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SENSOR NETWORK OPTIMIZATION FOR DAMAGE DETECTION ON ALUMINIUM STIFFENED HELICOPTER PANELS

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Abstract. Health and Usage Monitoring Systems (HUMS) has received considerable attention from the helicopter community in recent years with the declared aim to increase flight safety, increase mission reliability, extend duration of life limited components and of course reduce the maintenance costs. The latter is about 25 per cent of the direct operating cost of the helicopter, thus playing an important role especially in the case of the ageing aircrafts. In particular, with respect to helicopter fuselages, only some attempts were carried out to monitor directly on-line the damage accumulation and propagation during life. In this field, and in particular in the military applications, an integrated and reliable system for monitoring the damage in the fuselage and for evaluating the time inspections and remaining life (prognosis) is missing. However, because of the presence of many vibratory loads, the diagnosis of helicopter structures is very critical. From one hand, a very large number of sensors would be needed for a robust appreciation of the structural health, from the other hand the industrialization of the product brings the need for a low impact over the existing structures, or toward a reduction in the allowed amount of sensors. As a result, comes the importance for an optimization of the sensor network, with the aim to find out the regions inside the structure which are the most sensible to a damage and at the same time robust to noise. The aim of the present work is to define a methodology for optimising the sensors position inside an helicopter fuselage panel in order to obtain the best compromise between the simplicity and the robustness of a sensor network. In particular, a Finite Element (FE) model will be used to create a database of various damages inside the structure, thus consequently optimising the network sensitivity to any damage. The evaluation of the network performances is provided when some realistic noise [1,2] is added to the FE calculation.

1 INTRODUCTION

Structural Health Monitoring has received a lot of attention from the aerospace industry, where the costs related to maintenance and machine stops are very high and safety is a primary issue. In particular, vibrations play an important role in helicopters, where structural defects like cracks could propagate very fast causing unexpected failures of components. To date, fatigue behavior is controlled with a deep analysis in the design phase, governed by damage tolerant regulations, and with a clear schedule of inspections during life, which reduce a lot the availability of the machines, with a cost that is around the 25% of the operating effort.

The coupling of Finite Element Methods (FEM) with Artificial Neural Networks (ANN) has proved to be promising in the frame of Structural Health Monitoring applications, concerning aerospace industries as well as civil structural ones. The main advantage is that FEM allows for a low cost knowledge generation, upon which it is possible to optimize the ANN parameters. For a deeper introduction to the two tools, the interested reader could refer to [3,4]. Though many parameterized damages could be modeled with FE, it is however important to keep in mind that some test experiments are needed in order to validate the models as well as to calibrate the damage sensitive parameters and to appreciate the best direction for a network optimization. For instance, in [1] some data were presented about dynamic crack propagation tests in helicopter fuselage panels, and it has been possible to appreciate the extent of real world dispersion with respect to FEM crack propagation calculations, giving it as input to the current work. In fact, to deliver a critical product such as an SHM system, the most important point is to associate a reliability and availability to it, thus calculating the feasibility either from the economic or safety points of view. In fact, especially if the system has to interact with the pilot to suggest a certain flight profile according to the structural health of the machine, the False Alarm parameter should be reduced at a minimum. Different requirements arise if the system has to communicate with the maintenance center, where measured data are stored and processed by maintenance engineers in order to set up the proper maintenance schedule, concept at the basis of the Condition Based Maintenance (CBM). The former approach is by far more critical, thus requiring also higher performances, especially in terms of reliability.

Inside this work, the training data are provided by FE analysis, having the advantage of allowing a large range of damage parameters to be analyzed. However, if in FE analysis there is no limit the spatial resolution of the data which is obtained (either strains or mode shapes), in reality the number of sensors available will be limited and this will create restrictions on data resolution. As a result, it would be necessary to optimize the number and location of sensors for each given problem.

