

Transducer placement optimisation scheme for a delay and sum damage detection algorithm

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SUMMARY

In this work, a transducer placement scheme based on wave propagation is proposed, which enhances damage localisation. The method was tailored to seek an optimal transducer network placement for a delay and sum damage detection algorithm. The proposed method determines a coverage index map and utilises a genetic algorithm to determine an optimal transducer network. It can also minimise the impact of faulty transducers, incorporate the effect of stiffeners and different damage types. The method is initially verified using numerically simulated signals. The optimal network outperformed the suboptimal for detection of holes and debonding in a stiffened panel. It is also shown that the coverage index reflected the localisation accuracy. The method is then validated with experimental results and the generated optimal transducer network compared with a suboptimal arrangement. The optimal network is shown to locate an actual crack with significantly higher accuracy than the suboptimal arrangement. © 2016 The Authors. Structural Control and Health Monitoring published by John Wiley & Sons, Ltd.

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KEY WORDS: structural health monitoring; genetic algorithm; sensor placement optimisation; Lamb wave; damage detection

1. INTRODUCTION

Structural health monitoring (SHM) systems are increasingly being considered as a viable next step in non-destructive testing for the aerospace sector. The current schedule-driven maintenance regime can be transformed into a conditioned-based maintenance philosophy using real-time *in situ* structural integrity assessments provided by SHM systems. This makes SHM an appealing proposition for airlines and aircraft manufacturers. In recent years, SHM has seen a large level of interest with research on various aspects [1–5].

Implementation of SHM systems for real structures or as a bottom-up strategy, reducing design constraints and safety factors, rests largely on the effectiveness and cost efficiency of such systems. The performance should at least match that of existing non-destructive testing procedures, in addition to minimising added weight. Both requirements can be approached as an optimisation problem: given a minimum number of transducers seek the optimal network placement for damage detection accuracy. The main focus of this work is transducer placement optimisation for ultrasonic guided wave (GW) damage detection. A network of attached smart transducers must be positioned in such a way so as to enhance detection accuracy where it is required most.

Gao and Rose [6] developed a probabilistic damage detection model, based on a confident detection radius from the sensors. That is, the probability of detection would be set to one within the confidence radius. Outside this radius, the detection probability would be the inverse of the radius up to a certain

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limit beyond which detection was deemed not possible. The combined detection effectiveness of all sensors were mapped for a given sensor network; this was then optimised with an evolutionary strategy [6]. Kundu *et al.* [7] proposed a sensitivity-based sensor placement for multi-type sensors (PZT and fibre Bragg grating), with a simple Lead zirconate titanate (PZT) transducer placement approach. The coverage of a single sensor was governed simply by a circular area limited by a boundary. A point was assigned as ‘detected’ if a certain number of sensors could cover it and a genetic algorithm (GA) was used with overall fitness linked to the number of points covered [7]. Coelho *et al.* [8] used a critical sensor path to map the coverage of each sensor pair and optimised placement for a required coverage level with a simulated annealing algorithm. Soni *et al.* [9] proposed a placement optimisation based on a sensing radius and minimising sensor area overlap.

More recently, Fendzi *et al.* [10] combined geometric dilution of precision with a ray tracing principle to formulate a probability of detection and used this as the fitness function for a GA scheme. Flynn and Todd [11,12] developed a Bayesian approach, supplying to the optimisation the damage location probability as a priori along with attenuation and damage scatter information. Previous works have aimed to provide a general approach to SHM transducer network optimisation, formulated to enhance damage detection but not verified for a particular detection algorithm. Most detection methods have their specific detection characteristics that may be enhanced by a particular transducer arrangement, for example, blind spots [13] and coverage areas [14].

The transducer network optimisation method proposed in this work can have application to any ultrasonic damage detection methods and is verified with a delay and sum damage detection method [15,16]. The detection method used was developed from Michaels delay and sum approach [17] and requires GW signals recorded in the pristine and damaged state. Any residual between the pristine and current signals are assumed to be due to damage. The envelope of the residual signal is then found. For each transducer pair, the time of flight (TOF) to each point is calculated and the value of residual at the TOF is recorded. By fusing information from all transducers, it is possible to build a damage prediction map. An outline of the damage detection method is given in Figure 1. The proposed placement scheme determines an optimal transducer arrangement using a GA, facilitating accurate damage detection. The main novelties are the ability to account for stiffeners and transducer failure, incorporating minimum number of transducers with line of sight (LOS) for detection and minimising the impact of boundary-

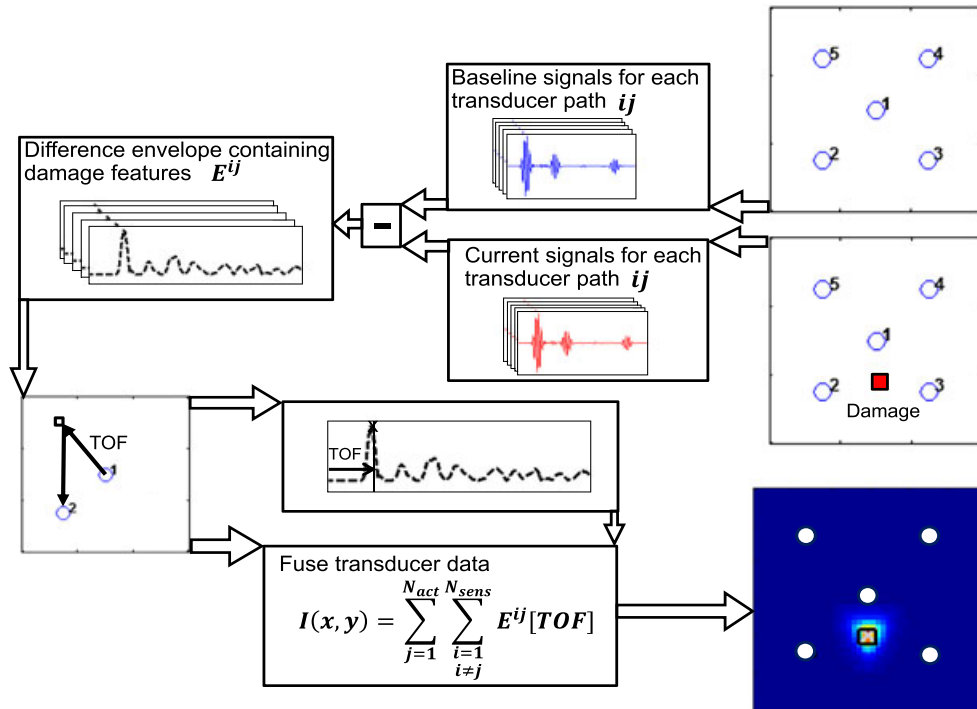


Figure 1. Outline of the damage detection method used [15,16].

reflected damage scatter waves, while using previously proposed damage scatter propagation models [11]. The proposed placement method was verified with a delay and sum damage detection algorithm [15]. It should be stressed, however, that it is not restricted to this particular algorithm and may still be applicable to other detection algorithms (i.e. RAPID [14]).

Presented in the first section of this paper is the methodology for calculating the transducer network fitness. In the following section, a strategy is outlined to deal with transducer failure through the best–worst case approach. The method is then shown to be effective with numerically simulated data. In the final section, the method is validated with experimental results.

2. METHOD

2.1. Transducer network fitness calculation

The transducer placement scheme developed considers each point P on the structure as a possible damage location. Assuming there is damage at P , the amplitude received at the sensor is calculated for n actuator–sensor pairs ij . The point fitness value f_p is calculated for each point:

$$f_p = \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \text{los}_{ipj} \gamma_s \gamma_d B_{ij} S(\mathbf{x}_p) A_s(\angle \mathbf{x}_i \mathbf{x}_p \mathbf{x}_j) \quad (1)$$

where $\mathbf{x}$ indicates a Cartesian position, A_s is the damage scatter profile, $\angle$ is the angle formed by the direct path consisting of the lines $\mathbf{x}_i \mathbf{x}_p$ and $\mathbf{x}_p \mathbf{x}_j$, γ_s and γ_d are stiffener and distance attenuation factors, los_{ipj} is the LOS factor, n is the number of actuators, S is the sensitivity map and B_{ij} is the boundary limit. The direct path is defined as the shortest wave propagation path from actuator i to P to sensor j . The network fitness f_N is found as the normalised sum of all point fitness values outlined in steps 1–8. Figure 2 depicts an overall flow chart of the scheme.

