The Application of Artificial Neural Networks on Flutter Suppression System

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Abstract

The study highlights the benefits of the implementations of artificial neural networks in aeroservoelastic problem. The neural networks are investigated as an alternative approach to flutter suppression system. Their use in both modelling the system identification and controller is studied for feasibility and to identify advantages and disadvantages. The connectionist neural networks approach implemented in an indirect adaptive control is demonstrated. The results from simulation were discussed, and the performance of indirect adaptive control using neural networks critically evaluated.

INTRODUCTION

With the progress of aircraft design optimization which results in the increase in speed and flexibility of modern aircraft, flutter has become a key feature in aircraft design. Many organizations as well as researchers have devoted their effort to develop flutter suppression system to increase flight safety. Experts from the area of aeroelasticity and control have cooperated to develop a new discipline known as aeroservoelasticity to tackle the implementation of control law to actively control aeroelastic instabilities within safety boundaries.

The contribution of the experts cover unsteady aerodynamic formulation and methods of solving flutter equations. In the realm of aeroservoelasticity, the major contribution has been the formulation of aeroelastic systems by finite-order constant-coefficient ordinary differential equation enabling control law to be easily applied. Since modern control theory provides a well developed design methodology for such system, a wide range of modern control methodologies has been succesfully applied on flutter suppression systems.

Many control synthesis were used by experts all over the world to develop active flutter suppression systems either on theoretical or experimental basis. Among pionering work devoted in this area one can mention the work of Edwards et al [7] and Newsom [23], who based their work on optimal control theory. Karpel's work in [13] especially presents the use of pole assignment technique. The optimization technique which simultaneously alleviates gust was used in that study. Considerable amount of work has also been carried out in the application of Linear Quadratic Gaussian method. Several papers of this kind are contributed by Mahesh et al [18] and Mukhopadhyay et al [21], which included reduced order model design. Another approach was made by Garrard et al using robust Kalman Filter in [10]. Nissim in [23], [24] and [25] gave another contribution by introducing aerodynamic energy method as an alternative of classical control theory application. The work based on this approach were [26] which studied the active external store flutter suppression in the YF-17 flutter model and [27]. Irving Abel in [3] reviewed the results of classical control theory and those of aerodynamic energy concept. A recent paper by Lu and Huang [17] suggests a new technique using active acoustic excitation of thin airfoil.

An interesting contribution was made by Harris et al [11] who presents adaptive flutter suppression system which automatically adjusts systems parameters based on changes in flight condition and store configuration. With specific respect to control technique, a considerable attempt has been made to develop an intelegent controller which can adapt to its changing environment.

In pace with the unfolding of the control technique, the recent decades have witnessed a great deal of time and effort spent in developing a new branch of computing and mathematics, the so-called artificial neural networks. This new approach is basically inspired by the physical working principles of the human central neural systems and operate in a very different manner to conventional engineering tools. Its implementation has been investigated in diverse areas including, but not limited to, flight control systems, instrument landing systems, large flexible space structure control systems, signal processing and pattern recognition. Several considerations below motivate the use of artificial neural networks in the area of aeroservoelasticity.

- In real operation, several parameters may be uncertain and not of constant value. This necessitates a learning-type controller.
- Components failure which may happen in aeroservoelastic systems establishes the requirement of an adaptive-type controller.

THE BASIC CONCEPT OF ARTIFICIAL NEURAL NETWORK (ANN)

THE ARCHITECTURE OF ANN

The basic feature of artificial neural networks approach in solving problems is that one need not have well-defined process for algorithmically transforming an input to an output. What one need for most neural networks is a set of representative examples of the desired transformation. The trained artificial neural networks then reproduce the desired outputs when presented to the example input. The power of an artificial neural networks approach lies not necessarily in the elegance of the particular solution, but rather in the generality of the networks to find *its own solution* to particular problems , given only examples of the desired behaviour [7].