The sensor network should thus be optimized in order to maximize the efficiency of the SHM, compromising between the increasing cost of a dense network and the lowering of performances by decreasing the number of sensors. An approach for sensor network optimization is proposed inside this paper, trying to find the best sensor position and number for a stiffened helicopter panel SHM. The aim is to estimate the amount of sensors necessary to obtain a certain performance, maybe required from regulations or from economic analysis. Given the repetitive structure of the typical aeronautical stiffened panel analyzed, the attention is not focused on the optimization algorithm but on performance results. However, the methodology is valid also for more complex cases where symmetries and repetitions couldn't be exploited, for which the coupling with more complex optimization techniques like those reported in literature would be useful. A detailed survey of recent works on sensor placement is given in [5], focusing the attention on combinatorial optimization, such as Genetic Algorithms (GA) and Simulated Annealing (SA), which proved to be particularly efficient. Again, in [6] the information entropy parameter is proposed as a measure upon which to minimize the uncertainties in the estimation of model parameters, however mostly suited for a Bayesian Network. Furthermore, in [7] the optimization of optical Fiber Bragg Grating sensor locations inside a composite repair patch is proposed, with the aim to determine the laminates between which the fibers should be embedded as well as the actual crack sensitivity of the sensor.

2 THE DIAGNOSTIC SYSTEM

In figure 1 the organization of the diagnostic system is reported. As suggested in [5] and reported in [8], one could distinguish many steps or levels, each one inferring over a particular aspect of structural diagnostic. In particular, [5] recommends 4 layers, named Anomaly Detection (alarm generation), Localization, Quantification and Prognosis. However, an additional knowledge layer is needed, that is to say Damage Recognition, or the ability of the algorithm to distinguish the correct damage the structure undergoes. This is mostly important for the Quantification phase, as a wrong estimation of the damage type could lead to wrong assumption in Layer 3, 4 and 5. In particular, as introduced before, helicopters are critical machines because of fatigue (connected with crack damage type) as well as low velocity impacts due to the harsh environment where they operate (impact damage type). Moreover, military helicopters are subjected to bullet impacts, once more connected with a different damage pattern.

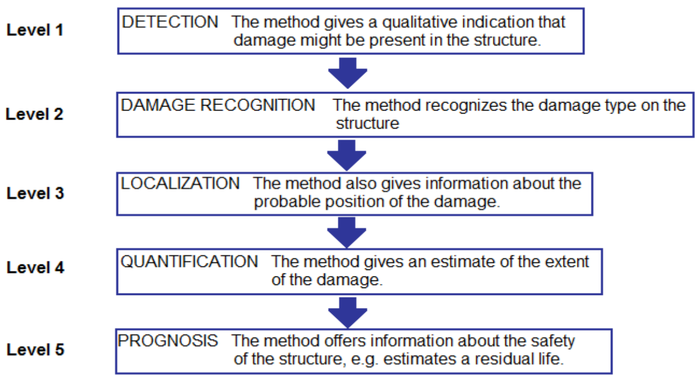


Figure 1: Flow Chart representing the organization of information inside the diagnostic system

An important thing to be decided is whether to unify two or more levels of diagnostic inside just one ANN with multiple output. According to some ANN performance analysis, using a separate ANN to infer over each single diagnostic layer appears to enhance the performances. This can be explained through the assumption that, when optimizing the ANN to solve one layer, each synapses weight is calibrated for that layer information. Obviously, it is important to remember that, given that the performance is measured through the percentage of right assumptions, the reliability of the coupled system has to be compared with the product of the uncoupled reliabilities.

3 PROBLEM DEFINITION

A FE model of a stiffened panel has been created in ABAQUS 6.9, consisting of a typical aerospace structure, referring in particular to helicopter fuselage design. Some geometry information are reported in figure 2, while for a detailed explanation of the model the interested reader could refer to [8]. Two crack damages have been modeled, one consisting of a rivet crack, starting from one of the rivet connections inside the panel, while the other consisting in a bay crack, randomly positioned in a bay to simulate a crack propagating from an accidental damage. A summary of the problem statement is reported in table 1.

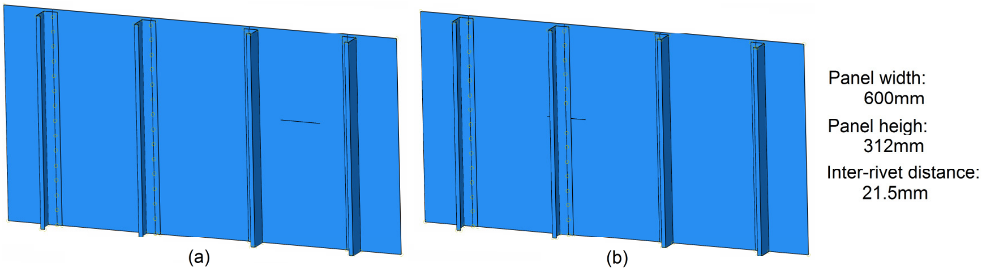


Figure 2: Panel geometry, with model for (a) bay skin crack and (b) rivet skin crack

