Available online at www.sciencedirect.com

ScienceDirect

Procedia Structural Integrity 52 (2024) 594–599

Structural Integrity Procedia

www.elsevier.com/locate/procedia

Fracture, Damage and Structural Health Monitoring

Optimizing Sensor Paths for Enhanced Damage Detection in Large Composite Stiffened Panels - A Multi-Objective Approach

Llewellyn Morse[a,*], Ilias N. Giannakeas[b], Vincenzo Mallardo[c], Zahra Sharif-Khodaei[b], M.H. Aliabadi[b]

[a]Department of Mechanical Engineering, University College London, Roberts Engineering Building, WC1E 7JE, London, UK
[b]Department of Aeronautics, Imperial College London, South Kensington Campus, City and Guilds Building, Exhibition Road, SW7 2AZ, London, UK
[c]Department of Architecture, University of Ferrara, Via Quartieri 8, 44121 Ferrara, Italy

Abstract

This work proposes a novel methodology for the automatic multi-objective optimisation of sensor paths in Structural Health Monitoring (SHM) sensor networks using Archived Multi-Objective Simulated Annealing (AMOSA). Using all of the sensor paths within a sensor network may not always be beneficial and could impair damage detection accuracy. Knowing which paths to include, and which to exclude, can require significant prior expert knowledge, which may not always be available, and may not result in optimal path selection. Therefore, this work proposes a novel automatic procedure for optimising sensor paths to maximise coverage level and damage detection accuracy, and minimise overall signal noise. This procedure was tested on a real-world large composite stiffened panel with many frames and stiffeners. Compared to using all of the available sensor paths, the optimized network exhibits superior performance in terms of detection accuracy and overall noise. It was also found to provide 35% higher damage detection accuracy compared to a network designed based on prior expert knowledge. As a result, this novel procedure has the capability to design high-performing SHM sensor path networks for structures with complex geometries, but without the need for prior expert knowledge, making SHM more accessible to the engineering community.

Keywords: Structural Health Monitoring (SHM); Composites; Impact Damage; Multi-Objective Optimisation; Simulated Annealing (SA); Archived Multi-Objective Simulated Annealing (AMOSA)

1. Introduction

Structural Health Monitoring (SHM) enables engineers to shift to Condition-Based Maintenance (CBM), where maintenance is performed only when damage is detected by integrated sensors, reducing overall maintenance costs.

* Corresponding author. Tel.: +44-771-159-8447.
E-mail address: l.morse@ucl.ac.uk

10.1016/j.prostr.2023.12.059

In the aviation industry, conservative safety factors are used for composite materials due to their vulnerability to low velocity impact damage. SHM systems provide regular and on-demand health assessments of the structure, allowing for optimized design, improved material utilization, and reduced weight.

The optimization of sensor placement is a crucial approach to enhance Structural Health Monitoring (SHM) systems, leading to improved damage detection capabilities. Researchers have devoted significant attention to this area, resulting in the development of various optimization techniques considering different sensor technologies and performance indices. A comprehensive review by Ostachowicz et al. (2019) provides an overview of these techniques. Among the commonly used indices is the "coverage area," which quantifies the extent of the sensor network's coverage. Thiene et al. (2016) proposed a Maximum Area Coverage (MAC) approach that utilizes a genetic algorithm to optimize sensor positions for damage localization in composite structures. Other performance indices include "signal attenuation" Salmanpour et al. (2017), "probability of sensor malfunction" Mallardo et al. (2016), "economic cost" Mkwananzi et al. (2022), and "modal characteristics" Sun and Büyüköztürk (2015). For more detailed information on these indices, refer to the review by Barthorpe and Worden (2020).