2.1.1. Line of sight. Damage scatter waves can only be detected if incident waves can arrive at the damage location. The scattered waves must then propagate to the location of the sensor. This requires $\mathbf{x}_p$ to have an LOS to both $\mathbf{x}_i$ and $\mathbf{x}_j$. When considering the direct path, los_{ipj} is set to zero if any part of the path falls outside the geometry of the structure. Figure 3 shows the number of transducer pairs that have LOS, as the sum of los_{ipj} , for every point on an arbitrary geometry.

2.1.2. Boundary limit. Ultrasonic signal responses from real structures are complex because of reflection of signal from geometric features specially the edges or boundaries. The elegance of GW

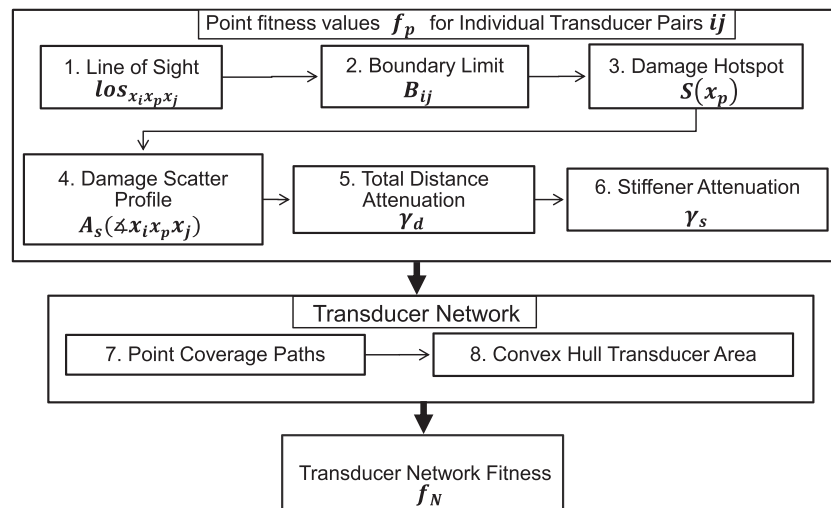


Figure 2. Flow chart outlining the main steps in calculation of transducer network fitness value.

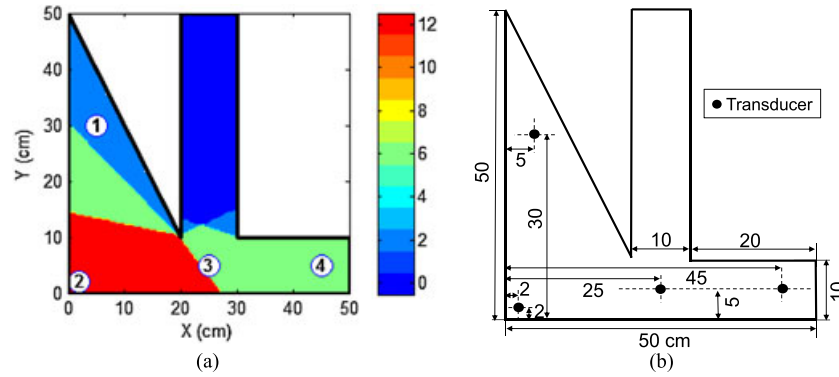


Figure 3. Contour showing number of transducers with line of sight to a given point (a), arbitrary geometry with positions of transducers (b).

baseline comparison methods, including the detection method used in this paper [15], are in that they are able to deal with complex signals in which individual wave features cannot be readily interpreted. That is, because the same reflections are present in both the baseline and current signal, they can be removed allowing for the extraction of damage scatter features from the complex signals. The direct arrival wave and the TOF are key features required for damage localisation. However, boundary-reflected damage scatter features are not present in the baseline signal, hence, not removed in baseline comparison [17]. This may cause noise in the damage detection map as reflections lead to an incorrect direct TOF from the damage [17]; see Figure 4. The limiting case is an infinite plate with only the first arrival wave features and no boundary reflections.

Transducers should be arranged in a way to ensure that the direct wave path to a point is shorter than the direct path to the boundaries, minimising the effect of boundary-reflected damage scatter signal. If the boundary limit criterion was to be set as the only fitness constraint for a square plate, the fittest arrangement would have all transducers placed centrally on the structure, an equal distance from each edge.

$$B_{ij}(\mathbf{x}_P) = \begin{cases} 0 & \text{when } LP_{ij} \leq |\mathbf{x}_i - \mathbf{x}_P| + |\mathbf{x}_j - \mathbf{x}_P| \\ 1 & \text{when } LP_{ij} > |\mathbf{x}_i - \mathbf{x}_P| + |\mathbf{x}_j - \mathbf{x}_P| \end{cases} \quad (2)$$

The boundary limit factor B_{ij} was set by finding the shortest distance to any of the geometry boundary edges for each traducer pair and defining this as the limiting path LP_{ij} .

Any point with longer direct path than the limiting path is deemed as not covered by the particular transducer pair ij under consideration and will result in a boundary limit value B_{ij} being set to zero; see Figure 5.

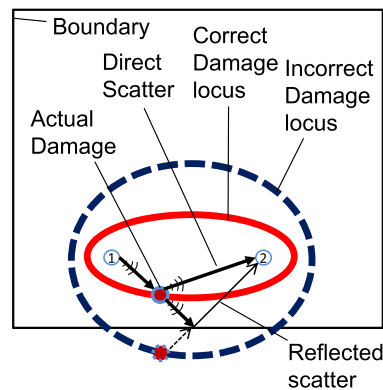


Figure 4. Schematic of boundary-reflected damage scatter and the incorrect damage locus.

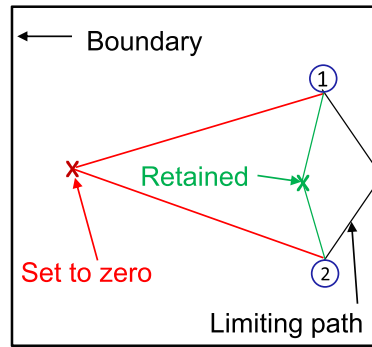


Figure 5. Calculation of boundary limited path and points that are deemed as covered by a transducer pair.

2.1.3. Damage hot spots. Damage hot spots or areas known to be more damage prone, can be incorporated as areas with increased weighting or sensitivity. Once the overall amplitude from these points is found, it is multiplied by the sensitivity factor to increase their weighting in the overall fitness. This was implemented in the form of a sensitivity map S in which hot spot areas have increased sensitivity.

As an illustrative limiting case, a significantly high sensitivity value (11 times more than the rest of the structure) was assigned to a central region of a homogenous square plate; see Figure 6. The optimal solution for this case was the transducers placed in such a way to enhance coverage of the central region because of the high weighting assigned to it.

2.1.4. Damage scatter profile. It is known that the damage scatter profile, A_s , is direction dependent, even for symmetric damage, that is, round hole [18]. This is significant for transducer placement as the amplitude of the damage scatter received would vary based on the position of the transducer in relation to a point P . So an optimisation objective would be to place the sensors in such a way to receive high amplitude of damage scatter from as many points as possible. This allows the placement optimisation to enhance detection of certain damage types, as each damage type has slightly different scatter profile. The primary input in this step is the scatter profile of a damage case of interest; alternatively, a uniform profile could be used for a more general case.

2.1.5. Distance attenuation. The amplitude of received waves depends predominantly on the propagation distance. The level of attenuation differs significantly between materials and observed to be higher in composite material compared with aluminium. Any wave attenuation model can be implemented in the developed scheme; square root attenuation is often used [19]. The adopted model was used by Flynn and Todd [12] and verified experimentally and is based on an attenuation parameter η_d indicating the distance by which amplitude drops to a half:

$$\gamma_d = \frac{\eta_d}{\eta_d + |\mathbf{x}_i - \mathbf{x}_P| + |\mathbf{x}_j - \mathbf{x}_P|} \quad (3)$$

2.1.6. Stiffener attenuation. In aerospace structures, stiffeners and stringers are used to enhance performance. One solution to sensor placement on stiffened panels could be to limit the inspection