Table 1: Summary of problem statement

Item	Description	Notes
Crack Types	Rivet Crack	The most common case
	Bay Crack	Simulating crack starting from accidental damage
Crack Length (for ANN training)	Constant, 60 mm	Inside this paper, a constant crack length is chosen to train the ANN, then evaluating the performances for different crack length.
Crack Angle	Constant, perpendicular to stringers	The loading on the panel is directed parallel to stringers
Crack Cases for ANN	80 cases for each bay	Total 80x3=240 cracks on the panel
	1 case for each rivet	Total 15x4=60 cracks
Allowed Sensor Positions	Skin	Along a path in the centre of the bay parallel to stringers
	Stringer	Along a path on the stringer next to rivets parallel to stringers
Sensor constraints	Skin/Stringer	The number of sensor is constant among all the stringers. The number of sensor is constant among all the bays.

The sensor network design will be based hereafter upon the optimization for Level 1 and 2 diagnostics. In fact, according to figure 1, Level 1 information appears to be the most critical point, as it influences the activation of all the consecutive level checks. In fact, the practical implementation of the on-board system should rely on the alarm generator, which has to produce the least number of False Alarms (damage doesn't exist but it is detected) and Missed Event (damage exists but it is not detected). Level 1 decision will be modeled by means of a *Pattern Recognition ANN* algorithm, inside the MATLAB environment. Only when the anomaly is detected, all the consecutive steps should be activated. In particular, the need for a damage type discrimination has been advanced above. Inside the present work, the Level 2 check has to distinguish between 2 damage types that are practically similar, as they both refer to a skin crack. However, the system feasibility will be demonstrated. For a more practical and useful solution one could try to model the rupture of a stringer, thus discerning it with respect to skin crack damages. Again, Level 2 decision will be modeled by means of a *Pattern Recognition ANN* algorithm, inside the MATLAB environment.

4.1 Performance indicators

It is important to define the performance indicators of the ANN. For this purpose, 3 parameters have been identified as the most indicative, that is to say, the Probability of damage Detection (PoD), the Probability of False Alarms (PFA) and the Probability of Wrong Assumptions (PWA):

$$PoD = \frac{Detected\_cracks}{Total\_crack\_cases} \tag{1}$$

$$PME = 1 - PoD \tag{2}$$

$$PFA = \frac{Correct\_alarms}{Generated\_alarms} \tag{3}$$

$$PWA = \frac{Wrong\_Decisions}{Total\_Nr.\_of\_analysed\_cases} \tag{4}$$

In particular, the parameter defined in Eq. (3) is able to synthesize the information gained through PoD and PFA. For that reason, PWA will be used in the next chapters to reason about the sensor number selection.

4.2 Noise extent appreciation

As introduced in Ch. 1, during the training phase, FE calculations for strains over the structure will be given as input to the *Pattern Recognition ANN*, while the output will be a binary variable indicating whether the damage is present or not. However, it is important to consider that, during the algorithm testing or, more generally, while using the properly weighted algorithm in a real environment, the input data will be noised, at least hopefully with a mean value near to the FEM prediction. In [1] some propagation tests were performed over the same structure geometry, thus appreciating the extent of the variability of strain measurements over the structure in function of the crack length (all the cracks were artificially initiated at the same location in a typical panel geometry).

The main output from [1] was that two classes of sensor positions could be established, that is to say sensors on skin or on stringers, with sensing direction parallel to maximum principal stresses. The sensors located on the skin presented a larger deviation from FEM with respect to those placed on the stringers. On the other hand, skin appeared as more sensitive to crack presence, which means that the strain parameter variation per unit of crack length increase was larger with respect to what happened for stringer sensor. However, being the noise robustness more influent with respect to the losses in sensitivity, stringer located sensors behaved better than skin sensors in crack hypothesis testing. The extreme variability of measures coming from skin sensors might be due to compressive stresses perpendicular to stringers generated in the bay skin, similar to buckling effects, very case to case dependent. On the other hand, stringers are designed to transmit a the load in a certain direction, thus acting as a filter with respect to noises coming from all the other directions. In table 2 is reported the extent of noise percentage superposed to FEM calculated inputs during the ANN TESTING phase.

