SOLVING AERODYNAMIC LOAD INVERSE PROBLEMS USING A HYBRID FEM - ARTIFICIAL INTELLIGENCE

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Abstract

This paper presents the development of a method for solving aerodynamic inverse load problems. A hybrid of Finite Element Method (FEM) and Artificial Intelligence (AI) is utilized as a basis for the method. Several illustrative problems are presented, involving static and dynamic load identification, which are solved by Artificial Neural Networks and Genetic Algorithm. FEM is used for generating data needed for the neural network training, and also for calculating fitness values in Genetic Algorithm. The MATLAB and its Neural Network Toolbox are selected as the main development tool.

1 Introduction

Modeling of physical phenomena always involves the formulation of differential or integral equations. Once these equations have been formulated with the necessary coefficients, initial and boundary conditions, then the behavior of the system can be simulated and studied. This is known as solving direct problems. In contrast, the determination of coefficients, initial or boundary conditions which give rise to any measured system's behavior is called inverse problems. Mathematically speaking, the inverse problem is ill conditioned. There is no guarantee of the existence of the solution. Furthermore, issues such as solution uniqueness, and its stability are also very significant.

Determination of aerodynamic load from its structural response measurement is categorized as an inverse problem. Aerodynamic load of a flying aircraft can not be measured easily. A direct conventional method of measuring pressure distribution on the aircraft structure becomes impractical for a flying aircraft. The instrumentation set-up is highly complex an expensive. Davis and Saltzman (2000) in their paper, for example, describe the complexity of the instrumentation for measuring the wing's pressure distribution on the F-16A aircraft.

One alternative method to measure aerodynamic load indirectly is by measuring the observed structural responses. These quantities are easier to measure. The process of reconstructing aerodynamic load from these structural measurements using a hybrid Finite Element Method and Artificial Intelligence is described here. MATLAB and its Neural Network Toolbox are used as the main tool for developing the algorithm for the whole process (Figure 1). Both the static and dynamic aerodynamic load estimation are presented to illustrate the effectiveness of the developed method.

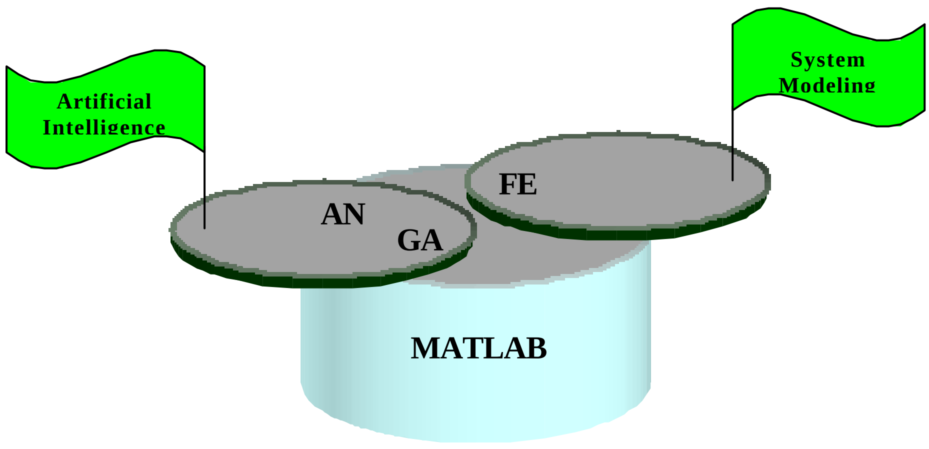

Figure 1: MATLAB Used as a Flatform for Developing a Hybrid FEM-Artificial Intelligence Method for Solving Inverse Problems

2 Artificial Intelligence Techniques

There are two artificial intelligence techniques which are suitable for solving many inverse problems, these are Artificial Neural Networks (ANN) and Genetic Algorithms (GA). Many authors have reported successful uses of these techniques.

Artificial Neural Networks

Artificial Neural Network is a massively interconnected processing units known as neurons. It is a simplified representation of the working knowledge of a human brain. The structural arrangement of the neurons and its interconnection gives rise to many different network characteristics. One of the most frequently used networks is the Feedfordward Neural Networks in which the data flows in one direction from the input to the output, i.e. no feedback loop presents.

