{net} of the given sensor network reduces with the increase in environmental temperature.

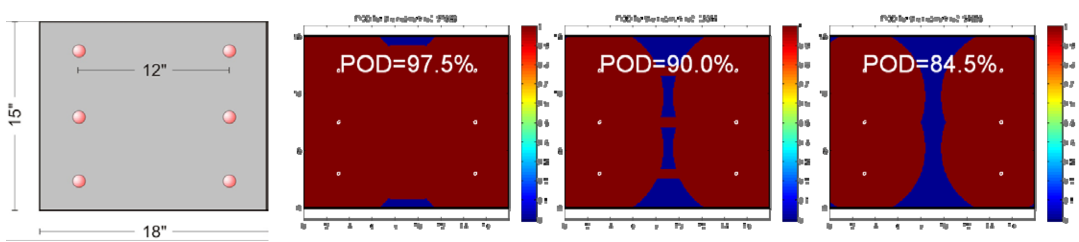

Figure 5. (a) Effect of temperature on POD_{net}

Diagnostic Methods

Higher damage detectability for a given sensor network can be achieved by fusing the data collected in pulse-echo (PE) and pitch-catch (PC) based data collection techniques. In this proposed sensor network optimization technique, pulse-echo and pitch-catch techniques are fused to improve the area covered by each sensor. As an example, for a given isotropic sample attached with two sensors, POD_{net} is estimated for pulse-echo, pitch-catch, and the data fusion technique. Figure 6 shows that combining the advantages of PE and PC through data fusion, POD_{net} increases considerably. The blind region in Figure 6 (a) represents the near-field area of sensors which has low sensitivity for damage detection due to the overlap of the actuation signal with the sensor signal. The size of the blind region depends on the actuation frequency, the number of cycles in the input signal and the velocity of wave. POD_a for the points inside the blind region is zero.

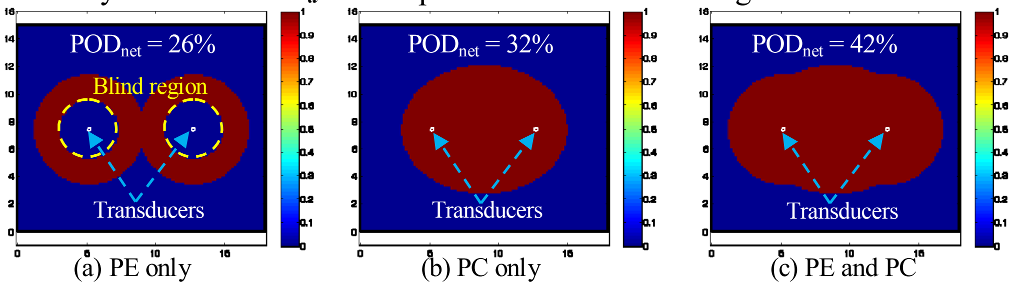

Figure 6. Comparison of coverage area with Pulse-echo and Pitch-Catch methods.

To compare the coverage area for isotropic and anisotropic in PE configuration, single sensor attached on an isotropic (aluminum) and an anisotropic (unidirectional carbon composite) samples is considered. Figure 7 shows the coverage area profile for isotropic and anisotropic samples, which is proportional to the attenuation profile of respective samples.

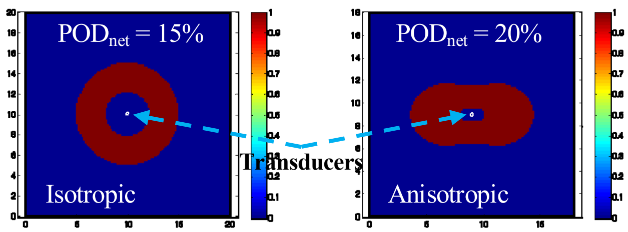

Figure 7. Comparison of single sensor coverage area for isotropic and anisotropic samples.

AN EXAMPLE

To summarize the proposed methodology of sensor network optimization, an aluminum stiffener panel with a cutout shown in Figure 8 was considered as an example. Dimensions of the structure were 375 mm × 375 mm × 2 mm thickness while the dimensions of cut-out were 50 mm × 50 mm with a crack initiated at one of the corners of the cut out. Required POD_{net} for the structure was specified as 100%.

