Sensor failure detection for robustness of SHM using a combined artificial neural network and finite element analysis approach

Amol M Khatkhate*, G M Kamath, M. Subba Rao
Advanced Composites Division,
National Aerospace Laboratories,
Bangalore – 560017, INDIA.

Keywords: sensor failure, robustness, health monitoring, composites, fiber bragg gratings

ABSTRACT

Structural Health Monitoring (SHM) technology has become increasingly important as an approach to increase the safety and reduce the maintenance costs of high performance co-cured/co-bonded composite aircraft structures. Affordable advanced miniaturized sensors like the Fiber Bragg Grating (FBG) sensor and continuous improvement in data processing technology combined with powerful hardware and software approaches have allowed this technology to become an integral part of such structures. However, failures of such sensors during flight can be of serious concern and the detection and isolation of such events is extremely critical in the context of a robust health monitoring scheme.

In this paper, a methodology combining the finite element (FE) analysis and Artificial Neural Networks (ANN) has been proposed to isolate sensor failure based on the observed static strain patterns. Artificial Neural Networks (ANN) has been used for the estimation of the load which is a global parameter from the various static strain patterns. The finite element (FE) model which has been experimentally validated in response to the estimated load provides the necessary information for isolation of localized sensor failure. The development and implementation of the methodology is discussed in the context of a composite spar/rib box structure designed and fabricated for this study.

INTRODUCTION

The emerging field of structural health monitoring (SHM) addresses the in situ behavior of structures by assessing their performance and recognizing damage or deterioration. SHM involves system state definition, data acquisition, data filtration, feature extraction, data reduction, pattern recognition and decision-making.

*Corresponding author email: amolmk@css.nal.res.in
Amol M. Khatkhate, Advanced Composites Division, National Aerospace Laboratories, Bangalore – 560017, INDIA
Each of these components is equally important to determine the state of health of a structure. However, the bulk of research on SHM has been focused on data acquisition, feature extraction and data reduction techniques. In this paper, with recent developments in artificial intelligence and digital signal processing [1-5], a more robust SHM system leading to isolation of sensor failures has been proposed for the structural health monitoring of aerospace structures.

The advent of fiber optic sensors in conjunction with the laminated composite technology has opened up possibilities of incorporating a ‘nervous system’ into an aircraft structure that senses, measures and communicates various environmental and structural parameters. Fiber optic (FO) sensors have several advantages such as small size, low weight, high sensitivity, immunity to electromagnetic interference (EMI), and multiplexing capability. This study focuses on the use of the Fiber Bragg Grating (FBG) sensor, which relies on the narrowband reflection from a region having a periodic variation in the core refractive index [6]. The shift in the reflected wavelength from the central wavelength of the FBG gives a direct measure of strain. The characterization and embedment of these sensors into composites is an important issue and has been addressed in detail earlier [7-8]. A 4-channel Fiber Bragg Grating Swept Laser Interrogator (FBGSLI) system made by Micron Optics Inc., USA was used for this study. This system operates in the wavelength range of 1525-1565 nm at a scan rate of 106 Hz. However, in such SHM systems, failures of sensors can lead to erroneous load estimation and inaccurate damage detection. Hence, isolation of sensor failure is extremely important as far as a comprehensive and robust SHM system is concerned. This study focuses on the use of artificial neural network (ANN) in combination with FE analysis as a tool towards developing an SHM methodology [7-8] robust to sensor failures.

The objective of this work is twofold: (i) to estimate the load on the structure to a sufficient level of accuracy based on the observed strain pattern and (ii) to isolate sensor failure from the neural network grid and finite element model of the structure. A composite test box with skin/stiffener construction has been designed and tested for healthy conditions at various load levels. FE model is developed for the same which is suitably modified to account for boundary condition effects, skin buckling phenomena and support conditions to match with the experimental data. Static strains are measured through Resistance Strain Gauges (SG) and Fiber Bragg Grating (FBG) sensors. FE data is used for the training of ANN. Performance of ANN is tested with experimental strain data at different load levels. Sensor failure is simulated by introducing abnormality in the data.

The construction of the box is typical of an aircraft structure with a skin-stiffener construction. The box comprises two skins, 5 spars and 1 rib. The rib and spars were co-cured with one of the skins. The other skin is bolted to the sub-structure. The fabricated test box, its schematic view and the overall dimensions (in mm) can be seen in Figure 1. FBG sensors were embedded in the skin at various locations. In addition, resistance strain gauges were also extensively used. The position of the sensors on the bolted skin of the box is shown in Figure 2.