Given sufficient number of neurons, the ANN can be trained to map any input-output relationships. Network parameters such as weights and bias are adjusted during training. Once successful training has been reached, these networks parameters are fixed and ready for use in operation. The training process is that in which a large computational burden occurs, especially when involving a large sample of training data. Many training algorithms have been developed, and the MATLAB Neural Network Toolbox (Demuth and Beale, 1998) provides a large number of training algorithms such as Lavenberg Marquadtl, QuickProp, Kohonen SOM, etc. Hagan (1996) provides extensive theoretical background of the many algorithms used in the Toolbox.

The authors have found that the MATLAB Neural Network toolbox version 3 is excellent software for the ANN development. It has a modular network representation, and hence provides a great flexibility for the ANN designer. The toolbox has fewer functions than earlier versions, and yet more powerful. However, it does not have a good graphical user interface. It is therefore not so suitable for interactive network development. Other commercial software, such as NeuroShell, FlexNN or STATISTICA Neural Networks are more suited for this purpose. Though, these softwares do not offer a great programming flexibility as offered by the MATLAB Neural Network Toolbox version 3.

Genetic Algorithms

Genetic Algorithm (GA) is one of modern heuristic optimization techniques. This algorithm is originally developed by Holland (1975) and is based on the mechanism of the Darwinian evolution. GA is a population-based algorithm. The population may consist of several potential optimal solutions which is called individuals. These individuals are subjected to different 'genetic operations' such as selection, crossover and mutation. These operations are designed to drive the whole population to a near global optimal solution. Many GA parameters can be tuned to produce a good performance. Parameters such as the number of individual in the population, crossover probability, mutation probability are tunable for any given problems.

The Genetic Algorithm is conceptually simple. The program can be easily written in MATLAB. Meanwhile, software products such as GENEHUNTER and FLEX-GA are commercially available, and can be easily run in MATLAB.

3 Static Aerodynamic Load Identification

The inverse problem discussed here is formulated as follows. It is desired to calculate the aerodynamic load acting on an aircraft wing as modeled in figure 2. Five deformation sensors are placed 20 cm apart along a 1-meter wing. The rigidity of the wing is 10^7Pa.kg.m^4. Two different approaches namely ANN and GA are used to solve this inverse problem. The structure of the wing is modeled using finite element method, and is written in MATLAB using object-oriented programming (OO). The MATLAB 5 or later versions offer a facility to write a program in OO philosophy. This has made the finite element programming much simpler than it would be otherwise with procedural language. For example, an FEM cantilever beam of length 1-meter, divided into 10 beam elements can be easily constructed using a command like, *cantilever(1,10,steel),* where steel is a material object (Sofyan, 1999).

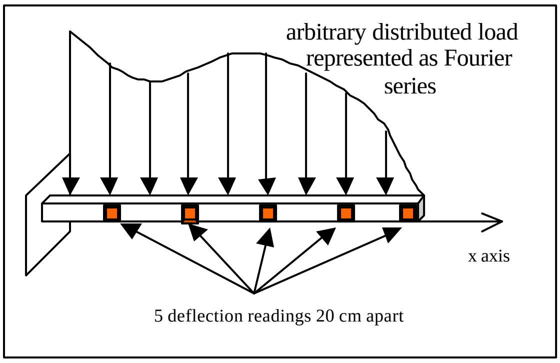

Figure 2: Static Aerodynamic Load on a Wing Estimated from Five Deformation Sensors

Table 0: The Effect of Measurement Noise to the Accuracy of the ANN Estimation

	Measurement noise level				
	0%	1%	3%	5%	10%
R	1	0.997	0.957	0.905	0.673
MSE ($x10^{-13}$)	0	6.922	103	164	374

Load Estimation Using Artificial Neural Networks

The MATLAB Neural Network Toolbox is used in designing the networks. The toolbox is highly flexible and can be used to design, train and simulate any kind of networks with relative ease. Here, a feed-forward neural network is used and trained using a Lavenberg-Mardquadtl algorithm. The training data is obtained by solving a number of direct problems as shown in Figure 3. The error estimate is then used to update the network weights and bias.

The training of the feedforward network converged to a small error of $9x10^{-13}Pa^2$ 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. The data shows that the ANN still gives a good result for up to 5% noise in the measurement.