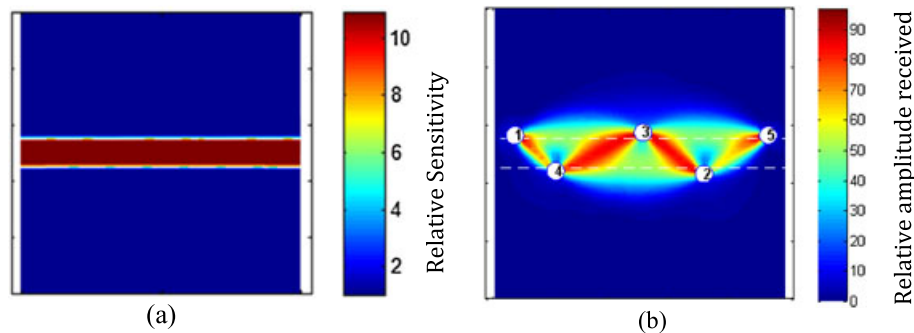


Figure 6. Damage hot spot sensitivity map (a). Optimal sensor placement based on exaggerated sensitivity (b).

areas to either side of the stiffener; however, this may not allow for adequate coverage of the area under the stiffener. Moreover, these areas are of added interest in stiffened panels as a debonding may lead to a significant drop in strength.

$$\gamma_s = \frac{\eta_s}{\eta_s + D_s} \quad (4)$$

Integration of the stiffeners and stringers in the transducer placement strategy was accomplished by taking into account their effect on the amplitude attenuation of the signal. The strategy centres on modelling amplitude attenuation based on the distance the direct wave packet propagates across the stiffeners, D_s , then applying an attenuation model. Depending on the actual structure under consideration, the relevant attenuation model can be used. To demonstrate a damping model is assumed (equation (4)) in which amplitude halves for a certain distance travelled through the stiffener, η_s , by the direct wave arrival. In any case, this would first require the distance to be calculated, the scheme developed can deal with most possible locations of transducers and inspection points in relation to the stiffener, as depicted in Figure 7.

It was found that for a high attenuation level (shorter distance to half amplitude), the transducers were only placed on one side; see Figure 8a. As the signal crossing the stiffener was almost entirely attenuated, the optimisation routine was forced to focus the inspection area on one side of the stiffener. The top section was covered because of the random initial population. As depicted in Figure 8b, reducing the stiffener attenuation five times (wave amplitude crossing the stiffener is reduced less), it was observed that the transducers were placed on either side of the stiffener.

2.1.7. Point coverage paths. The detection algorithm is able to predict damage location via the superposition and fusion of damage scatter information from different transducers. Each transducer pair gives a locus of possible damage locations with the transducers at the foci. To uniquely identify a single point, at least three loci are required; see Figure 9. The three loci yield an overlap zone; the point with highest index is chosen as the predicted damage location. Implementing this requirement into the procedure was achieved through only including the points that have at least three transducer paths covering them. So effectively, the smallest unit for damage detection is a network with three transducers allowing for three distinct transducer pairs.

2.1.8. Convex hull transducer area. The damage detection algorithm has been found to perform best within the enclosed area of the transducer network. This is partly because the simulated damages considered have dominant forward scatter amplitude. Also the data fusion process enhances the damage location accuracy within the transducer area; see Figure 9. It can be observed that outside

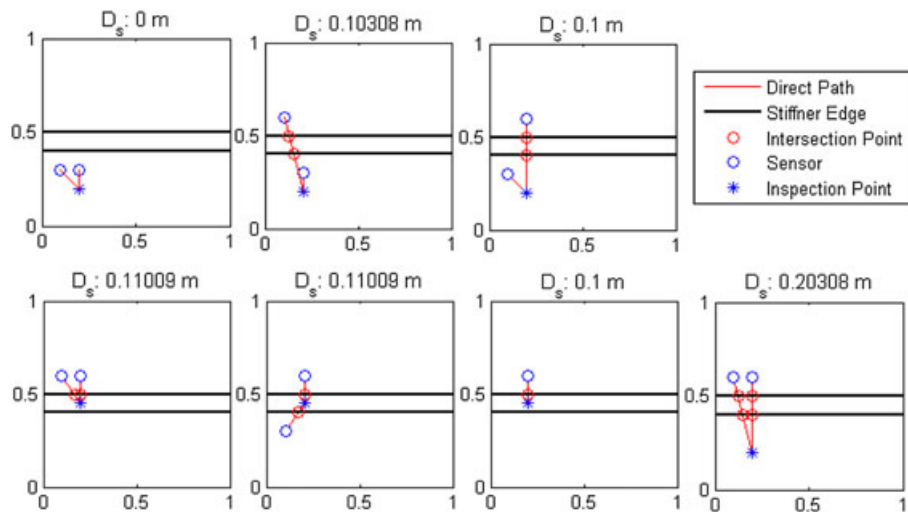


Figure 7. Different possible locations of the transducers and inspection point in relation to the stiffener. D_s is the distance travelled through the stiffener by the direct arrival wave.

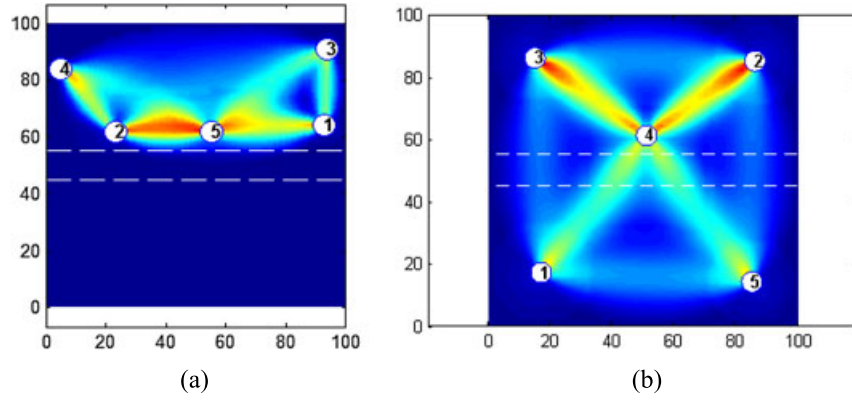


Figure 8. Relative fitness (coverage index) plots for stiffened panel with high stiffener attenuation (a), attenuation level reduced (b).

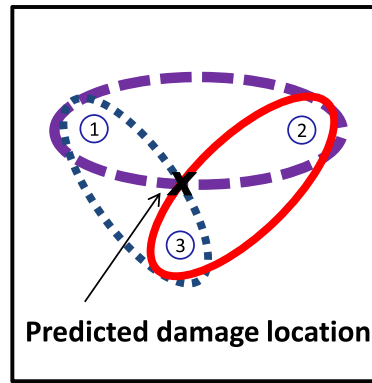


Figure 9. Three damage loci uniquely predicting damage location based on the zone with most overlap.

the transducer network, there are various locus overlaps that do not correspond to damage. To account for this in the placement optimisation, only points contained within the convex hull of three or more transducers had contributions towards the network overall fitness function f_N .

2.1.9. Fitness weighting. The fitness f_N is weighted to adjust for the size of the structure and discretisation level used in the optimisation scheme. The overall fitness value f_N is found as the sum of all fitness values f_P (as calculated in previous stages) multiplying by the ratio of points that have fitness greater than or equal to the mean value.

2.2. Sensor redundancy

The optimal transducer network can operate with good performance when all transducers are functional; however, in practical applications, defective transducers are a possibility. Transducer defects could occur because of impact or physical damage, or even a fault with connection wires or debonding. It is assumed that defective transducers can be found (e.g. with electro-mechanical impedance approaches) and excluded from the damage detection algorithm. It is possible that defective transducers can reduce the network performance to an unacceptable level. The strategy adopted considers the worst case when seeking a robust transducer placement. The overall fitness f_N of a given network with N transducers is set to the worst fitness of a subset with $N - FT$ transducers:

$$f_N = \min(f_{N-FT}) \quad (5)$$

where FT is the number of faulty transducers.

It is also possible to incorporate a probability distribution for the number of failed transducer, P (FT); here, P indicates a probability distribution. The overall network fitness value is calculated based on a probability weighted worst case of various numbers of failed transducers; see equation (6). A minimum of three transducers are required for the damage detection algorithm to locate damage with meaningful levels of accuracy.

$$f_N = \sum_{FT=0}^{N-3} P(FT) \min(f_{N-FT}) \quad (6)$$

When considering seven transducers on an irregular-shaped geometry, with uniform sensitivity, the GA optimisation found the optimal layout to be focused on the main flange providing no coverage to the top small flange; see Figure 10a. There will be various outcomes for two failed transducers in the optimal network, depending on the location of failed transducers. For instance, if transducers one and two were to fail, there would be a minor drop in fitness with minimal bearing on the overall coverage area. However, if transducers five and seven failed, the network coverage will be reduced four times compared with all transducers operative case, resulting in the worst case scenario shown in Figure 10b. Implementing the best–worst arrangement step, the worst case of transducer failure would only result in minor reductions in performance by around a third, still allowing for reasonable damage detection as depicted in Figure 10c.