Another point to be discussed is whether to introduce or not the noise also in the ANN TRAINING phase. In fact, the proper ANN optimization would stop before starting to learn the noise coming from the input data, thus maintaining the property of generalization. However, if the network training is done with deterministic data (FEM based), practically the algorithm doesn't recognize that the same defect could produce a certain distribution of possible strain outputs, instead of just one value. The proposal inside the current work is to introduce a certain amount of noise also in the training phase of the neural network. This has been done by creating 25 replies for each strain measure associated to each damage case, sampling from a Gaussian distribution with mean equal to the FEM prediction and variance connected to the percentage variation expressed in table 2 for the training phase (the choice for the noise model has to be carefully justified, as explained later on). In particular, the performance evaluation for sensor network modeling has been repeated for 3 noise amounts applied in the training phase, as reported again in table 2.

Table 2: Noise Estimation for ANN training and testing

Training Phase	Sensor on Skin	0%, 6%, 10%
	Sensor on Stringer	0%, 4%, 8%
Testing Phase	Sensor on Skin	15%
	Sensor on Stringer	7.5%

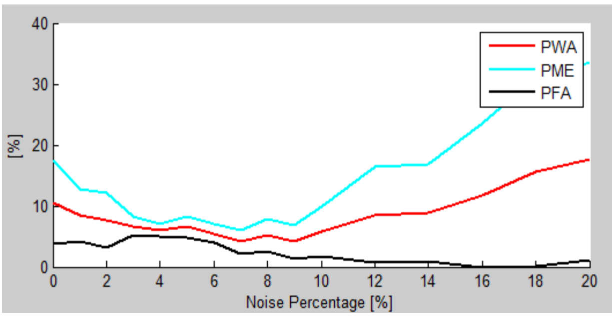


Figure 3: Probability of False Alarm (PFA), Probability of Missing Event (PME) and Probability of total Wrong Decision as a function of noise added in the ANN training

The noise amount to be introduced in the training phase should be estimated upon appreciation of the actual noise present on the real case structure (Testing Phase Noise). In figure 3 the performance variation is reported in function of the noise added to FE data in the training phase. It can be noticed that a beneficial effect in performances is obtained by adding noise up to a certain value, below which the algorithm starts to decrease its detection capabilities.

Finally, the choice for a Gaussian distribution for noise modeling has to be justified according to the assumption that the causes of that noise are also Normal distributed. The following are the main reasons for real data dispersion with respect to FEM prediction on strain measures:

- Manufacturing process
- Material non-uniformities
- Non Linearity (different from damage)
- Environmental influences
- Sensor locations
- Crack angles

Under the hypothesis of material uniformity and linearity, allowing a 1-2% variation in material properties, it will be reflected in the same percentage uncertainties on the FEM prediction. In figure 4 it is possible to appreciate the effect on the strain FEM outputs due to a ±5.5° variation in crack angle (corresponding to ±5% of the 90° target angle with respect to stringer direction). In case of perfect Gaussian error propagation, the lines relative to ±5.5° angle variation should be mirrored with respect to 0% difference horizontal line. This is not happening which means that, though the angle dispersion could be Normal distributed, its noise propagation at sensor measure level won't still be Normal distributed. However, it rarely exceeded the 2% threshold variation in strain field output.