This study focuses on guided wave-based SHM systems that utilize piezoelectric transducers to generate and detect ultrasonic guided waves in thin-walled structures. These systems have shown reliable detection of Barely Visible Impact Damage (BVID) in composites. Previous research has developed various methodologies to optimize sensor positions for objectives such as damage detection accuracy and coverage level. However, the selection of optimal *sensor paths* for damage detection has not been extensively studied. Including all possible sensor paths may not be optimal due to signal attenuation, noise, and mode conversion. When determining optimal sensor paths, manual approaches based on expert knowledge have been used, as shown by Yue et al. (2021) and Giannakeas et al. (2022), but they require significant expertise and may not guarantee the best combination of sensor paths. This limitation is particularly evident in complex geometries where expert knowledge may be unavailable.

It is therefore clear that an automatic approach is needed to select the optimal combination of sensor paths while requiring minimal prior expert knowledge. This paper introduces a novel automatic procedure for optimizing sensor paths in a SHM network. By adopting an automatic approach, the developed procedure achieves performance comparable to a manually generated network without requiring extensive prior knowledge or user intervention. Additionally, the procedure utilizes experimental data, strengthening its real-world relevance.

The objectives of the methodology in this work are to (1) Maximise the damage detection accuracy of the sensor network, (2) Maximise the sensor coverage area of the sensor network, and (3) Minimise the total noise present in the sensor network.

The validation of the proposed optimization procedure is conducted on a large flat aircraft stiffened composite panel. Experimental measurements obtained from the integrated SHM system guide the path selection process. The procedure's performance is compared to scenarios where all sensor pairs are chosen and where expert knowledge, as in Yue et al. Yue et al. (2021), is available.

2. Damage Detection Methodology

This study utilizes the damage detection approach introduced by Yue et al. (2021) and Giannakeas et al. (2022) to extract damage sensitive features indicating the presence of damage. This approach involves comparing a baseline measurement taken when the structure is defect-free with a current measurement of its unknown state. This comparison is facilitated using a damage index based on the correlation coefficient. Let $B_{[i,j]}(t)$ and $C^m_{[i,j]}(t)$ represent the baseline and current signals recorded for the path between the i-th and j-th sensors ($i, j = 1, \ldots, N_s$):

$$DI^m_{[i,j]} = 1 - corr\Big[B_{[i,j]}(t), C^m_{[i,j]}(t)\Big] \quad \text{where} \quad m = 1, \ldots, M \tag{1}$$

where, N_s is the total number of sensors and M is the total number of measurements. During the path optimization process, each sensor path in the network is considered once. Utilizing signal reciprocity, a damage index is computed for each path. The average damage index is then calculated for the paths between sensor k ($k = 1, 2, \ldots, N_s - 1$) and sensor l ($l = k + 1, k + 2, \ldots, N_s$) to generate a single damage index for each unique path using the following formula:

$$DI^m_{unique,[k,l]} = \frac{\left(DI^m_{[k,l]} - DI^m_{[l,k]}\right)}{2} \quad \text{where} \quad m = 1, \ldots, M \tag{2}$$

The total number of unique sensor pairs considered in the network is denoted as N_p. To represent the m-th measurement, a vector $D_m = [\mu_m, \sigma_m]$ can be defined, where μ_m and σ_m are the mean and standard deviation, respectively:

$$\mu_m = \frac{1}{N_p} \sum_{k=1}^{N_s-1} \sum_{l=k+1}^{N_s} DI^m_{unique,[k,l]} \tag{3}$$

$$\sigma_m = \sqrt{\frac{1}{N_p} \sum_{k=1}^{N_s-1} \sum_{l=k+1}^{N_s} \left(DI^m_{unique,[k,l]} - \mu_m\right)} \tag{4}$$

To assess the health of a structure, the Mahalanobis distance (MSD) is computed using a reference dataset $\mathbf{D}^0_r$. This dataset is constructed using pristine measurements:

$$MSD_m = \sqrt{\left(\mathbf{D}_m - \overline{\mathbf{D}^0_r}\right)^T \mathbf{\Sigma}^{-1} \left(\mathbf{D}_m - \overline{\mathbf{D}^0_r}\right)} \tag{5}$$

where $\overline{\mathbf{D}^0_r}$ and $\mathbf{\Sigma}$ are the mean and covariance matrices, respectively. In Eq. (5), a normal distribution is fitted to the reference dataset $\mathbf{D}^0_r$ to compute $\overline{\mathbf{D}^0_r}$ and $\mathbf{\Sigma}$. For further details on the damage detection algorithm, readers are referred to Yue et al. (2021) and Giannakeas et al. (2022).

