SENSOR PLACEMENT OPTIMIZATION AND MODELING FOR STRUCTURAL HEALTH MONITORING

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Abstract- Monitoring large civil infrastructures often require multiple sensors at multiple locations. However, it is uneconomical to install sensors to cover the entire structure. Therefore, an optimal sensor placement scheme for structural health monitoring (SHM) applications is crucial. Many methods have been developed in the field of sensor placement optimization (SPO). However, most of these optimization approaches are deterministic with unspecified types and sources of uncertainty. In addition, a predefined number of discrete sensor configurations are required, in which the global optima is not guaranteed. In order to satisfy operational and geometrical constraints, there is a need to combine constraint satisfaction with heuristic search. To tackle this challenge, this research presents a new sensor placement methodology for damage detection in multistory buildings. In fact, the predicted optimal sensor locations provided an improved estimates of the quantity and location of damage. Also, the power of damage detection occurred in the benchmark structure using the proposed SPO methodology can be quantified.

Index Terms- sensor placement optimization (SPO), structural health monitoring (SHM), multistory buildings, ASCE benchmark structure

I. INTRODUCTION AND RELATED RESEARCH

Optimal sensor placement applications cover several related and overlapping research fields such as condition monitoring of machines and structures, damage detection, structural integrity, and assessment and failure prevention [1]. The types of structures include aerospace, aircraft and civil infrastructures such as bridges and buildings. Other applications include, but not limited to, environmental protection [2], homeland security for early warning and detection of possible bioterrorist attacks [3] and vibration control of large flexible space structures and noise control of aircraft fuselages [4]. Sensor placement optimization aims at determining the spatial locations for a collection of sensors, in which the accuracy in parameter identification is maximized [5]. Several sensor placement techniques have been developed using genetic algorithms (GA) in active vibration control [5]. The applicability of combining the GA with evolutionary computation to develop an SPO for SHM schemes is investigated in Ref. [6]. This study presents a tradeoff relationship between the performance of a limited number of sensors and the overall sensor network performance. However, sensor placement optimization methods based on GA often generate invalid solutions during the evaluation process [6]. Gao et al. [7] proposed a probabilistic sensor placement optimization approach, in which for every sensor of a given sensor set, a probabilistic damage detection model is defined over a confident monitoring region. The joint effectiveness of all sensors is estimated as the union of the individual sensor detection probabilities for all sensors within the network. The previous approach uses a covariance matrix adaptation evolution technique for the purpose of searching the decision variable domain. According to Ref. [4], oversimplified probabilistic damage detection models, and unspecified types and sources of uncertainty are two main drawbacks of the probabilistic sensor placement optimization approach. Integer and combinatorial optimization methods are widely used in SPO for vibration control and noise attenuation [8]. Choosing potential sensor locations is a subjective task and may cause significant variation of the optimal solution [8]. A method using the information measure based on the sensitivities of the frequency response function was reported in Ref. [9]. This method not only minimizes the number of sensors placed on a structure but also increases the amount of information gathered by the sensors.

In the present study, an optimal sensor placement methodology for damage detection in multistory buildings under uncertainty is developed. The proposed methodology has used a multi-component objective function based on Fisher Information Matrix (FIM)to minimize the overall uncertainty of the estimated parameters.

II. ASCE BENCHMARK STRUCTURE

The benchmark structure was designed by the American Society of Civil Engineering (ASCE) for the application of SHM. It is a 4-story, 2-bay by 2-bay steel frame scale model structure and one floor slab per bay per floor as shown in Fig.1. It is located in the Earthquick Engineering Research Laboratory at the University of Britsh Columbia Available (http://wusceel.cive.wustl.edu/asce.shm/). It consists

of a symetric plan with an area of 2.5 m by 2.5 m and a height of 3.6 m. To emulate a real structure, a concrete slab was built on each floor, and the removal of this bracing system is designed to simulate damage to the structure. A simulation program for generating the response of force sensor data in the ASCE benchmark structure is available in Ref. [11]. It is a MATLAB program based on a 120- degrees of freedom (DOF) finite element model [34]. The finite element model assumes a root mean square (RMS) 10% of the largest RMS of the acceleration response [10]. One undamaged pattern and six damage patterns generated from this benchmark model were used, defined in Table 1[36]. A more detailed description of the benchmark structure problem can be found in the work of Johnson et al. [10]