The key to an effective SHM system is not only to estimate the loads on the structure but also in detecting the failure of sensors and compensating for them in the service life of the structure.
LOAD ESTIMATION USING ANN

Unlike flight parameters such as altitude or speed, flight loads cannot be directly observed and measured in flight [9]. Consequently, it raises an inverse problem, i.e. it is required to identify flight loads acting on aircraft wings on the basis of some kind of structural response of the wing, such as the strain response, which is caused by flight loads and can be measured in flight. Even though the relation between loads and the structural response of the wing only depends on the wing structure itself, due to the complexity of the wing structure, the relation cannot easily be formulated [10]. In most cases, while direct problems may be easily formulated, their inverse problems are usually difficult or even impossible to formulate. The solution to the problem is focused on finding a means of establishing a load-strain relationship that represents dynamically mechanical characteristics of the wing structure. Artificial neural networks have attracted considerable attention and shown promise for modeling complex nonlinear relationships.

This paper utilizes the modeling capabilities of ANN’s as the framework for constructing a relationship between load and strain. The feed forward neural network based load estimator is designed and implemented for the test box described earlier. There are three neural networks designed for each of the three grids in Figure 2. The network comprises of three layers: input, hidden and output. The discussion and results presented here are specifically for Network # 2 as seen in Figure 2. However, similar procedures have been followed for the remaining grids. The input layer has 16 neurons, which corresponds to the 4 sensors in the grid at 4 different layers (top-top skin, bottom-top skin, top-bottom skin and bottom-bottom skin) on the test box. The hidden layer has 10 neurons. The output layer is assigned with one neuron which gives the load estimate. A pure linear transfer function is assigned to the input, hidden and output layer and Levenberg-Marquardt optimization algorithm has been used for training with a performance goal of 1e-5.
The learning data that is used to train ANNs is obtained from the finite element analysis. The finite element model is first validated with experimental results for some typical loading cases [11]. Under healthy condition of the test box, strain data was generated for 25 loads ranging from 240Kgs to 6000Kgs in steps of 240Kgs. Each set of strain data contains the strain values of the 16 sensors (for Network # 2) described in the earlier sections. The 25 sets of 16 strain values are further subdivided into training and validation sets. Alternate sets with intermediate repetition are used as learning data for artificial neural networks, in which strains are used as input signals and loads as teaching signals that represent desired outputs. It is to be noted that the training data is done only with healthy strains. The neural network so designed is then tested against the validation set for performance evaluation. The validation set errors lie between +/- 0.2 % for all load estimation cases from 240Kgs to 6000Kgs which indicate reasonably good network design.

In order to check the accuracy of the network, experimental strains are fed into the network and the load estimates are obtained and checked with applied load as shown in Table 1. The experimentally measured strains at various trials for the healthy case at 6000 Kgs and 4000 Kgs load are fed into the network. Some typical cases are shown in Table 1. It can be seen that the neural network estimates the load rather well with the worst case showing only an error of 1.53%. Table 1(b) shows the estimate for a load of 4000 Kgs with the worst case error of 1.808%.

Table 1: Neural Network Grid # 2 (see Figure 2) performance for load estimation for healthy case with Load = 6000Kgs in (a), and 4000Kgs in (b).
In order to implement a robust SHM system, detection of sensor failure is very important. In case of fiber optic sensors, unlike strain gauges, there are no failures like drift or bias. The two types of failures that predominantly occur are (i) Sensor reading going to zero because of damage to the sensor or if sensor has de-bonded from the structure and (ii) Splitting of wavelength due to micro-buckling effects that occur during embedment of fiber in the structure. The second problem is tackled by carefully embedding the fiber in a layer which has composite fibers in the same direction as the optical fiber. This paper specifically deals with the first issue of sensor failure and assumes that the second problem has been tackled with during embedment.