2.3. Genetic algorithm realisation

Alan Turing [20] was arguably the first to propose the idea of intelligent computers and methods for artificial intelligence. Box [21] was amongst the first to explore the idea of bio-inspired optimisation

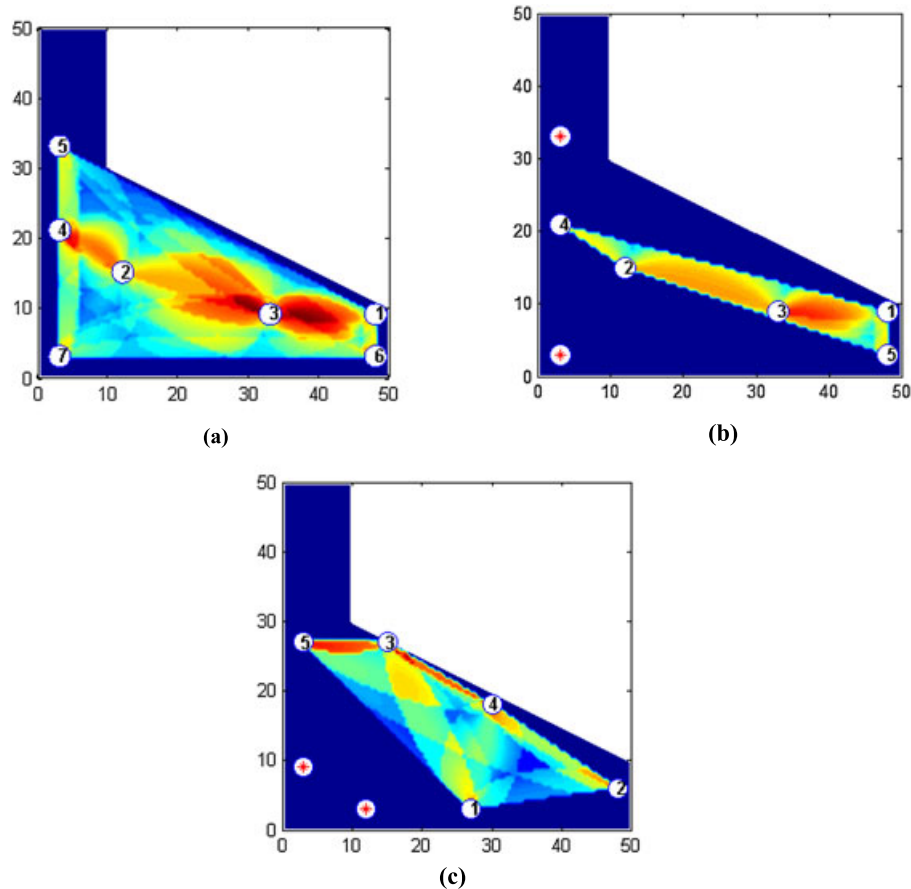


Figure 10. Normalised contours of coverage index for the optimal network (a), the worst case of two faulty transducers in the optimal network (b) and best–worst case network with two faulty transducers (c).

algorithms. Evolutionary numerical procedures influenced the works of many other researchers including Baricelli [22,23] and Fraser [22,23]; however, little interest was generated outside their direct field because of the limited computational power available at the time. With a huge rise in computational power, these methods have become viable for practical applications [24]. Inspired by the principle of natural selection, GAs introduced by Holland [25] are a robust optimisation tool with the ability to locate global optimal solutions. GA has previously been used by researchers for transducer placement optimisation [11,26]. A MATLAB implementation of the GA [27] was used in this work to maximise the network fitness function:

$$\max(f_N) = f_N\left(\mathcal{J}_{\text{optimal}}\right) \quad (7)$$

In this work, a transducer network or layout vector $\mathcal{J}$ corresponds to an individual with transducer locations $\mathbf{x}$ or genes form the network. The initial generation consists of an initial population $\mathcal{J}_1^0 \dots \mathcal{J}_k^0$, with a total of k individuals. The initial population in this work was randomly chosen transducers located at feasible points. This could have been governed through linear and non-linear constraints, that is, transducers cannot be located partly outside the geometry, two on the same location or on a stiffener. However, it was found that the algorithm efficiency could be increased many fold if non-linear constraints were avoided. To this end, all possible locations were generated as an input to the optimisation routine in the form of a stencil with the required clearance for the particular transducer size. This could be carried out for any arbitrary geometry for different placement densities, as illustrated in Figure 11, for an arbitrary L shape with and without a stiffener exclusion zone.

At each generation, all individuals are ranked in order of fitness f_N . Based on the crossover ratio, elite individuals in the population are allowed to reproduce and pass on their genes (i.e. transducer locations) to the next generation $\mathcal{J}_1^1 \dots \mathcal{J}_k^1$. The fittest transducer network is passed directly to the next generation, ensuring the fittest individual in any successive generation is at least as fit as the one before it (Figure 12).

Analogues to narrowing of the gene pool in genetics, only allowing genes (i.e. transducer locations) from the initial population to get passed onto the next generation, may lead to a local optimal solution. This brings about the need for mutation: at every generation, a ratio of genes will be randomly chosen from the feasible locations set. The process of producing successive generations is repeated until a stop condition is reached. In this work, the stop condition used was defined by the limiting number of generations with no change in the fittest individual: stall generation limit.

3. NUMERICAL AND EXPERIMENTAL VERIFICATION

The developed transducer placement method was verified with numerical and experimental results. Numerical simulations were carried out using the ABAQUS explicit finite element package and experimental results were obtained using a National Instruments system outlined in this section.

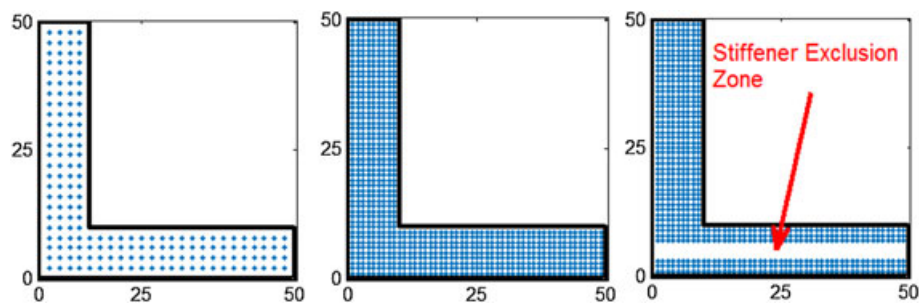


Figure 11. Feasible transducer locations with different transducer separations (2 and 1 cm), with and without a stiffener exclusion zone.

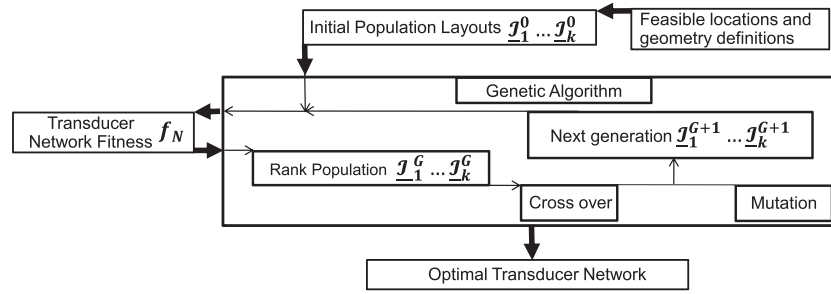


Figure 12. Overview of the genetic algorithm scheme used. Process starts from defining geometry and feasible points, then generating an initial population.

3.1. Numerical procedure

The finite element method has successfully been used for development and application of GW SHM [15,19]. Other numerical techniques are available including spectral element [28] and boundary element [29] methods. It has been suggested that a key parameter in finite element methods' numerical accuracy is the number of nodes per wavelength (NPW), with a recommended minimum of 10–20 [19]. In a study, it was found that at least 30 NPW were required to capture important propagation features [30]. A concise review of modelling aspects in the simulation of wave propagation can be found in works by Su and Ye [19].