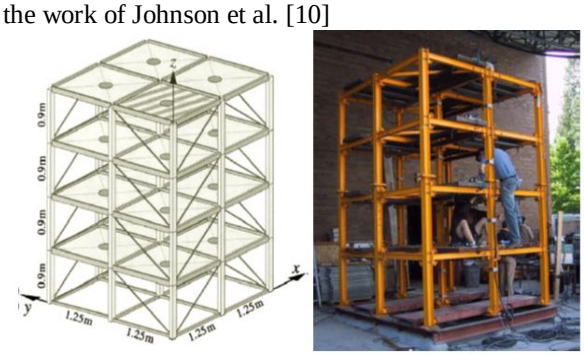


Fig.1 Benchmark structure: (left) Diagram of the analytical model and (right) Steel-frame structure [10]

Table 1 Damage patterns of the ASCE benchmark structure [12]

Damage pattern	Damage description
D_0: Damage pattern zero	No damage
D_1: Damage pattern one	Remove all braces in 1st floor.
D_2: Damage pattern two	Remove all braces in 1st and 3rd floor.
D_3: Damage pattern three	Remove a brace near sensor location 2 at 1st floor
D_4: Damage pattern four	Damage pattern 3 & remove a brace near sensor 9 at 3rd floor.
D_5: Damage pattern five	Damage pattern 4 & loosen floor beam near sensor 3 at 1st floor.
D_6: Damage pattern six	Remove 2/3 stiffness of a brace near sensor 2 at the 1st floor.

III. FISHER INFORMATION MATRIX FOR SENSOR PLACEMENT OPTIMIZATION

According to Refs.[13], the FIM can be written as,

$$FIM = \phi^T\phi$$

Here, ϕ refers to the Jacobian matrix of the acceleration of the multistory structure with respect to each sensor location. Using the Singular Value Decomposition (SVD) [14], ϕ can be defined as,

$$\phi = USV^T$$

where, $U \in \mathbb{R}^{m\times m}, V \in \mathbb{R}^{n\times n}$ is an orthogonal matrix whose columns are left (right) singular vectors that define an orthonormal basis for the output sensor measurement space and for the input parameter space, respectively; and $S \in \mathbb{R}^{m\times n}$ is a rectangular diagonal matrix with nonnegative real numbers on the diagonal called singular values σ.

IV. THE OBJECTIVE FUNCTION BASED ON FISHER INFORMATION MATRIX

In this study, the objective function has three components. The first one is based on the determinant of FIM [15] which is the product of the singular values. The determinant of FIM has to be maximized since its inverse is a measure of the overall uncertainty on the estimated parameters [5]. The second component of the objective function for the sensor placement is the trace of the FIM defined as the sum of the singular values. The last component of the objective function is the condition number of the FIM [16] which is defined as the ratio of the largest to the smallest singular value. Each of the previous metrics emphasizes on a specific aspect of the optimization problem. Thus, it is recommended to combine them in aggregated Figure of Merit (FOM), which should be maximized and can be expressed as,

$$FOM = w_1(Det) + w_2(Tr) - w_3(CN)$$

where, CN, Tr and Det are the condition number, trace and determinant of the FIM, respectively; w_i are weighting factors between the components of the objective function.

V. APPLICATION TO ASCE BENCHMARK PROBLEM

This section uses the benchmark structure as a case study for the proposed optimal sensor placement methodology. Three different optimization algorithms, namely, Sequential Space Filling (SSF) [17], Genetic Algorithm (GA) [5], and the simulated annealing Algorithm (SA) [18] were adopted to optimize the final locations of the eight sensors.