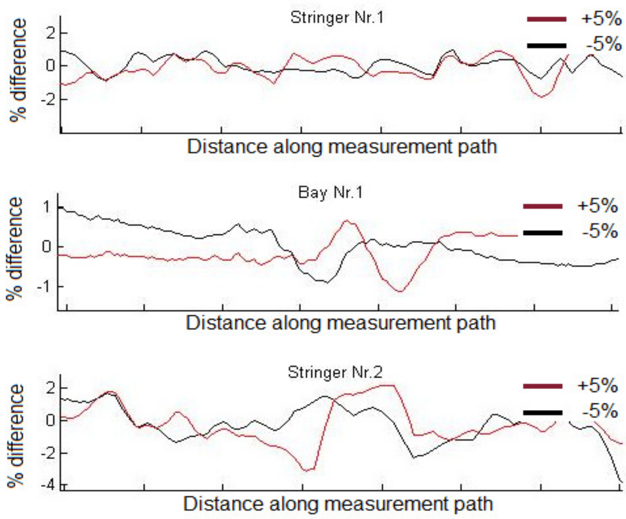


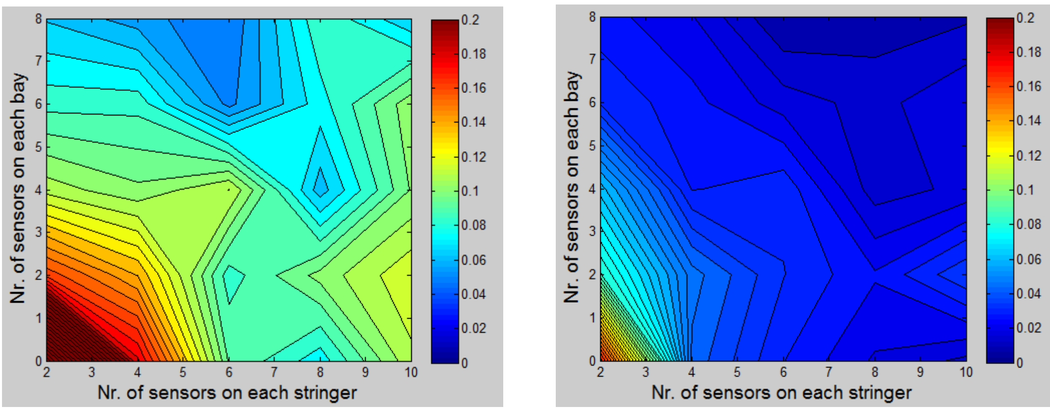
Figure 4: Uncertainty in FEM strain measures estimation for ±5.5° variation of crack angle w.r.t. nominal crack angle (90°)

5 RESULTS AND CONSIDERATIONS

According to the problem statement discussed above, some sensitivity plots have been produced in order to evaluate the performances of the ANN in function of the PWA parameter, as defined in Ch. 4.2. For each sensor number combination inside the plots, the ANN (pattern recognition) performance has been evaluated trying 5 different hidden layer numbers and repeating the network training 4 times, in order to select the best trial. This because, by varying the number of hidden layers, the structure of the ANN is changed, and thus its performances. Moreover, the optimization process itself isn't deterministic, thus producing a different ANN for each training trial. For a better understanding on the structure of ANN the interested reader could refer to [3,8].

5.1 Case 1 (a, b)

Problem	Level 1: PATTERN RECOGNITION (Distinguish damaged from undamaged panel)		
Noise in training set	Sensor on Skin (a,b,c)	0%	10%
	Sensor on Stringer (a,b,c)	0%	8%
Noise in testing set	Sensor on Skin	15%	
	Sensor on Stringer	7.5%	
Crack Length for training	60mm		
Crack Length for testing	60mm		
Crack Angle	Perpendicular to stringer		
Crack Type	Either rivet crack or bay crack		

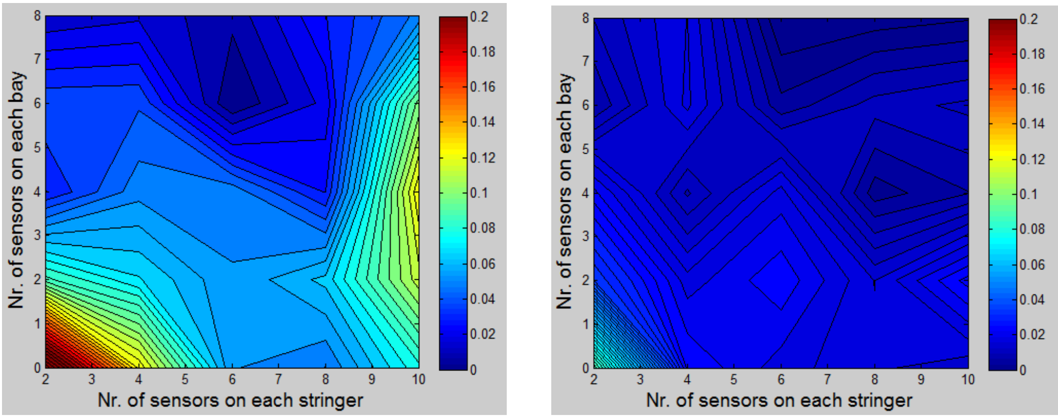


(a) (b)

Figure 5: Case 1 sensitivity plots for PWA with (a) no noise in ANN training (b) noised training set