Plates were modelled as aluminium 6082 T6 with 1.3-mm thickness using shell elements (S4R). Material properties of the plate were Young's modulus $E=72.5$ GPa, Poisson's ratio $\nu=0.33$ and density $\rho=2700$ kg m⁻³. Transducers were modelled as PIC 255 PZTs with properties $E=70.5$ GPa, $\nu=0.31$, density $\rho=7800$ kg m³, dielectric constant $K3=1685$, radius 10 mm and thickness of 0.5 mm. To ensure at least 30 NPW for 200 kHz actuation, an element size of 4.9×10^{-4} and 2.9×10^{-4} m were used for the plate and PZTs, respectively. Simulations were performed for a time period of 5.0×10^{-3} s with maximum time increment of 2.5×10^{-7} s to ensure at least 2000 data points. However, the actual increment used was found to be 2.05×10^{-8} s with critical elements in the PZTs. Diagnostic waves were actuated and sensed using the SMART finite element approach [31]. Transducers were attached to the plate via surface tie constraints, and a displacement constraint was imposed on the top circumference, with a five-cycle Hann-windowed input at 100 or 200 kHz central frequency. This is a typical actuation signal used for active GW SHM applications [32].

The first set of numerical examples consisted of a large rectangular plate with properties defined as aforementioned, measuring 0.25×1 m with a 0.5-cm diameter hole at (12.00, 7.00) cm. Feasible transducer locations for the optimisation were 2 and 1 cm apart in the x and y directions, respectively, as shown in Figure 13. Signals were obtained for three network arrangements outlined in Section 4.1 for the pristine and damaged states.

A second set of numerical results were obtained for a stiffened panel. The 'T' stiffener (1×0.13 cm flange) shown in Figure 14b was modelled using shell elements. Stiffeners were positioned horizontally centred at $y=13.67$ and 33.33 cm. In these cases, damage was modelled as a round hole or stiffener

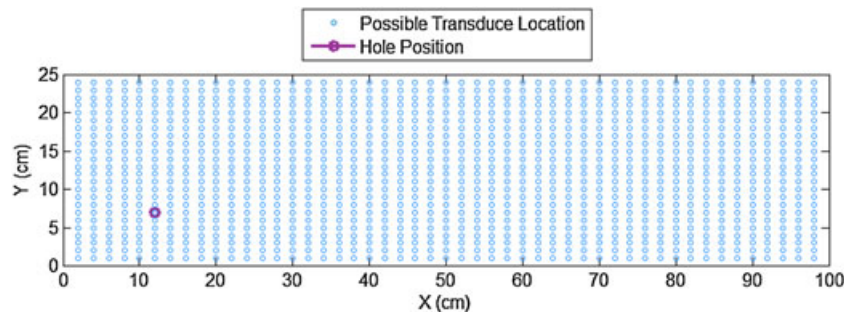


Figure 13. Rectangular plate with all feasible transducer locations.

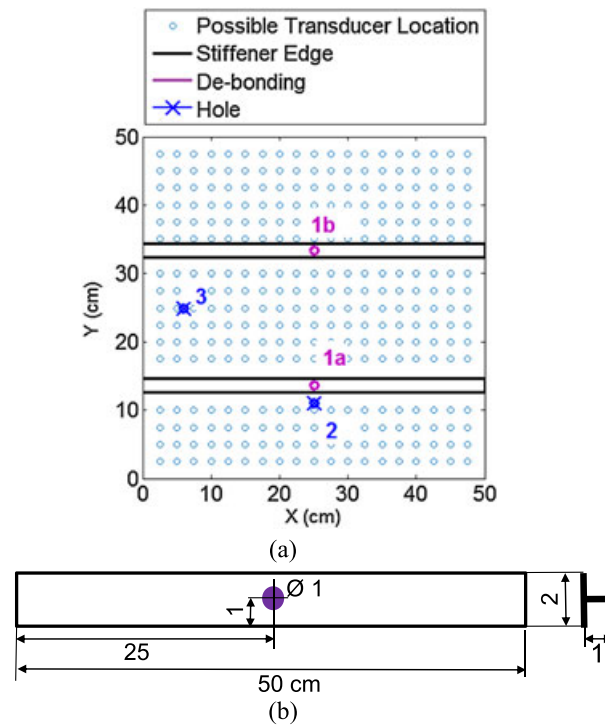


Figure 14. Stiffened plate with all feasible transducer locations (a). Stiffener profile highlighting debonded area (b).

debonding, both with 1 cm diameter. Debonding was modelled by removing the tie constrained between the stiffener and plate at the relevant partitioned area. As shown in Figure 14a, debondings were at locations 1a (25.00, 13.67) and 1b (25.00, 33.33) and the holes located at position 2 (25.00, 11.00) and 3 (06.00, 25.00). The feasible transducer positions were spaced 2.5 cm apart as depicted in Figure 14a.

Damage scatter profiles were obtained numerically with 19 transducers evenly spaced around a circle of radius 0.15 m; see Figure 15. These were attached to a 0.7×0.7 m square plate with a central damage. Distance and stiffener attenuation factors were also found $\eta_d = 3.8$ and $\eta_s = 2$. Actuation central frequencies of 100 and 200 kHz were investigated for the two hole diameter sizes and at 200 kHz for stiffener debonding. The damage scatter map was found by subtracting the pristine response from the damaged response.

The damage scatter profile indicates that forward and backward directions are most dominant in terms of amplitude; see Figure 16. This is consistent with the observation that damages near the direct

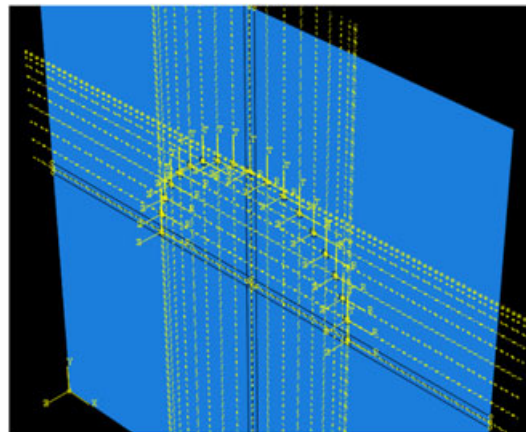


Figure 15. Finite element model used to investigate damage scatter (hole) with a circular arrangement of transducers on a partitioned plate.

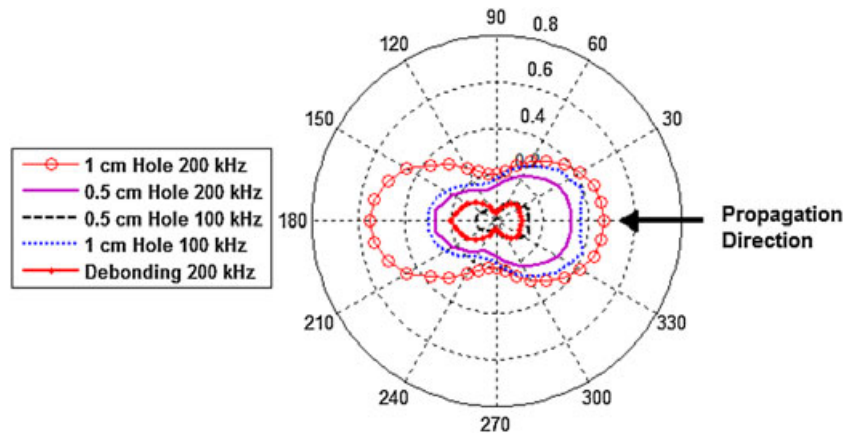


Figure 16. Simulated damage scatter profiles for holes with different diameter and 1-cm-diameter stiffener debonding. Amplitude normalised based on the amplitude of the actuation.

path of transducers are more accurately detected by the detection algorithm. It should be noted that for similar damage types (0.5 vs 1 cm diameter round hole) scatter profiles differ slightly; moreover, the scatter profile for the same damage type also varies between 100 and 200 kHz. The highest relative amplitude of damage scatter is received at all positions for 200 kHz as there is more significant wave interaction with damage because of the smaller wavelength, compared with lower frequencies [19]. It should be noted that the shadow left by debonding in the forward direction was larger than the back scatter.

3.2. Experimental set-up

The developed transducer placement optimisation approach was applied to an aluminium 6082 T6 plate of size $1.3 \times 300 \times 300$ mm. Figure 17a shows the positions of the 12 PZT disc transducer, each attached to the plate with cyanoacrylate adhesive. A National Instruments platform was used for experimental data acquisition. This consisted of a PXIe 5412 arbitrary signal generator with voltage output of 12 V, to generate the actuation ultrasonic signal. Signals were recorded with a PXIe 5105 eight-channel oscilloscope card, sampled at 60 MHz for 1 ms. Each transducer acted as an actuator with others used as sensors. This task was significantly shortened by employing a Pickering 40-726A switching card; see Figure 18. Each actuation signal was recorded 10 times, averaged and band-pass filtered. In all cases, a five-cycle tone burst signal with 300 kHz central frequency was used. Free boundary conditions were maintained by resting the plate on packaging foam.