3. Experiment Details

A flat composite stiffened panel with dimensions of 1.624 m x 0.94 m was used in this study Yue et al. (2021). The panel consists of aluminium frames and Carbon Fiber Reinforced Polymer (CFRP) laminates for the skin and stiffeners. The CFRP laminates were made using thermoset M21/194/34%/T800S unidirectional prepreg from Hexcel. The stacking sequence of the composite material is $[\pm 45/0_2/90/0]_s$, and the total thickness is 2.208 mm.

The panel under investigation is shown in Figure 1 and consists of two bays separated by a central frame. To evaluate the SHM system's performance, measurements were taken in both the pristine and damaged states of the structure. Impact tests were carried out using an INSTRON CREST 9350 drop tower with a 20mm hemispherical impactor to introduce Barely Visible Impact Damage (BVID). The impact energy was selected to produce interlaminar delamination that cannot be detected visually. The presence and size of the BVID were confirmed using a portable C-scan device. Three panels were used, and a total of eight impacts were conducted.

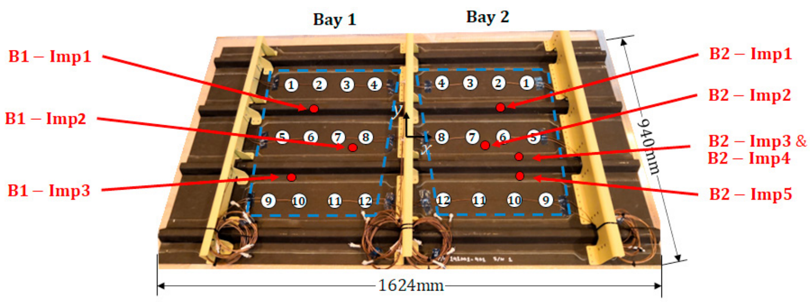

Fig. 1: The flat panel used in this work. The locations of the impacts are shown.

4. Sensor Path Network Optimisation

In this study, the panel under investigation has 12 sensors ($N_s = 12$). This corresponds to 66 unique sensor paths ($N_{p_{unique}} = 66$), resulting in a number of possible path combinations of $N_{p_{unique,combs}} = 7.38 \times 10^{19}$. The optimization procedure aims to identify an optimal or near-optimal sensor path combination from this vast pool of unique combinations.

To reduce the computation time needed to investigate this large number of combinations, the procedure is split into two stages. In the initial stage, Simulated Annealing (SA) is employed to determine the optimal paths connecting the 10 sensors located on the network boundary. In the second stage, the optimal path combinations for the remaining 56 paths are determined using Archived Multi-Objective Simulated Annealing (AMOSA), which is a multi-objective variant of Simulated Annealing Bandyopadhyay et al. (2008). This stage allows for the selection of up to 56 paths. AMOSA is employed to create a Pareto front that balances the three competing objectives described in section 1. Figure 2 provides a visual representation of an optimized network at the end of both stages.