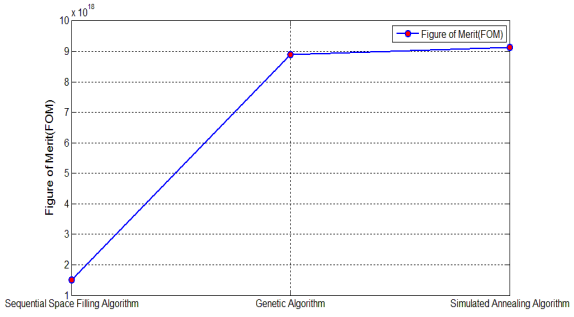


Fig.2 Performance comparison of the FOM for different optimization algorithms

After running each method thirty times and choosing the best results for each method, it has been found that the performance of the Simulated Annealing algorithm is the best in solving the sensor placement

problem in the optimality of sensor location (See Fig.2).

VI. OPTIMIZATION OF THE SENSOR CONFIGURATION USING THE SIMULATED ANNEALING ALGORITHM

Simulated Annealing is a probabilistic method to find the global optimal of an objective function that may possess several local optimal [19]. The SA is analogue to the physical process in thermodynamics, especially to the way that liquids freeze and crystallize, or metals cool and anneal [19]. The algorithm starts with a random initial sensor configuration then the perturbation operator works on each decision variable. In an iteration of the SA, each variable is randomly selected for perturbation and the new sensor configuration is randomly found around its neighbors, where the distance of random search is proportional to the annealing temperature. Next, the new sensor configuration is compared with the previous one and the a better solution with respect to the objective function is always accepted, while the weaker solution is accepted only if a randomly threshold is greater than a probability value which is defined in Ref. [19] by,

$$p = e^{(\Delta E/T)}$$

in which ΔE denotes the change in objective function value and T is the temperature control parameter which will be gradually reduced until the objective function value has converged or reach maximum number of iteration.

VII. OPTIMIZATION RESULTS AND DISCUSSION

A schematic of the benchmark structure is shown in Fig.3, where the locations of the existing sixteen sensors are indicated by circles (four sensors in each floor). Moreover, the 3D graphic random field of the objective function (Fig. of Merit) for the fourth floor is shown in Fig.4.

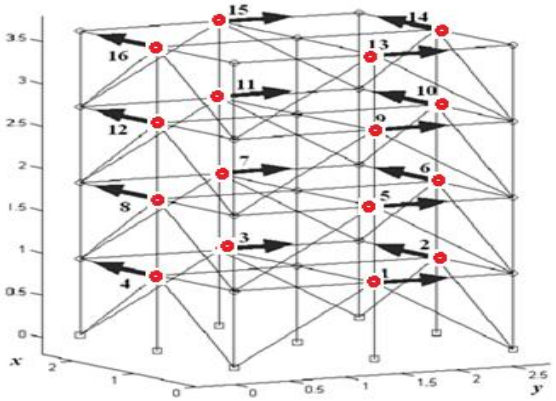


Fig.3 Existing placements of sensors on the ASCE benchmark structure [10]

In this section, the optimal sensor placement of the benchmark structure is studied using the simulated annealing algorithm (SA). Eight sensor locations are randomly selected as an initial input and a 0.98 of cooling factor is applied.

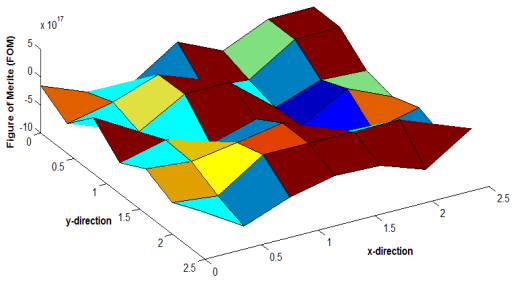


Fig.4 3D graphic random field for the fourth floor of the benchmark structure

Applying unit weights to each component of the FOM, the objective function of the FIM is computed as shown graphically in Fig.5. Moreover, the optimal sensor coordinates are given in Tables 4.5