The pristine signals were recorded for each transducer pairs. The signal was recorded again after a 30×0.5 mm crack was introduced.

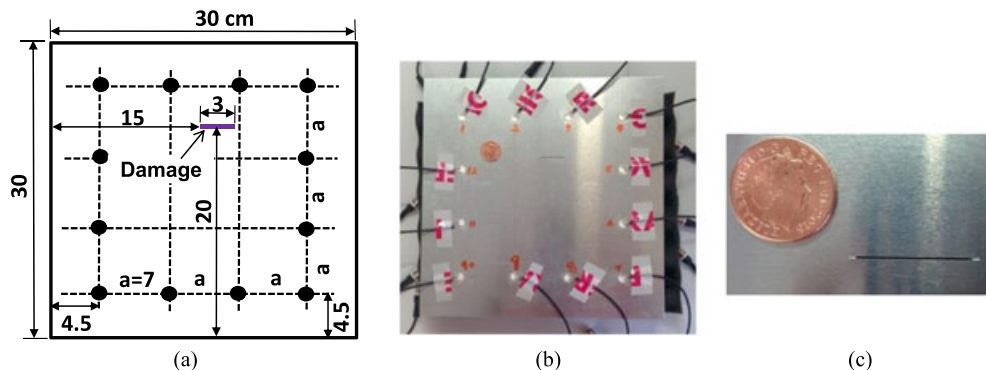


Figure 17. Plate with damage (30×0.5 mm), 12 evenly spaced transducer positions used as feasible locations (a), actual plate (b) and close up of introduced damage (c).

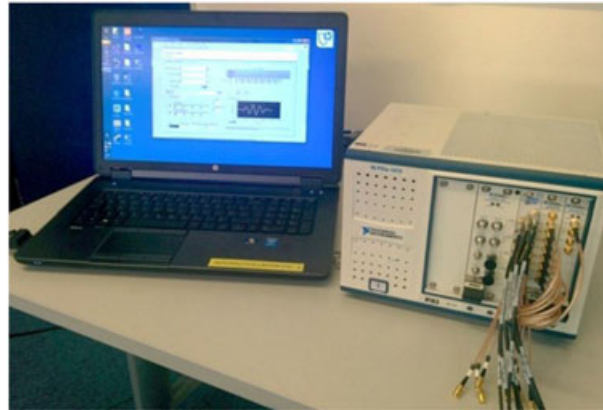


Figure 18. National Instrument PXIe acquisition system used in experiments.

4. NUMERICAL RESULTS

4.1. Rectangular plate with hole

An initial population size of 100 was set for the GA approach and crossover ratio of 0.8, generation limit of 1000 and a stall limit of 100. An optimal network with five transducers was to be selected from the feasible locations shown in Figure 13. To ensure a globally optimal solution, the procedure was repeated three times with a different initial population, verifying that each time the same solution was obtained. The obtained optimal network shown in Figure 19 did reflect that of an intuitive layout of transducers, but it would not have been immediately clear how far from the edge to place the transducers. The ultrasonic signals were also generated for two suboptimal transducer layouts with five transducers as shown in Figure 19. These had relative network fitness 1.62 and 2.04 times lower than the optimal, for suboptimal networks 1 and 2, respectively.

The damage detection algorithm was performed for the optimal and suboptimal 1 and 2 network layouts. The damage detection maps were normalised and presented in Figure 20. It can be observed that all the network layouts were able to locate the damage. However, as predicted, the optimal network does so with a higher level of accuracy as there is less noise in the damage prediction map. The worst case was that of suboptimal network 2 where the noise area was large in size and relative magnitude.

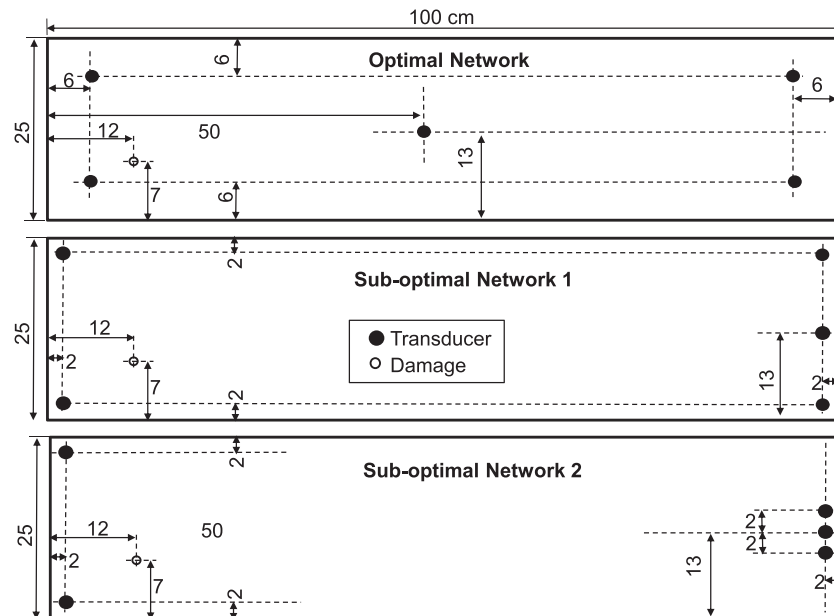


Figure 19. Transducer position for the optimal transducer network, suboptimal network 1 and suboptimal network 2.

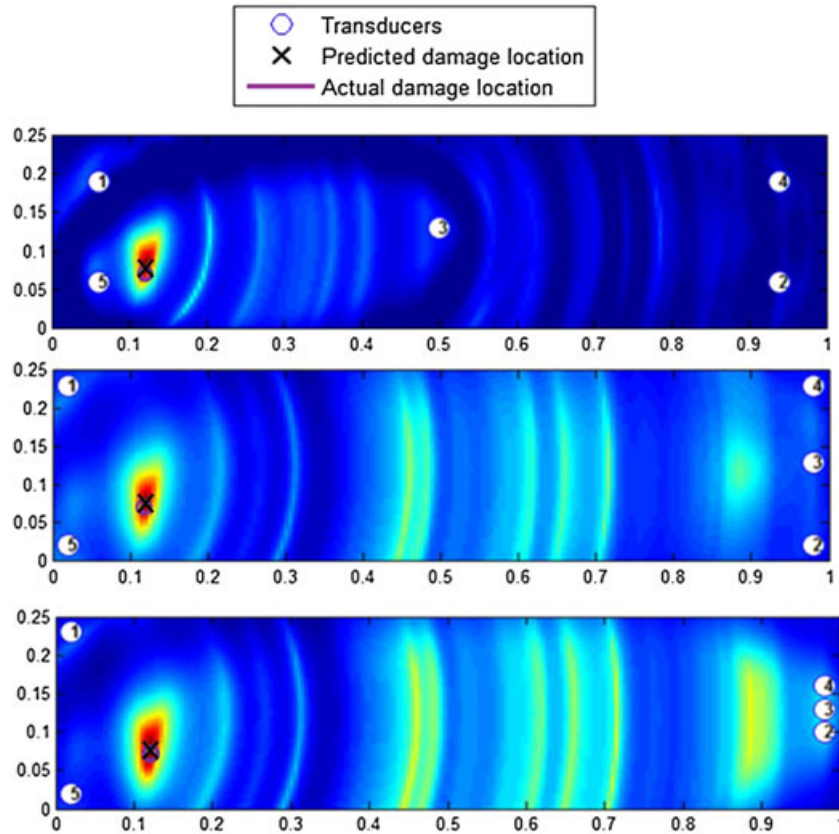


Figure 20. Normalised damage maps for the optimal (top), suboptimal 1 (middle) and suboptimal 2 (bottom) network, using finite element analysis-simulated signals. Dimension is in metres.

This was because damage scatter features are reflected from the boundaries. These reflections have a TOF that places a false residual peak within the inspection area because of proximity of the sensors to the boundary. For suboptimal network 1, the noise reduces in relative magnitude and size; hence, better detection accuracy is achieved, as predicted by the optimisation routine.