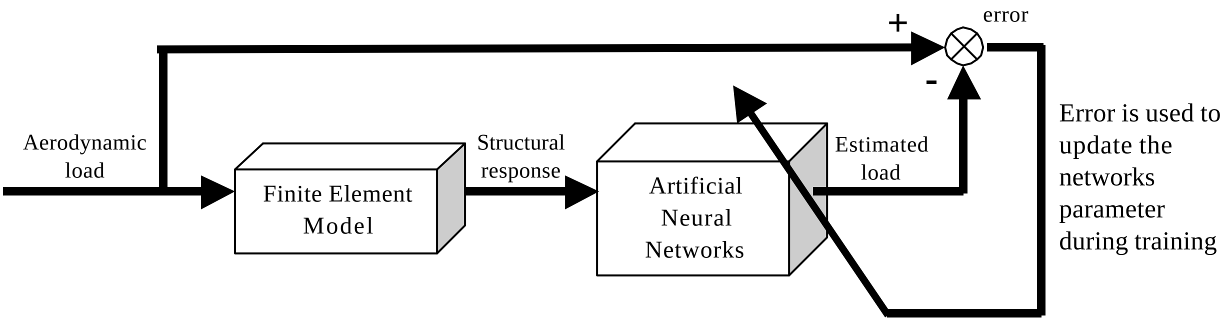

Figure 3: Aerodynamic Load Reconstruction Using Artificial Neural Networks

Load Estimation Using Genetic Algorithm

The same problem as described above is solved here using Genetic Algorithm (see Figure 4). Here suppose that a 5% noise is present in all the deformation measurements. A binary representation with 5 bits resolution is used to estimate the Fourier parameters describing the aerodynamic load. Two hundreds individual were used to initiate the population. The algorithm was run with crossover and mutation probabilities of 0.9 and 0.01 respectively. Figure 5 shows the convergence history of the algorithm, whilst Figure 6 shows the comparison between the estimated and true aerodynamic load.

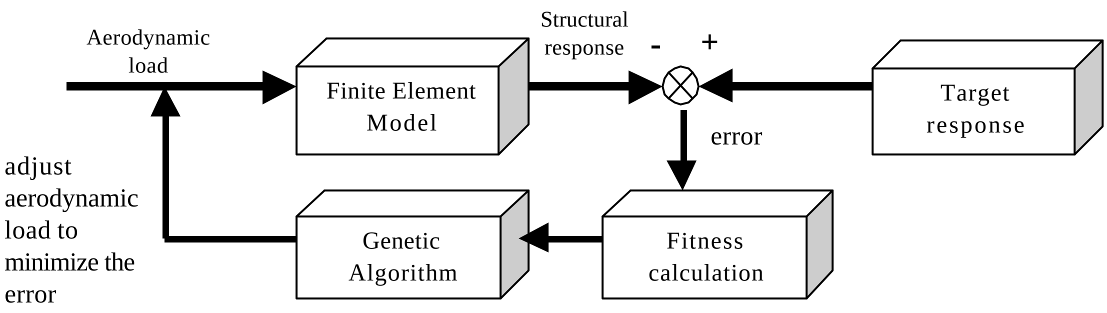

Figure 4: Aerodynamic Load Reconstruction Using Genetic Algorithm

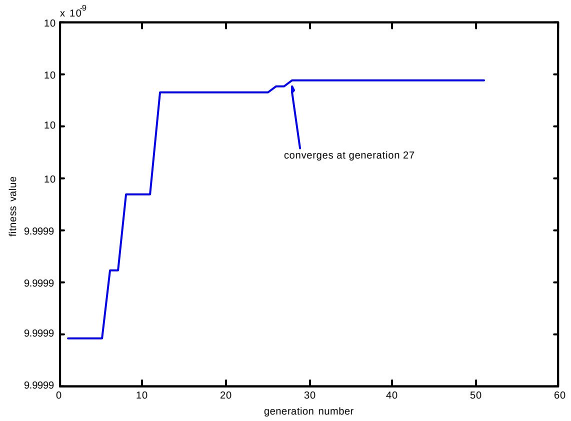

Figure 5: Convergence History of the Genetic Algorithm

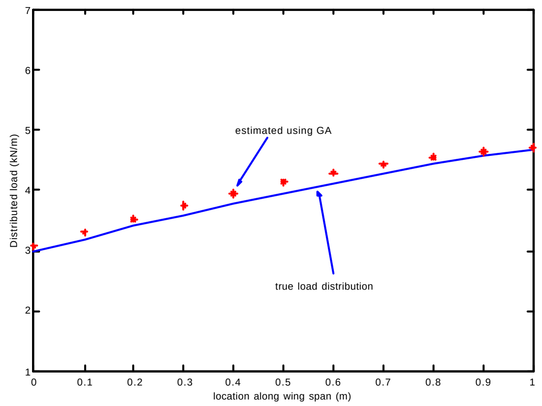

Figure 6: Distributed Load Estimated Using GA

4 Dynamic Aerodynamic Load Identification

In contrast to static load identification, the dynamic load identification involves temporal and spatial variations. The aerodynamic load to be estimated varies with time, and so too the structural response measurements. Here the mass and damping distribution of the structure should be included in the modeling.