5.2 Case 2 (a, b)

Problem	Level 1: PATTERN RECOGNITION (Distinguish damaged from undamaged panel)		
Noise in training set	Sensor on Skin (a,b,c)	0%	10%
	Sensor on Stringer (a,b,c)	0%	8%
Noise in testing set	Sensor on Skin	15%	
	Sensor on Stringer	7.5%	
Crack Length for training	60mm		
Crack Length for testing	100mm		
Crack Angle	Perpendicular to stringer		
Crack Type	Either rivet crack or bay crack		

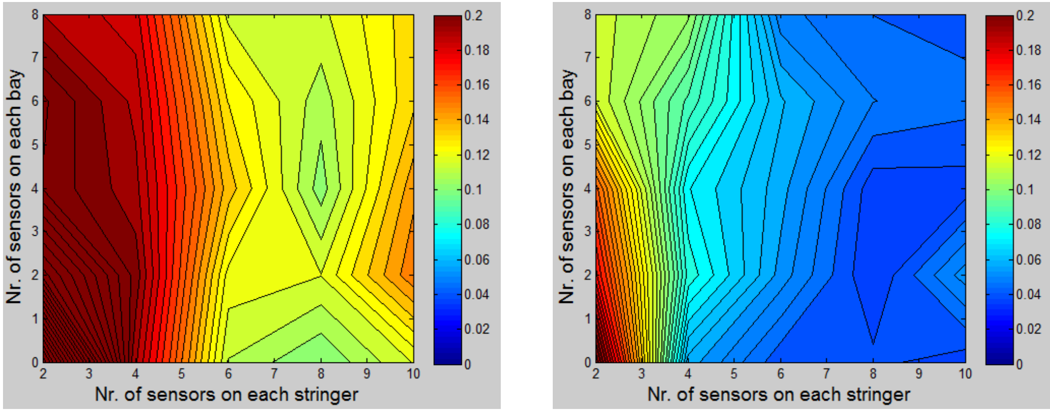


(a) **(b)**

Figure 6: Case 2 sensitivity plots for PWA with (a) no noise in ANN training (b) noised training set

5.3 Case 3 (a, b)

Problem	Level 1: PATTERN RECOGNITION (Distinguish damaged from undamaged panel)		
Noise in training set	Sensor on Skin (a,b,c)	0%	10%
	Sensor on Stringer (a,b,c)	0%	8%
Noise in testing set	Sensor on Skin	15%	
	Sensor on Stringer	7.5%	
Crack Length for training	60mm		
Crack Length for testing	40mm		
Crack Angle	Perpendicular to stringer		
Crack Type	Either rivet crack or bay crack		

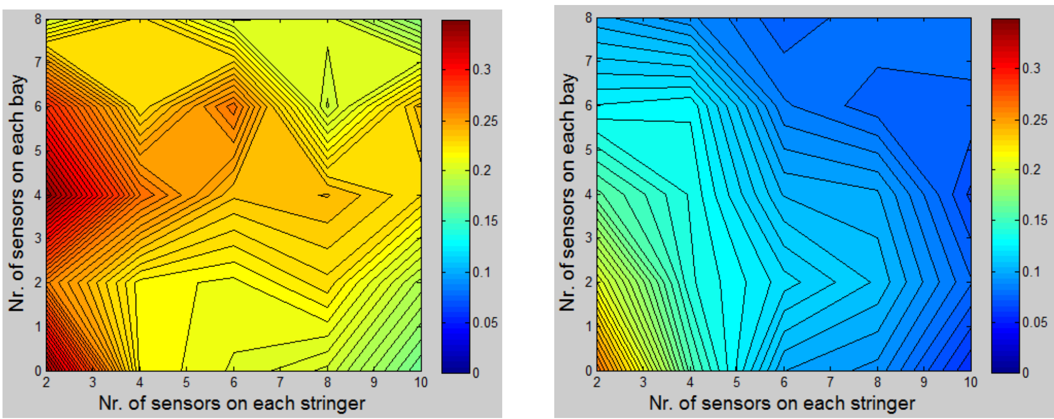


(a) (b)

Figure 7: Case 3 sensitivity plots for PWA with (a) no noise in ANN training (b) noised training set

5.4 Case 4 (a, b)

Problem	Level 2: PATTERN RECOGNITION (Distinguish skin crack from rivet crack)		
Noise in training set	Sensor on Skin (a,b,c)	0%	10%
	Sensor on Stringer (a,b,c)	0%	8%
Noise in testing set	Sensor on Skin	15%	
	Sensor on Stringer	7.5%	
Crack Length for training	60mm		
Crack Length for testing	60mm		
Crack Angle	Perpendicular to stringer		
Crack Type	Either rivet crack or bay crack		