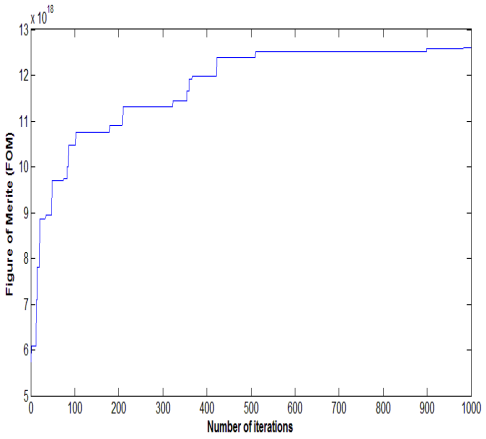


Fig.5 FOM using simulated annealing algorithm

Table 2 Optimal sensor coordinates based on the FOM

Sensor number	S_1	S_2	S_3	S_4
Coordinates	(0.0, 2.2, 0.9)	(2.2, 0.3, 0.9)	(0.1, 2.5, 1.8)	(0.2, 2.5, 1.8)
Sensor number	S_5	S_6	S_7	S_8
Coordinates	(0.6, 2.3, 2.7)	(2.5, 0.0, 2.7)	(2.4, 0.4, 3.6)	(0.7, 1.4, 3.6)

Based on the optimization results, it is observed that the FOM values converge directly after 150 iterations with a maximum average value of 12.6×10^{18}. From Table 2, it can be seen that the optimal sensor locations are located near the boundaries of the

benchmark structures. This result may due to the nature of the bracing system placed diagonally on each floor of each exterior face. In fact, the removal of this bracing system is designed to simulate damage to the benchmark structure.

VIII. CAPABILITY OF DAMAGE DETECTION FOR THE ASCE BENCHMARK STRUCTURE

In order to validate the efficiency of the selected optimal sensor sets using the simulated annealing algorithm, six damage patterns generated from the benchmark model, taken from Ref. [34] and summarized in Table 1, are considered. Each test case is repeated forty times with different realization of measurement noise and the average of each test case is further investigated.

In addition, the Hotelling T^2 multivariate control chart [21] for monitoring the mean vector of the process is used. The out-of-control average run length (ARL_1), which is the number of observations needed until the change is detected, was investigated for the sensor configuration of the benchmark structure before and after the optimization. The results of the comparison using ARL_1 as a performance measure are summarized in Table 3.

Table 3 ARL_1 results for the sensor configuration of the benchmark structure using Hotelling T^2 control charts for all six different damage patterns

Operating condition	ARL_1 (before optimization)	ARL_1 (after optimization))
Very slight damage Patterns 6 and 3	P 6: ARL_1= 10.6 P 3: ARL_1= 5.2	P 6: ARL_1= 6.2 P 3: ARL_1= 3.1
Medium local damage Patterns 4 and 5	P 4: ARL_1= 2.6 P 5: ARL_1= 2.5	P 4: ARL_1= 2.3 P 5: ARL_1= 2.0
Severe damage Patterns 1 and 2	P 1: ARL_1= 1.0 P 2: ARL_1= 1.0	P 1: ARL_1= 1.0 P 2: ARL_1= 1.0

From Table 3, we noticed that, the Hotelling T^2 control chart after optimization has shorter ARL_1 than that before optimization except for the severe damage cases (patterns 1 and 2); in other words, the Hotelling T^2 control chart captures the damage earlier using the optimized sensor locations.

Based on reported percentage loss in stiffness associated to each damage pattern shown in Table 4 [10], the power of damage detection occurred in the benchmark structure using the proposed SPO methodology can be quantified.

Table 4 Percent loss in stiffness associated to different damage patterns for the benchmark structure

Damage patterns	D_0	D_1	D_2	D_3	D_4	D_5	D
Percent loss in stiffness (Johnson et al., 2004)	N/	30	60	5.6 %	10.2 %	11.3 %	2.

From Table 4, the proposed SPO methodology using the simulated annealing algorithm has the capability to differentiate between operating conditions with different levels of damage. In fact, the optimal sensor configuration has improved the detection performance in capturing all different levels of percent loss in structural stiffness, especially, the operating conditions with slight damage.