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 (1985). 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.

Load Estimation Using Artificial Neural Networks

A time delayed neural network is used for the estimation of the dynamic aerodynamic load. Figure 7 shows the structure of the network with the addition of delay units at the input neurons. The delays at the input neurons are created by setting *net.InputWeight{..}.delays* to, for example [1 2 3 4] for the addition of four delay units. The network was then trained with data from running FEM simulations of several input forms with different spatial and temporal variations. The equation for the applied aerodynamic load is in the following form:

$$P(x,t) = (ax^2 + bx + c)\sum_{1}^{n} \sin(\boldsymbol{w}t + \boldsymbol{q}) \tag{1}$$

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.

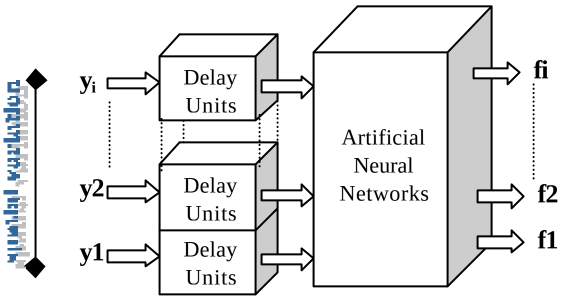

Figure 7 Network's Configuration for the Temporal and Spatial Load Identification

A feedforward neural network with four delays was successfully trained in 6 epochs. The mean square error achieved was $4.9 \times 10^{-5} Pa^2$. 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 8 and 9 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.

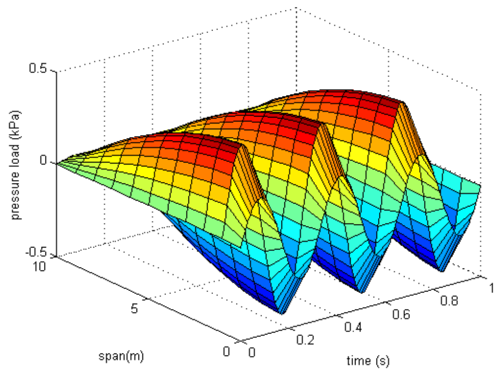

Figure 8: Dynamic pressure load estimated from strain data

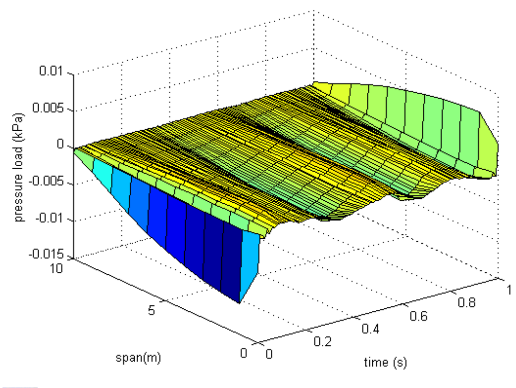

Figure 9: Errors in estimating pressure load using ANN

Sensor Selection Using Genetic Algorithm

It has been shown above that a delayed neural network can be trained to learn the inverse relationship between the measured structural responses and the applied aerodynamic load. The success of the training and the resulting network's performance depends on the information content and its quality of the measured data. Hence, the selection of this measured data is crucial. Here, an optimization using genetic algorithm was carried out to select the sensor data needed for the selection of the best sensor combination in the estimation of aerodynamic load (see Figure 10). For this particular problem, two sensors are to be placed on the wing to measure bending strain. The possible sensor locations are given as shown in Figure 11.