The diagram in Fig. 1 displays a typical neural networks. The network architecture is defined by the basic elements and the way in which they are interconnected. The basic processing element of the connectionist (ANN) architecture is often called a neuron, but other names such as unit [28], node [16] or perceptron [20] are also used. The neurons are connected by weights, also referred to as connections, or synapses, which conveys the information. Neurons are also often collected into group called layers within which the neurons have a similar function or structure. Depending on their function in the net, one can distinguish three types of layers. The layers whose activations are problem input to the net are called input layers, the layers whose output represent the output of the net output layers. The remaining layers are called hidden layers, because they are invisible from outside.

In general, there can be any number of layers, and neurons in any layer can be connected to neurons in any other layers. Some neurons have no inputs from other neurons, and known as bias or threshold units. The memory content or signal strength of neuron is referred to as activation level. Usually, the activation levels of the input and output units are scaled such that the activation levels are appropriate to the neuron functions and the observable values are given a physical meaning.

THE ANN MODEL

Let us review a single neuron from the networks structure which is depicted in Fig. 2. An individual neuron has many inputs depending on the number of connections. Each connection to the neuron has a weight associated with it. After the total neuron input signal is calculated, that is given the sum of the product of inputs and weights :

$$x_{j,i} = \sum_{k=1}^{n} w_{j,i\times k}\, y_{j-1,k} \tag{1}$$

it is converted into an activation value through a functional relationship. The power of ANN lie within this transfer function.

$$y_{j,i} = f(x_{j,i}) \tag{2}$$

The sigmoidal function is the most commonly used in neural networks since it accomodates unlimited degree of non-linearity. This function is differentiable, step-like and positive (bounded by (0,1)) function. In addition to sigmoidal function, hyperbolic tangent, threshold and ramp functions are occasionally used.

The output of the neuron is obtained from the activation value also through functional relationship. Identity function is usually used in this step. In general, the selection of the function used in neural networks depend on the type of patterns (input-output value pair). At present, the selection of an activation function is more an art than science and subject to much research. The important point to remember is that any nonlinear function will provide the networks with the ability of representing any nonlinear mappings.

LEARNING METHODS

Various learning rules in neural networks training has been the subject of investigation of many studies. In the following paragraphs we will review briefly supervised learning (role-model following) known as backpropagation, which is probably one of the most widely used learning methods in training neural networks. The equations used follows those given by Werbos in [30].

For the shake of clarity, layered networks shown in Fig. 1 will be taken as an example. In basic backpropagation, how the output of a neural network depend on its inputs and weights is defined using the following algorithm :

$$x_i = X_i \quad ,1 \le i \le m \tag{3}$$

$$net_i = \sum_{j=1}^{i-1} W_{ij} x_i \quad ,m \le i \le N+n \tag{4}$$

$$x_i = s(net_i) \quad ,m < i \le N+n \tag{5}$$

$$Y_i = x_{i+N} \quad ,1 \le i \le n \tag{6}$$

where m is the number of input neurons in the networks, n the number of output neurons and N any integer larger than m. The value N+n determines the number of neurons in the network.

The main idea of backpropagation is somewhat similar to that of the famous least-squares method in which one minimizes square error shown below :

$$E = \sum_{t=1}^{T} E(t) = \sum_{t=1}^{T}\sum_{i=1}^{n} \frac{1}{2}(\hat{Y}_i(t) - Y_i(t))^2 \tag{7}$$

The way by which the error is minimized is the essence of the backpropagation method. The process begins with computing partial derivatives of the error with respect to the output :

$$\frac{\partial E}{\partial \hat{Y}_i(t)} = \hat{Y}_i(t) - Y_i(t) \quad ,1 \le i \le n \tag{8}$$

Using the definitions of ordered derivatives [30], one can write :

$$\frac{\partial^+ E}{\partial X_i(t)} = \frac{\partial E}{\partial X_i(t)} + \sum_{j=i+1}^{N+n} \frac{\partial^+ E}{\partial X_j(t)} \times \frac{\partial X_j(t)}{\partial X_i(t)} \quad , N+n \geq i \geq 1 \tag{9}$$

where

$$\frac{\partial E}{\partial X_i(t)} = \begin{cases} 0 & 1 \leq i \leq m \\ \dfrac{\partial E}{\partial \hat{Y}_{i-N}(t)} & N+n \geq i \geq m+1 \end{cases} \tag{10}$$

and

$$\frac{\partial X_j(t)}{\partial X_i(t)} = s'(net_j) \times w_{ji} \quad , \text{with } s'() = \frac{\partial s()}{\partial ()} \tag{11}$$