CONCULSION

An optimal sensor placement method based on FIM was developed to the benchmark problem, in which the uncertainty in the estimated parameters was minimized. Results of the test benchmark case study indicated: 1) the proposed method based on the simulated annealing algorithm is effective in determining the optimal sensor locations; 2) it also illustrated that in damage detection applications, the optimized sensor locations result in an improved capability for damage detection.

REFERENCES

[1] Marquardt, D.W., An algorithm for least-squares estimation of nonlinear parameters. Journal of the Society for Industrial & Applied Mathematics, 1963. 11(2): p. 431-441.
[2] Zemmour, A.I., The Hilbert-Huang Transform for Damage Detection in Plate Structures. 2006.
[3] Chiang, L.H., E. Russell, and R.D. Braatz, Fault detection and diagnosis in industrial systems. 2001: Springer Verlag.
[4] Pappa, R.S., G.H. James, and D.C. Zimmerman, Autonomous modal identification of the space shuttle tail rudder. Journal of Spacecraft and Rockets, 1998. 35(2): p. 163-169.

[5] Guo, H., et al., Optimal placement of sensors for structural health monitoring using improved genetic algorithms. Smart Materials and Structures, 2004. 13(3): p. 528.
[6] Cox, D.R. and N. Reid, The theory of the design of experiments. Vol. 86. 2000: Chapman & Hall/CRC.
[7] Fedorov, V.V. and P. Hackl, Model-oriented design of experiments. Vol. 125. 1997: Springer Verlag.
[8] Qureshi, Z., T. Ng, and G. Goodwin, Optimum experimental design for identification of distributed parameter systems. International Journal of Control, 1980. 31(1): p. 21-29.
[9] Green, K., Optimal sensor placement for parameter identification. 2006, Rice University.
[10] Johnson, e., et al., Phase I IASC-ASCE structural health monitoring benchmark problem using simulated data. Journal of Engineering Mechanics, 2004. 130(1): p. 3-15.
[11] Task-group. ASCE benchmark structure. ASCE-SHM 2004 [cited 2012 May, 20th]; Available from: http://wusceel.cive.wustl.edu/asce.shm/).
[12] Johnson, E., et al., Phase I IASC-ASCE structural health monitoring benchmark problem using simulated data. Journal of engineering mechanics, 2003. 130(1): p. 3-15.
[13] Lieven, N. and D. Ewins. Spatial correlation of mode shapes, the coordinate modal assurance criterion (COMAC). in International Modal Analysis Conference. 1988.
[14] Lay, D.C., Linear algebra and its applications. Addison Wesley, Pearson Education, Inc, 2003.
[15] Borguet, S. and O. Léonard, The Fisher information matrix as a relevant tool for sensor selection in engine health monitoring. International Journal of Rotating Machinery, 2008. 2008.
[16] Sohn, H., et al., A review of structural health monitoring literature: 1996-2001. 2004: Los Alamos National Laboratory Los Alamos, New Mexico.
[17] Huang, W., Z. Kong, and A. Chennamaraju, Robust design for fixture layout in multistation assembly systems using sequential space filling methods. Journal of computing and information science in engineering, 2010. 10(4).
[18] Johansson, A.T., T. Abrahamsson, and F. van Keulen. Comparison of several error metrics for FE model updating. in Proceedings of the 25th International Modal Analysis Conference (IMAC-XXV), February 19-22, Orlando, Florida, USA. 2007.
[19] Staszewski, W.J. and K. Worden. Overview of optimal sensor location methods for damage detection. in SPIE's 8th Annual International Symposium on Smart Structures and Materials. 2001: International Society for Optics and Photonics.
[20] Tong, K., N. Bakhary, and A. Kueh, Optimal Sensor Placement for Structural Health Monitoring Using Improved Simulated Annealing.
[21] Montgomery, D.C., Introduction to statistical quality control. 2007: John Wiley & Sons

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