4.2. Stiffened panel

The performance of the network optimisation was assessed for a panel with two stiffeners shown in Figure 14, with a network of five transducers. These were selected from the feasible locations shown in Figure 14. As before, the transducer placement scheme was used in conjunction with a GA optimisation routine to find the best network in terms of overall fitness function. The damage scatter profile for a debonding or 1-cm-diameter hole was used as an input. The optimal network produced was compared with a suboptimal network with overall fitness being 2.7 and 2.3 times lower for the debonding and hole, respectively; see Figure 21. The suboptimal network was chosen to focus the coverage area to the top half of the plate and the top stiffener, resulting in higher point fitness or coverage index values in these areas. The coverage index values in the top half of the plate are doubled because of the near halving of the distance between the transducers compared with the optimal. The optimal network provided a more even coverage for a larger area, covering both stiffeners. It should be noted that the optimal layout for detection of a hole and debonding were the same. In both cases, the stiffeners have a significant impact on the overall coverage indices, as observed by comparing Figures 21 and 22.

As depicted in Figure 21, the suboptimal network was predicted to provide no coverage of the bottom stiffener. This was found to be consistent with the poor detection of stiffener debonding 1a, with 9 cm localisation error, as illustrated in Figure 23 debonding 1a. In contrast, the optimal network was able to predict the location of damage 1a accurately with 3.4-mm localisation error. A similar

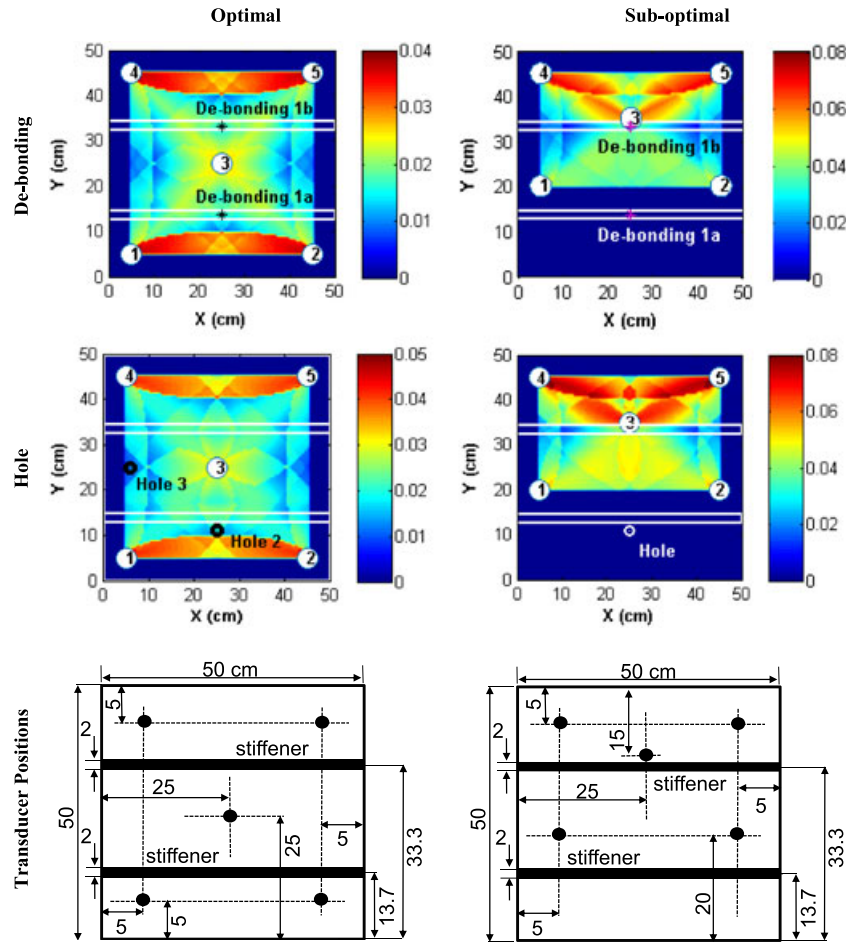


Figure 21. Contours of coverage index for different damage types with optimal and suboptimal networks, the position of the transducers and stiffeners highlighted.

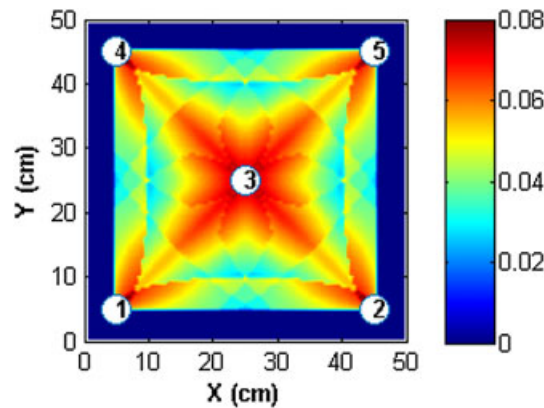


Figure 22. Contour of coverage index for stiffener optimal network on a plate with no stiffeners.

outcome was observed for detection of hole 2 with the optimal network correctly predicting the location of damage, while the suboptimal network performed poorly.

The suboptimal network was expected to detect debonding in the top stiffener more accurately because of a higher coverage index value. The coverage index at location 1b for the optimal and suboptimal network was 0.0165 and 0.0314, respectively. The damage localisation error was found

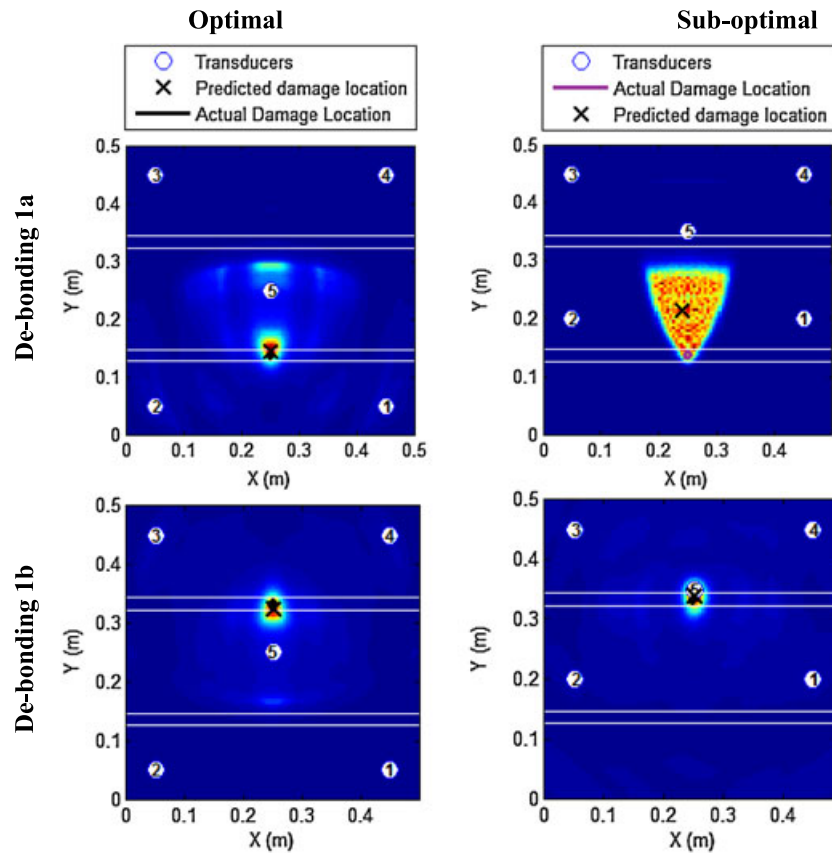


Figure 23. Damage detection maps for the optimal and suboptimal transducer network for detecting stiffener debonding 1a and 1b.

to be 3.3 and 1.7 mm (lower is better) for the optimal and suboptimal network; hence, damages were located more accurately in areas with higher coverage index.

The coverage index for the optimal arrangement at locations 2 and 3 were 0.0194 and 0.00885. The error in damage localisation was found to be 5.1 and 15.0 mm respectively for holes 2 and 3; see Figure 24. The damage location was predicted with higher accuracy for locations with higher coverage

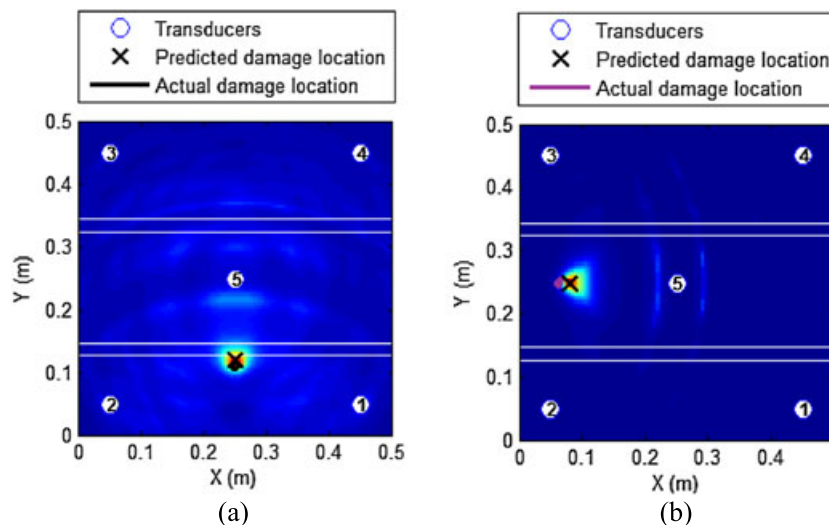


Figure 24. Damage detection maps for the optimal network for detecting hole 2 (a) and 3 (b). Hole 2 was detected more accurately as predicted by a higher coverage index.

index. This underlines the validity of the point fitness calculation (coverage index) in reflecting the detection accuracy.