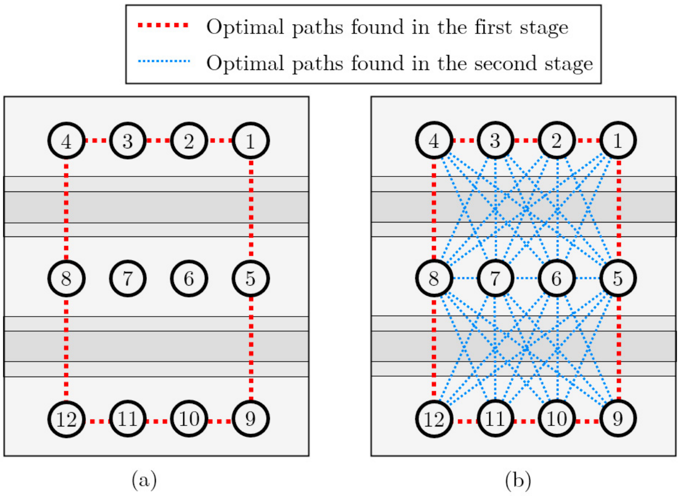

Fig. 2: A example of an optimised network at (a) the end of the first stage and (b) the end of the second stage.

5. Results

The results from AMOSA are shown in Figure 3. Out of 10,000 AMOSA iterations, 1,148 solutions were non-dominated (Pareto front solutions), represented by red markers, while 8,852 solutions were dominated (non-Pareto front solutions), represented by blue markers.

To simplify the selection process among the 1,148 Pareto front solutions, engineers can apply filters based on suitable ranges for the objective functions. For instance, defining a suitable range for coverage as $Coverage > 60\%$ and for the MSD ratio as MSD ratio > 1.5. By applying these filters, the 1,148 solutions can be narrowed down to 48 Pareto front solutions displayed in Figure 4. Three potentially suitable solutions are highlighted with blue circles and labeled 'A', 'B', and 'C'. Table 1 presents the values of coverage, MSD ratio, and total path noise for these solutions. To evaluate the performance of these solutions, Table 1 also shows the results for the case where all sensor paths are used and the case where prior expert knowledge. The later case corresponds to the path network used in Yue et al. (2021).

Solution 'A' and solution 'C' offer the lowest and highest coverage levels, respectively, among the considered AMOSA solutions. The solution utilizing all sensor paths achieves the highest coverage by utilizing paths that cross both stiffeners. The coverage level of the solution with prior expert knowledge is comparable to solution 'A', likely due to a similar number of sensor paths being used.

Both Solution 'A' and the solution with prior expert knowledge yield similarly low total path noise values. This similarity may be attributed to the fact that neither of these solutions employ any paths that cross over both stiffeners.

Solution 'A' exhibits a 35% higher MSD ratio compared to the solution with prior expert knowledge, indicating superior detection accuracy. This distinction may arise from the utilization of a slightly different path network compared to the solution employing prior expert knowledge. Unlike the latter solution, Solution 'A' incorporates paths