(a) (b)

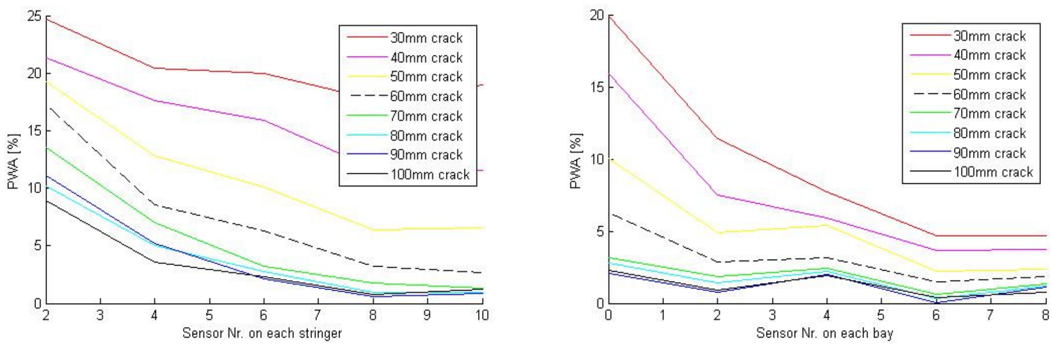
Figure 8: Case 4 sensitivity plots for PWA with (a) no noise in ANN training (b) noised training set

5.5 Considerations

In figure 5 the ANN performances in terms of PWA are plotted as a function of the sensor combination over the structure. The first thing that should be noticed it the improvement in detection capabilities because of the introduction of a certain level of noise inside the training phase (figure 5b). In addition one could notice that, while for a lower number of stringer sensors it could be worth to acquire some skin measurements, when increasing the sensor number on the stringer it becomes practically negligible the additional information gained with skin bay measures. On the other hand, the information gained by adding one more stringer sensor is higher with respect to that of a skin bay sensor, maybe due to the noise model, however in agreement with experimental test conducted in [1, 2].

If results reported in figure 5 refer to a case where crack length for training (60 mm) coincide with that for testing (60 mm), in figure 6 and 7 the testing crack length has been respectively moved to 100 mm and 40 mm. As expected, the detection performances got worse when detecting cracks smaller than those for training and rather better when moving in the opposite direction. A similar information can be retrieved from figure 9, where the changes in ANN capabilities as a function of sensor number and crack length are clearly appreciable for the cases with no sensors on the skin but varying sensors on the stringers (figure 9a) and 6 sensors on each stringers and varying number of skin sensors (figure 9b). It is however demonstrated (at least for stiffened panels) that designing a training set with a threshold crack length allows to detect also longer cracks with a reliability at least equal to the design point.

Finally, in figure 8 the capabilities on damage recognition for Level 2 diagnostic is reported as a function of sensor number combinations. Again it is clear that the information gained with a stringer sensor is by far more effective than the one of a skin located sensor. It is also possible to appreciate that sometimes adding additional sensors on the skin could worsen the ANN performances.



(a) **(b)**

Figure 9: (a) PWA as a function of sensor Nr. on each stringer (with no skin sensors) for different crack length in testing phase and (b) PWA as a function of sensor Nr. on each bay (with 6 sensors on each stringer) for different crack length in testing phase. Training has been done with 60mm cracks (dashed line)

6 CONCLUSIONS

According to some preliminary studies on helicopter fuselage damage tolerant design [1, 2], it has been possible to appreciate the extent of variability in strain measures for stiffened panel like structures subjected to growing damages. The information retrieved has been used inside this work to enhance the performances of an ANN, thus selecting the best sensor arrangement in terms of numbering and position, according to the capabilities of different configurations, expressed as PWA, PME and PFA. It was demonstrated the performance increase due to the superposition of even a small noise to the deterministic training set coming from FE simulations. Moreover, it was confirmed [1] the best performance of a stringer sensor with respect to skin bay measure points. Finally, the configuration suggested for the current case test is a 6-sensor-per-stringer/320mm-stringer. The choice can be taken as a good compromise between the additional information that could come from one more sensor in stringer/skin and the feasibility of the SHM hardware. However, according to the new sensor technologies based upon Fibre Bragg Grating (FBG) systems, even more sensors could be distributed along the stringer direction thanks to the possibility for multiplexing.

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