5. EXPERIMENTAL VALIDATION

In this section, the developed transducer placement was validated using experimental results from an aluminium panel with a crack representative of fatigue.

5.1. Problem description

By using available transducers as a stencil of feasible transducer locations, the optimisation algorithm was used to find an optimal network with five transducers. This allowed for a simple yet effective test of the network optimisation scheme in detecting a crack.

The damage type of interest in this section is a thin notch/crack with horizontal orientation; see Figure 17. It is known that the Lamb wave damage scatter is direction dependant even for a uniform hole [18]. However, for a crack, the relative position of sensor and actuator are only part of the picture. The orientation of the crack with respect to the propagation path is also a key factor. Based on results for scatter around a crack [33], a normalised scattering profile was used as the input for the fitness function calculations. Maximum scatter amplitude is generated when both actuator and sensor are located in the normal direction of the crack, that is, 90° to the crack; see Figure 25.

The damage hot spot was defined as shown in Figure 26 and given five times more weighting to priorities intense coverage of this area. The crack orientation was set as horizontal. This information is typically available for most structures, that is, impact-prone areas, stress concentration and cyclic loading direction, hence serve as reasonable priori inputs to the optimisation procedure.

The procedure was repeated with random inputs three times, each yielding the same final layout, confirming the layout is the global optimum. The population size was set to 20 with a relatively high mutation ratio of 0.3 [27] and a final generation limit of 200. Combining these, it can be said that at the 150th generation, all 792 possible networks would have been tested. However, it was found that the procedure converged to the final solution before 20 generations, highlighting the efficiency and high level of applicability of GA to this problem.

5.2. Experimental results

The optimal network arrangement is shown in Figure 27b. Additionally, a suboptimal arrangement with a similar coverage area and transducer number but with reduced fitness was selected. The network fitness of the suboptimal network was nearly 1.2 times lower than the optimal.

As depicted in Figure 28a, the suboptimal network was not able to localise the damage with the prediction near sensor 1 far from the actual location. The optimal network accurately detected the crack with the peak index area reflecting the location and approximate size of the damage; see Figure 28b.

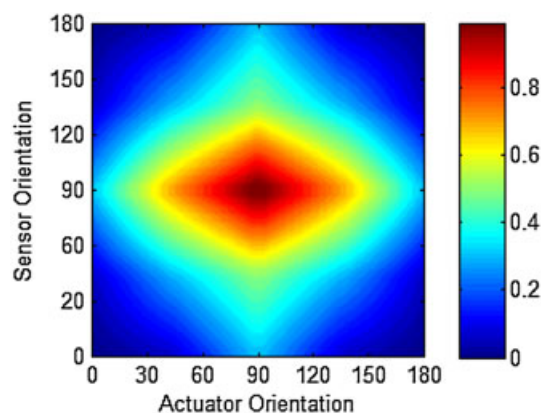


Figure 25. Normalised scatter amplitude for sensor actuator path each oriented with respect to the crack.

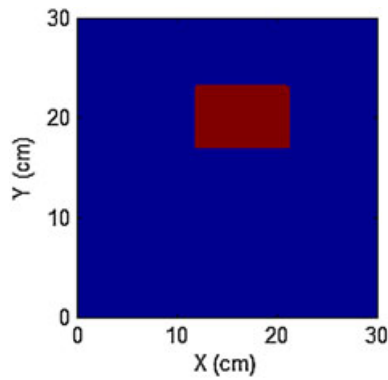


Figure 26. Damage hot spot for area with increased sensitivity (five times).

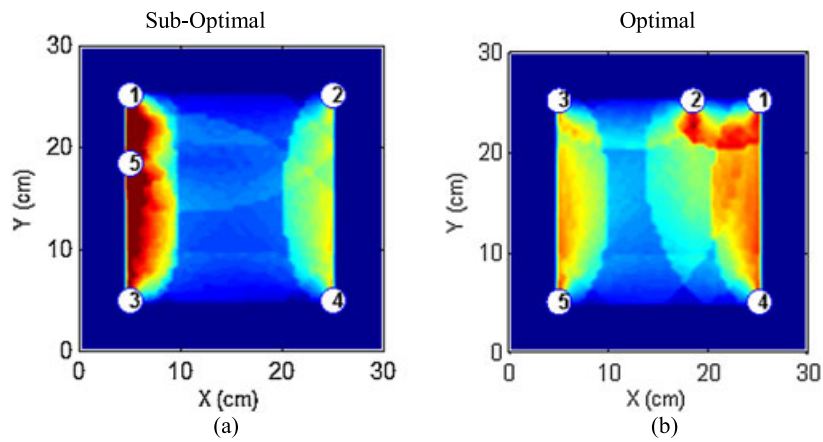


Figure 27. Normalised coverage index contour map for suboptimal (a) optimal network (b).

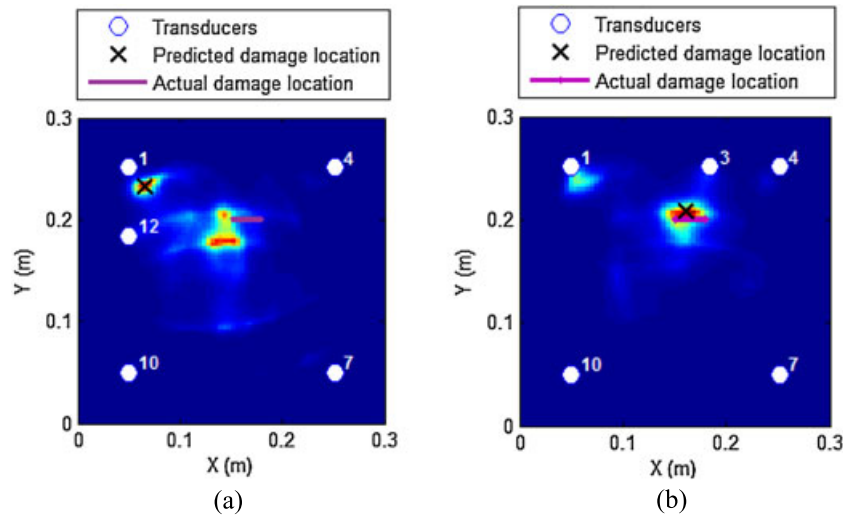


Figure 28. Damage location prediction for experimental signals. Suboptimal (a) and optimal (b) network arrangement, used transducers indicated on plot.

6. CONCLUSIONS

A scheme for robust transducer placement optimisation was developed with provision to deal with irregular shapes, stiffeners and defective transducers. It incorporated physical wave propagation

information and specific damage types of interest. First, the effectiveness of the placement optimisation strategy was shown through a comparison of the damage predication maps using finite element analysis-simulated signals. This was carried out for optimised transducer networks and two other networks known to be suboptimal. It was found that the optimally placed network outperformed the others in terms of detection, low noise levels and false peak regions because of boundary-reflected signal. In addition, as predicted, the least optimal arrangement performed the worst. It was also shown with numerical results for a stiffened panel that an optimal network can predict the location of a hole or stiffener debonding with a higher level of accuracy for a larger inspection area. The point fitness or coverage indices were an important factor in the overall fitness of a network; importantly, the calculated point fitness values reflected the accuracy of damage location prediction.

The proposed scheme was then used to find an optimised transducer network on an aluminium plate, and compared with a suboptimal layout. It was shown that the optimal transducer network detected a crack with a higher level of accuracy with experimental results.

It can be concluded that the proposed optimisation method can be used to find an optimal transducer layout that enhances the detection performance. The algorithm should be developed in future work to incorporate network complexity cost and also minimise the number of transducers used. In future works, the procedure will be applied to experimental results for a more complex damage scenario and for stiffened composite panels.

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