SEM based wave propagation model was used for the structure shown in Figure 8 (a) and is calibrated to estimate in-situ material properties, and attenuation profile. Several transducer elements were modeled on the structure and calibrated SEM model was used to generate simulated sensor signal with and without simulated damage. Simulated sensor signals were analyzed, as mentioned in previous section, to estimate D^3 profile in different regions on the structure.

In order to achieve practical sensor network, along with D^3 profile, a few more parameters such as the minimum distance from edges, the minimum and maximum distance between any actuator-sensor pair were given as input to the sensor network optimization tool. The minimum distance between PZT elements and edges of the structure was selected as 3" so that direct and boundary reflected sensor signal were well separated. In order to remove the effect of crosstalk in PC network configuration, the minimum distance between actuator and sensor was constrained to 4" and to improve the damage detectability maximum distance between any actuator-sensor pair was constrained to 90% of D^3 in that direction. The above parameters allowed the sensor network optimization tool to minimize the computational time in designing a more practical sensor network to satisfy the required performance levels set for the structure.

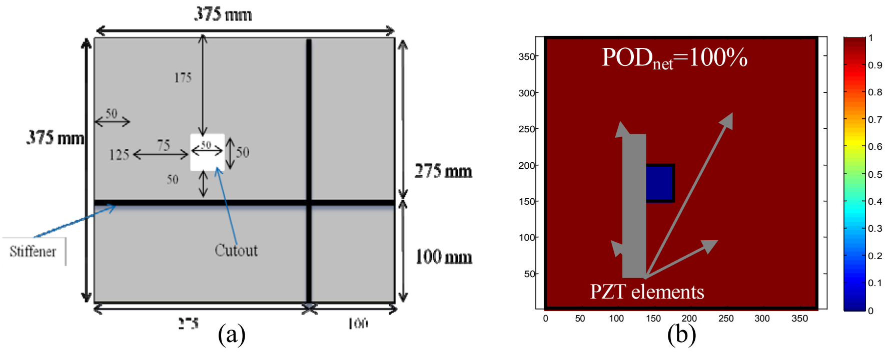

Figure 8. Demonstration of sensor network optimization tool (a) Schematic of aluminum structure with stiffeners and a cutout, and (b) Optimized sensor network.

The estimated D^3 profile and the above constraints on sensor locations were given as input to the GA based optimization tool to optimize sensor network to achieve 100% detection capability. GA was implemented with following GA parameters. Number of generations was set as 250, crossover was set as 1.0, mutation chance and creep chance were set as 0.25, and creep amount was set as a random amount within ± 5% from the mean of candidate solution. To preserve top candidate solution from GA based operations, candidate solution that corresponds to the highest fitness in a generation was directly placed into the next generation. The optimization process started as two sensor optimization problem and was run for 250 generations. At the end of 250 generations, the maximum POD_{net} corresponding to the optimized sensor network was less than the required POD_{net}, hence, one more sensor was added to the parameter set and the optimization process was started all over again. This optimization process was repeated until the maximum POD_{net} was equal to 100%. The optimized sensor network for the given structure is shown in Figure 8(b). The optimized sensor network configuration is tested by simulating 10 mm crack at top left hand corner of the cut-out. The damage was detected by the diagnostic algorithm [14] fusing PE and PC data. Damage was also simulated at few other locations and was detected by the diagnostic algorithm.

CONCLUSION

A probability of detection (*POD*) based sensor network optimization tool is developed which uses a physics-based wave propagation model and genetic algorithm evolution process. A detailed description of the tool and the effects of different parameters such as sensor spacing, number of sensors and environmental conditions on the overall damage detectability are discussed. The proposed methodology also defines the damage detectable distance and considers fusion of pulse-echo and pitch-catch sensor data to optimize sensor network for detecting damage of size '*a*' under different environmental conditions that prevail in the practical usage of the structure. Performance of the proposed optimization tool was tested on simulated signals generated for a complex aluminum structure with stiffeners and a cutout. The optimized sensor network was tested through simulated sensor data for damage at different locations on the structure. Efforts are underway to experimentally validate the proposed methodology and also to develop a sensor network optimization tool for composites and more complex structures.

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