Inverse Technique for Aerodynamic Load Identification of an Aircraft Wing

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1 Introduction

Conventionally, the aerodynamic load on a structure such as an aircraft's wing is determined by measuring its pressure distribution around its contour. This however, requires a large number of pressure sensors to enable accurate determination of aerodynamic load on the structure. Moreover, this method of measuring aerodynamic load becomes impractical when the aerodynamic load of an aircraft in-flight is to be estimated [1, 4].

Alternatively, the aerodynamic load on the wing can be measured indirectly by measuring the wing's structural responses such as wing's deformation, structural acceleration, and structural strain. These structural responses are easily measured and require no expensive instrumentation to be set up [6].

In this paper, the aerodynamic load is to be estimated from the structural response measurements. This process involves solving an inverse problem which is normally ill posed. An artificial neural network (ANN) is used here to solve this inverse problem. The capability of ANN to learn any mapping between variables is exploited. The network is to learn the data obtained from structural finite element simulations. The effectiveness of this approach is demonstrated by solving cases involving static and dynamic aerodynamic load on an aircraft wing.

2 Inverse Load Identification

The inverse load problem addressed here involves with the identification of the possible applied load on a structure from the knowledge its structural response. For example, consider a simple cantilever beam structure, given as:

$$E(x)\,I(x)\frac{\partial^4 y(x,t)}{\partial x^4} + m(x)\frac{\partial^2 y(x,t)}{\partial t^4} = P(x,t) \qquad (1)$$

Where P(x,t) is the applied load, and y(x,t) is the deformation. The beam properties are given as Young's modulus E(x), inertia I(x) and mass m(x).

In a direct problem, y is calculated from the knowledge of load P from applied to the structure. In contrast, the inverse problem calculates the load P the measurement of y. A number of difficulties associated with solving such an inverse problem includes the possibility of having multiple solutions, and the stability of the solutions. Normally, a regularization method is used to 'smooth' the solution due to the ill posedness of the problem.

Here, the inverse problem is solved using artificial neural networks combined with finite element methods. First, a forward problem is solved using finite element method to obtain several structural responses for several sets of aerodynamic load. The result is then used to obtain an inverse mapping using artificial neural networks. The structural response data becomes an input to the ANN, and the applied aerodynamic load an output (see Figure 1). The error between actual and estimated ANN is used to iteratively update the neural network's parameter until the error reaches its minimum. The Backpropagation method is used here to train the neural network [2, 3]. Enhancement of the basic backpropagation method is possible by adding the

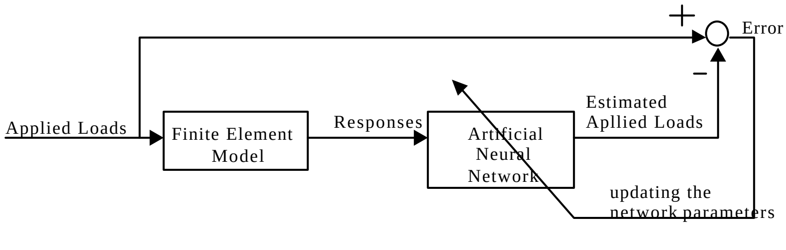

FIGURE 1. ANN for inverse load identification

momentum and adaptive learning rate terms in the optimization process of the training.

The success of the network training depends heavily on the information content of the data. The training data should be unique, i.e. no ambiguity in the inverse mapping. This can be achieved by separating the training region appropriately, or by extending the input dimension of the network i.e. increasing the number of sensors.

3 Static Aerodynamic Load Identification

A problem of estimating static aerodynamic load on an aircraft wing is approach by assuming the wing as a cantilever beam subjected to arbitrary distributed load represented as a Fourier series. The values of the Fourier coefficients are to be estimated from the structural response measurements.

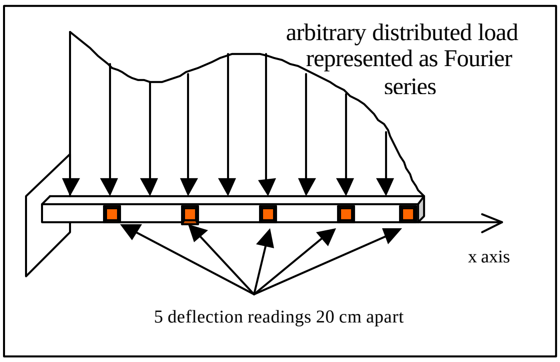

FIGURE 2. Static aerodynamic load on a wing estimated from five deformation sensors

As an illustration, here the wing is 1 metre in span with flexural rigidity EI=10^7Pa.kg.m^4. Five sensors are placed 20 cm apart to measure deformations (Figure 2).

A feed-forward neural network, trained by a back-propagation method was used. The data for the training was created using finite element simulation written in Matlab script language. Similarly, the design of the neural network was created with the help of the MATLAB Neural Network Toolbox [2].

The training of the feedforward network converged to a small error of $9\times10^{-13}Pa^2$ in 15 epochs. One epoch is defined as one iteration of the network training utilizing the whole training data. This indicated that the designed network had successfully mapped the inverse relationship.

Next, the effect of noise in the measurement on the accuracy of the identification was investigated. The noise was simulated as a white Gaussian noise added to the measurement. Table 1 shows the error of the estimation from different signal to noise ratio in the measurement. It is shown that the ANN still gives a good result up to 5% noise in the measurement. Figure 3 shows the result of the load estimation when the deformation contained 5% measurement error.