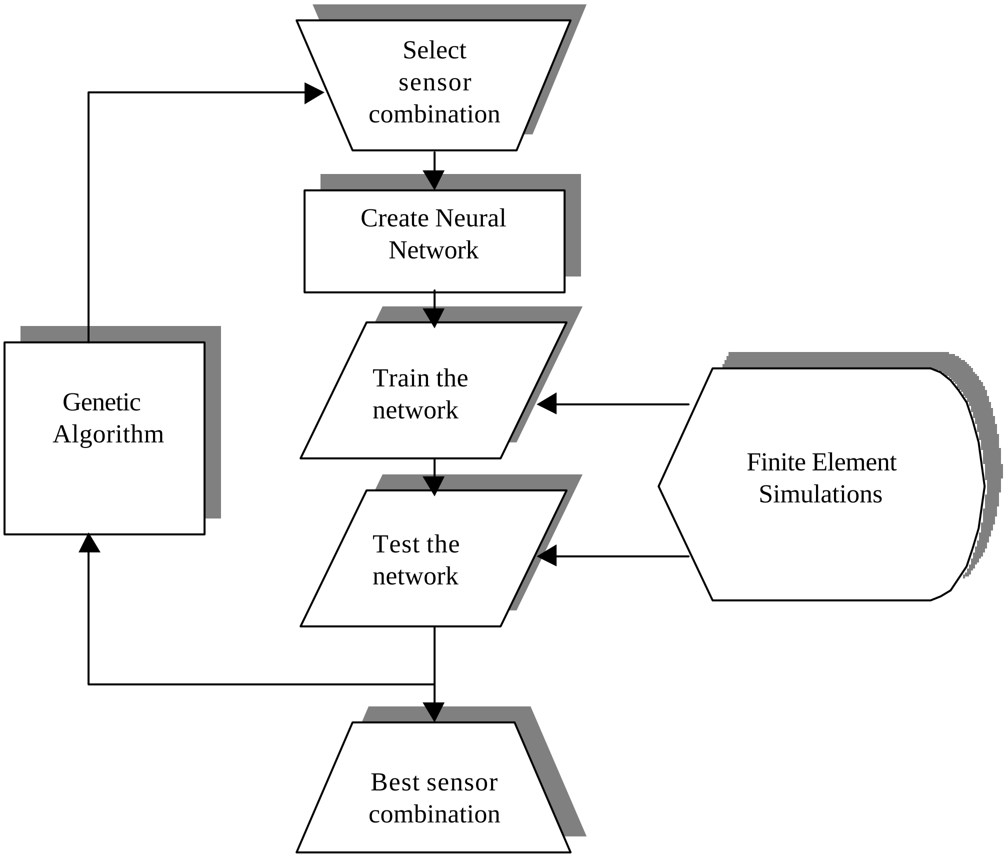

Figure 10: Sensor Selection Using Genetic Algorithm

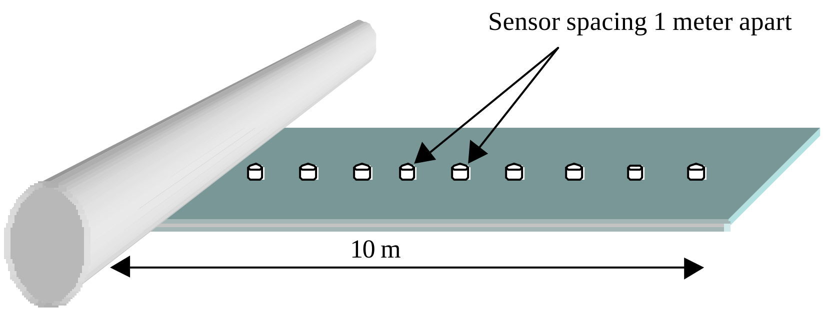

Figure 11: Strain Gage Sensor Locations on the Wing

Table 2 shows the results of running the algorithm 10 times. It can be shown that the optimal sensor location for this particular problem is found to be at 1 and 3 meter from the wing's root. Alternatively, combination sensors 1-5 or 1-4 can also be used with less accuracy.

Table 2: Sensor Optimization Result Using GA

No run	Best sensor combination	Achieved MSE	Generation number
1	1 - 3	3.5574e-5	3
2	1 - 4	3.7028e-5	9
3	1 - 4	3.7028e-5	5
4	1 - 3	3.5574e-5	3
5	1 - 3	3.5574e-5	3
6	1 - 3	3.5574e-5	9
7	1 - 5	3.6998e-5	4
8	1 - 5	3.6998e-5	7
9	1 - 7	3.9536e-5	4
10	1 - 4	3.7028e-5	5

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, and an optimization strategy of Genetic Algorithm, combined with structural Finite Element Modeling (FEM). The FEM is used to generate data required for training the neural networks, and to provide data for the fitness calculation for the GA. MATLAB and its Neural Network Toolbox have been used intensively in the development of the method. Lastly, the effectiveness of the method has been demonstrated on the identification of both static and dynamic aerodynamic load on a wing structure.

6 Acknowledgements

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