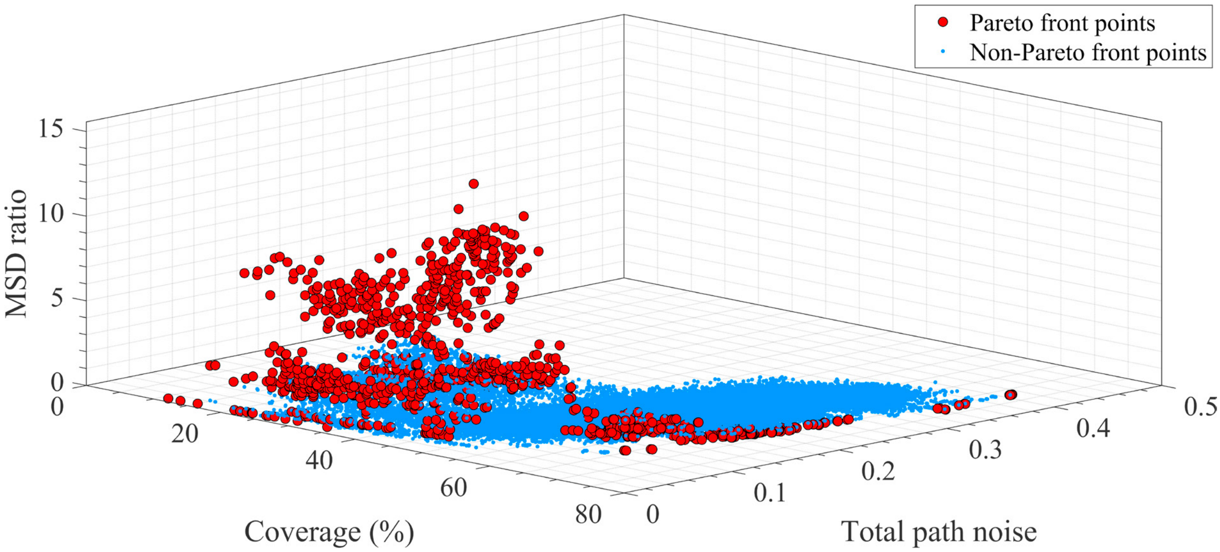

Fig. 3: Results from AMOSA.

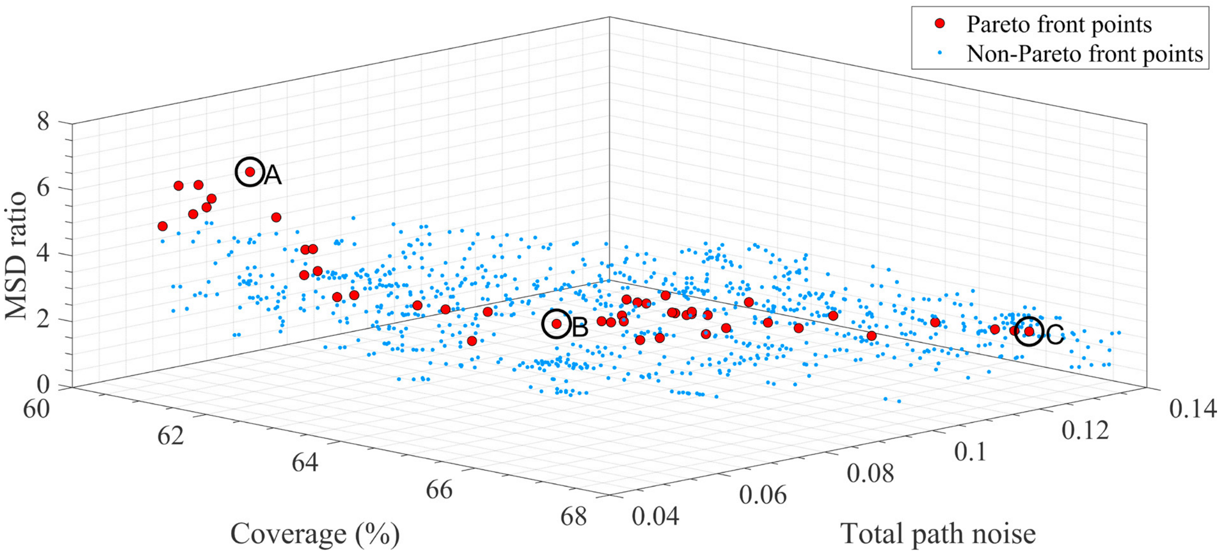

Fig. 4: AMOSA solutions for which the coverage level is above 60% and the MSD ratio is greater than 1.5. Three potentially suitable Pareto front solutions have been highlighted by blue circles and labelled 'A', 'B', and 'C'.

1-3, 2-4, 6-8, and 10-12, while excluding path 6-7. Conventionally, paths such as 1-3, 2-4, 6-8, and 10-12 are not considered in SHM networks. According to Yue et al. (2021), if a network already includes paths 1-2, 2-3, and 3-4, the addition of path 1-3 or 2-4 does not significantly enhance network coverage. However, the high MSD ratio of Solution 'A' suggests that incorporating these paths could potentially enhance damage detection and overall SHM network performance.

Table 1: Results of solutions 'A', 'B', 'C', the case where all sensor paths are used, and the case where prior expert knowledge was used.