Now the ordered derivatives for the weights can be calculated as :

$$\frac{\partial^+ E}{\partial X_i(t)} = \frac{\partial E}{\partial X_i(t)} \times s'(net_i) \times X_j(t) \tag{12}$$

Finally the weights are updated using :

$$new\ w_{ij} = w_{ij} - \varepsilon \times \frac{\partial^+ E}{\partial w_{ij}} \quad , 1 \leq i \leq N+n; \quad 1 \leq j \leq N+n \tag{13}$$

where ε is defined as the learning rate which is some small constant chosen on adhoc basis.

AEROSERVOELASTIC SYSTEM

The aeroelastic system depicted in Fig. 3, showing definitions of coordinates and system properties, is taken as the plant under study. The parameters of the flutter model are that given by ref. [13]. The oscillation of typical section in three degree of freedom: heaving motion (bending), pitching motion (torsion) and control surface (aileron) deflection, represent the wing flexibility.

The motion of the plant can be described by the following equation :

$$[M]\{\ddot{q}\} + [D]\{\dot{q}\} + [K]\{q\} = \frac{1}{2}\rho U^2 [A]\{q\} \tag{14}$$

where **[M], [D], [K]** and **[A]** is the matrix of mass, damping, stiffness and unsteady aerodynamic operator, respectively. $\{q\}$ is the generalized coordinate vector which represents vibration modes. Equation (14) can be rewritten in Laplace domain by substituting $\{q\} = \{\hat{q}\}e^{st}$ where $s = \sigma + i\omega$. Through the use of Roger's approximation the unsteady aerodynamic forces can be expressed in the form of rational function of finite-order polynomial so that the equation of motion of the plant can be written in the state-space form. Fig. 4 and Fig.5 depicts the flutter characteristics diagrams of the system under study. The diagrams show that the flutter which consists of two coupled modes (bending and pitching) prevails at the speed of $U / b\omega_\alpha = 3.02$.

The control equations are then obtained by adding single-input multi-output equation, which reads

$$\begin{aligned} \{\dot{x}\} &= [A]\{x\} + \{B\}u \\ \{y\} &= [C]\{x\} + \{D\}u \end{aligned} \tag{15}$$

where $\{x\}$ and $[A]$ is state vector and dynamic matrix, respectively, u is the control variable and $\{y\}$ is the measurement vector. $\{B\}$, $[C]$ and $\{D\}$ is input, calibration and input-output relation matrix, respectively.

The parameters of Equation (15) are $\{x^T\} = \{h/b, \alpha, \beta, \dot{h}/b, \dot{\alpha}, \dot{\beta}, B_1, B_2, B_3, B_4\}$ and $u = \beta_c$. For simplicity $[C]$ is taken to be identity and $\{D\}$ zero in this present work. The design target is for constant coefficient control law,

$$u = [G]\{y\} \tag{16}$$

which suppresses flutter throughout the desired flight envelope i.e . $U / b\omega_\alpha = 0 - 3.5$.

NEURAL ADAPTIVE CONTROL

The application of neural networks for adaptive-type controllers have been studied by several authors (Narendra[21], Garcia-Padilla & Morant-Anglada [8], Wharington [30], Rickard and Bartholomew [28], Krisnakumar [14]) and has shown to be reliable thus far. Its use in control area is justified by the following aspect : the need of controlling systems which are difficult to model; design requirements which must be met by this type of systems and finally, to achieve the objective of control with less precise knowledge of the plant and its environment. The application of artificial neural networks for control will allow us to obtain benefits such as: undertaking faster computations since this will be carried out in parallel; tolerance to failure, and moreover artificial neural networks present a natural robustness to calculate the parameters without previous modelling due to its generalization properties [8].