The methodology for detection of sensor failure is formulated below. This is specifically targeted for Network # 2 in this paper, but similar procedures can be applied to the other grids and in general can be adapted for a SHM scheme over a large scale structure. In general, any response to the load for a structure is manifested as strains in some strategic locations. For a structure in the healthy condition, there exists a specific strain pattern for all such grids. In the event of a sensor failure in a particular grid, the corresponding reading goes to zero. This results in some amount of error in load estimation for that particular grid. However, since the load on the structure is a global parameter, the estimates from the remaining grids contribute to a large extent and an average of all such estimates converges to the true estimate. Thus, the effect of sensor failure remains local and does not affect the estimated load globally. In such a scenario, one can apply the same estimated load to the finite element model (which represents the structure in its healthy state) in-order to get the healthy strain pattern response for the structure. A one to one comparison of this pattern with the sensor failure pattern will result in isolation of the failed sensor(s).

### RESULTS AND DISCUSSION

The sensor failure detection scheme has been validated for load case of 4000 Kgs. The actual experimental strains under the healthy conditions for an applied load of 4000 Kgs is shown in Figure 3 using dotted line. We assume that one sensor # 6 (i.e., sensor located at spar 2 under the top skin) in grid # 2 has failed as shown in Figure 3. In-order to account for this failure, the strain value in the experimental data set for the corresponding sensor is made zero. This is depicted by the curve using a dashed line as shown in Figure 3. The neural network for grids 2-4 when fed with the experimental strains (for the unhealthy sensor case) for the actual load of 4000 Kgs provides with an estimated load of 4271.9 Kgs, 3721.9 Kgs and 4208.3 Kgs respectively. An average of the above loads leads to a collective estimate of 4067 Kgs.

<table>
<thead>
<tr>
<th>Trial No.</th>
<th>Load predicted by network # 2 (Kgs)</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6092.1</td>
<td>1.53</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Trial No.</th>
<th>Load predicted by network # 2 (Kgs)</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3927.7</td>
<td>1.81</td>
</tr>
</tbody>
</table>
This load is applied to the finite element model to generate the strain pattern which is shown in Figure 3 by a solid line.

Sensor failure detection is successfully accomplished by computing the largest distance between the unhealthy strain values obtained in real time shown by dashed line in Figure 3 and the strains generated by finite element analysis shown by solid line in Figure 3. As the strain vector is finite dimensional, any vector norm is sufficient to isolate the failed sensor. The norm used here is the index of the maximum of the absolute difference between the two strain patterns as shown in Equation below.

\[ s = \text{ind} \left( \max_{k \in S} \left| X^i_k - Y^i_k \right| \right) \]

where \( X, Y \) represent the two strain patterns at any time instant \( i \), \( k \) is the sensor from the set of sensors denoted by \( S \). The value of this norm in this particular case is 300 \( \mu \varepsilon \) and the corresponding index for the sensor is 6. The methodology is in general applicable to other sensor failures as well. Care must be taken however, to place the sensors in appropriate locations such that the applied load causes sufficient strains (> 200 \( \mu \varepsilon \) which is the threshold for failure for all sensors). This will ensure that sensor failure detection under such loads would be possible as the change to zero during failure provides sufficient bandwidth for change in the sensor pattern at that particular location. Also, the estimated load must be sufficiently close to the actual which has to be ensured by a very good neural network design. Similar analysis as shown above for 4000 Kgs case can be applied to loads at other levels.
CONCLUSIONS AND FUTURE WORK

This work aims to develop a sensor failure detection methodology using artificial neural networks and finite element analysis. The inputs for this methodology are static strains measured on the structure using embedded fiber Bragg grating (FBG) sensors. This methodology is tested and verified using a composite test box with typical skin-stiffener construction resembling the wing of an aircraft. The training data for the network was generated using FE analysis. The results obtained show that the neural network and FE based approach is capable of isolating single sensor failures. A more robust sensor and structural failure classification strategy is being studied to separate the occurrence of sensor and structural failures like skin stiffener de-bonds that may exist simultaneously in the service life of a structure.

ACKNOWLEDGEMENTS

This study builds upon the experimental and analytical work carried out earlier at the Advanced Composites Division, NAL as cited below. The authors acknowledge this support. The help of Nitesh Gupta and Ramesh Sundaram is specially acknowledged. The authors acknowledge the financial support of the Aeronautical Development Agency (ADA) under the Development Initiative for Smart Aircraft Structures (DISMAS) programme, and the Aeronautical Research and Development Board (ARDB) under the Centre of Excellence for Composite Structures Technology programme. The authors thank Dr. A. R. Upadhya, Director, NAL for his support.

REFERENCES