Sensor network	Number of sensor paths	Coverage (%)	MSD ratio	Total path noise
AMOSA solution 'A'	44	61.3	6.51	0.057
AMOSA solution 'B'	45	63.4	1.80	0.087
AMOSA solution 'C'	50	67.1	1.71	0.13
All sensor paths	66	74.0	0.05	0.42
Prior expert knowledge Yue et al. (2021)	41	60.7	4.83	0.054

6. Conclusions

This study presents a novel methodology for automatically optimizing sensor paths in Structural Health Monitoring (SHM) sensor networks using Simulated Annealing (SA). It is observed that including all sensor paths may not always enhance network performance, and removing certain paths can actually improve multiple objectives.

The novel methodology is tested on a large composite stiffened panel with multiple geometric features, using a multi-objective variant of SA called Archived Multi-Objective Simulated Annealing (AMOSA). The optimized sensor paths exhibit improved damage detection accuracy and reduced signal noise compared to selecting all possible paths, albeit with slightly lower coverage. Compared to expert knowledge-based selection, the proposed procedure achieves similar coverage and total path noise but offers a 35% higher damage detection accuracy. These findings demonstrate the capability of the automatic optimization procedure to deliver sensor path networks that outperform or match those designed with prior expert knowledge, while requiring minimal user input.

Acknowledgements

The research leading to these results has gratefully received funding from the European JTICleanSky2 program under the Grant Agreement n° 314768 (SHERLOC). This project is coordinated by Imperial College London.

References

Bandyopadhyay, S., Saha, S., Maulik, U., and Deb, K. (2008). A simulated annealing-based multiobjective optimization algorithm: Amosa. *IEEE Transactions on Evolutionary Computation*, 12(3):269–283.

Barthorpe, R. J. and Worden, K. (2020). Emerging trends in optimal structural health monitoring system design: From sensor placement to system evaluation. *Journal of Sensor and Actuator Networks*, 9(3).

Giannakeas, I. N., Sharif Khodaei, Z., and Aliabadi, M. H. (2022). An up-scaling temperature compensation framework for guided wave–based structural health monitoring in large composite structures. *Structural Health Monitoring*.

Mallardo, V., Sharif Khodaei, Z., and Aliabadi, F. M. H. (2016). A bayesian approach for sensor optimisation in impact identification. *Materials (Basel)*, 9(11). Mallardo, Vincenzo Sharif Khodaei, Zahra Aliabadi, Ferri M H eng Switzerland 2017/08/05 Materials (Basel). 2016 Nov 22;9(11). pii: ma9110946. doi: 10.3390/ma9110946.

Mkwananzi, T., Louw, T. M., Auret, L., Mandegari, M., and Görgens, J. F. (2022). Combined optimal sensor network design and self-optimizing control with application in a typical sugarcane mill. *Journal of Process Control*, 114:82–91.

Ostachowicz, W., Soman, R., and Malinowski, P. (2019). Optimization of sensor placement for structural health monitoring: a review. *Structural Health Monitoring*, 18(3):963–988.

Salmanpour, M. S., Sharif Khodaei, Z., and Aliabadi, M. H. (2017). Transducer placement optimisation scheme for a delay and sum damage detection algorithm. *Structural Control and Health Monitoring*, 24(4).

Sun, H. and Büyüköztürk, O. (2015). Optimal sensor placement in structural health monitoring using discrete optimization. *Smart Materials and Structures*, 24(12).

Thiene, M., Khodaei, Z. S., and Aliabadi, M. H. (2016). Optimal sensor placement for maximum area coverage (mac) for damage localization in composite structures. *Smart Materials and Structures*, 25(9).

Yue, N., Khodaei, Z. S., and Aliabadi, M. H. (2021). Damage detection in large composite stiffened panels based on a novel shm building block philosophy. *Smart Materials and Structures*, 30(4).