	Measurement noise level				
	0%	1%	3%	5%	10%
R	1	0.997	0.957	0.905	0.673
MSE (Pa^2)	0	6.922	103	164	374

TABLE 1: The effect of measurement noise to the accuracy of the ANN estimation, given as regression coefficient (R) and mean square error (MSE)

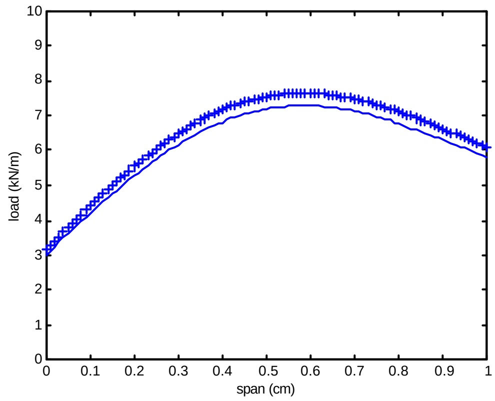

FIGURE 3. Static load estimated in the presence of 5% measurement noise (+) as compared to no noise case (-)

4 Dynamic Aerodynamic Load Identification

In contrast to static load identification, the dynamic load identification involves temporal and spatial variations. The structure of the neural network must be modified by adding a series of delay units at the input layer to capture the temporal variation of the load (Figure 4). This in effect increases the dimensionality of the input variables and hence increases the approximation capability of the network.

To illustrate the effectiveness of the method to the identification of dynamic aerodynamic load, the simulation of a wing modeled as a plate structure was performed using the finite element modeling package NASTRAN [5]. The wing's dimension was 10x1 metre with elastic modulus E=12000 Pa, density = 10^6 kg/m^3 and Poisson's ratio of 0.3. The wing was trained with several input forms with different spatial and temporal variations.

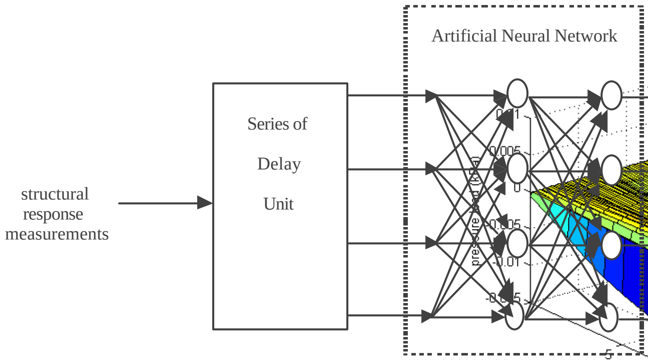

FIGURE 4. The layout of the ANN used for the dynamic load identification

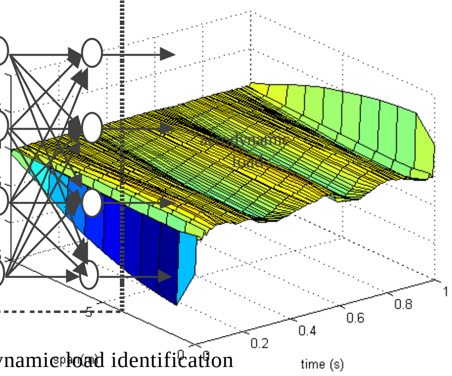

FIGURE 5. Dynamic pressure load estimated from strain data using ANN

The equation for the applied load is of the form:

$$P(x,t) = (ax^2 + bx + c)\sum_{1}^{n} \sin(\omega t + \theta) \qquad (2)$$

Where a, b, c represent spatial variation, whereas ω and θ are frequency (rad/s) and phase shift (rad) respectively.

The structural responses used to estimate aerodynamic loads were strain data at the wing root and quarter span. The sampling rate of 100Hz was used to record the structural responses.

A feedforward neural network with four delays was successfully trained in 6 epochs. The mean square error achieved was $4.9\mathrm{x}10^{-5}\mathrm{Pa}^2$. To test the generalization of the network, an unseen aerodynamic not used in the training, was estimated from strain measurements. Here the load to be estimated was $P(x,t)=(0.5-0.5x^2)\sin(6\pi t)$.

Figure 5 and 6 show the estimated aerodynamic load and its error respectively. It can be seen that the dynamic applied load can be estimated accurately using this approach.

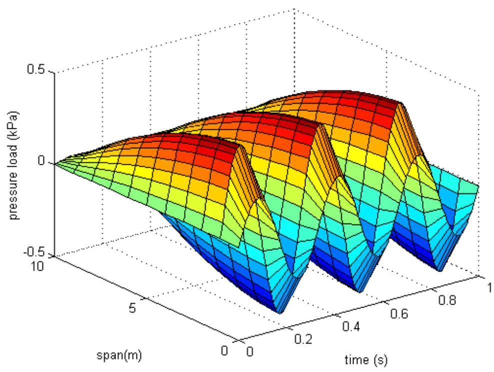

FIGURE 6. Errors in estimating pressure load using ANN

5 Conclusions

A method of solving an inverse aerodynamic load from structural response data has been presented. The method is based on applying a mapping capability of neural networks, combined with structural finite element modeling (FEM). The FEM is used to generate data required for training the neural networks. The effectiveness of the method has been demonstrated on the identification of both static and dynamic aerodynamic load on a wing structure. The structural response used to estimate the load can be of deformation, strain or acceleration measurements. The next stage of the research will involve the development of an optimization procedure in selecting the best sensor types and locations to estimate aerodynamic load on a given structure.

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