ADAPTIVE NEURO-CONTROL CONCEPTS

The implementation of neural networks in control problems can be divided into two general categories : direct and indirect control. Under the first category one can distinguish two general approaches. These are copying an existing controller and reinforcement learning. The second category also consists of two fundamental approaches, namely : inverse control and supervised control using error propagation through a model. The discussion that follows will be restricted to the supervised control since it is chosen as the control technique in this work.

Supervised neuro-control is similar to indirect control used in adaptive one; a linear system model is identified and using this model the control is adapted. Similarly, in supervised neuro-control, the first system is available for the sole purpose of training a neuro-controller. Neuro-model which is often called neural network model of the plant is used to generate partial derivatives of the error between the identified model and the desired (reference model) outputs with respect to the control inputs. The neuro-controller can then be directly updated using back-propagation of error through the neural network model. While updating the neuro-controller, the neural networks model weights are held constant. Again, the role of neuro-model is to relate the output error to the controller error. It should be emphasized , though, that the error definition for the model and the controller are different as shown in Fig. 6. The error in case of the controller is the error between the actual system output and the desired output generated by the desired model.

INDIRECT ADAPTIVE CONTROL FOR FLUTTER SUPPRESSION

The previously mentioned indirect adaptive control scheme is implemented as a tool for flutter suppression system. For the sake of clarity, time delays and other possible sources of non-linearities such as back-lash in the aileron hinge is not taken into account in this present work. The supervised control using error propagation through a model is demonstrated. First, the aeroelastic plant is copied using artificial neural networks and supervised learning techniques. Neural networks controller is then designed using the supervised control technique and a fixed neural network model. It should be noted here that the controller acts as a regulator functioning as flutter suppression means. In this case, there is no model to be tracked. Instead, the output of the plant (of the neural networks model) is compared with a certain set point which is zero position. The scheme of aeroservoelastic plant using neuro-controller is depicted in Fig. 7.

The logic of the indirect adaptive control system is as follows,

1. The neural networks model (NNM) is first trained to imitate the dynamic of the system
2. Apply a control command to the plant and NNM
3. Calculate the error between plant output and setting point

4. Inversely propagate the error through the networks model to find the control command which minimizes the error
5. Train the neural network controller (NNC) *with the target of* control command found in the previous step
6. Execute control command resulted from trained NNC

RESULTS AND DISCUSSION

The actual system was simulated for one second to generate patterns data (input and output value pair) which was used to train the neural networks model. Two architectures of neural networks model are studied. The first networks model is one with interconnections between neurons in adjacent networks (*fully-connected layered networks*). The second architecture is partly connected networks, i.e. the first model in which some interconnections are truncated. Fig. 8 shows the performance of the first networks model and Fig. 9 the second model. The figures display that the second architecture outperforms the first one. The results indicate that tracking performance can be improved by reducing interconnections between neurons to some extent.

With the second architecture as the identification systems, the indirect adaptive control for flutter suppression system was performed at $U / b\omega_{\alpha} = 3.5$ (16% above the flutter speed). The results are shown in Fig. 10 and Fig.11. The results show that the neural control system can suppress the violent bending-torsion flutter at the targeted velocity above the flutter speed. However, small low frequency oscillations still remains. The study to improve the suppression quality is the subject of the current work.

The results displays the promising benefits of implementing indirect adaptive control technique as it involves a learning-type controller and identification system. This type of controller will be especially advantageous in real operation where most of the parameters are not of constant value.

CONCLUSIONS AND FURTHER WORKS

The implementation of neural networks in aeroservoelasticity has been shown to be possible. The work on this particular area using new emerging connectionist approach should be considered as an early step towards a real implementation. It should be noted that the theoretical background regarding control system involving neural networks is still preliminary in nature. Besides, there are few other design tools for the system employing neural networks. Therefore, many studies, particularly with respect to the closed loop stability of the dynamic system are still to be conducted before starting the experimental step.

In order to arrive at a realistic implementation of the neuro-controller, the trade-off between practical performance and control has to be carried out first. This means that the next problem of neuro-control application for flutter suppression to be adressed is how to find the best possible performance within the physical limits of the actuators.

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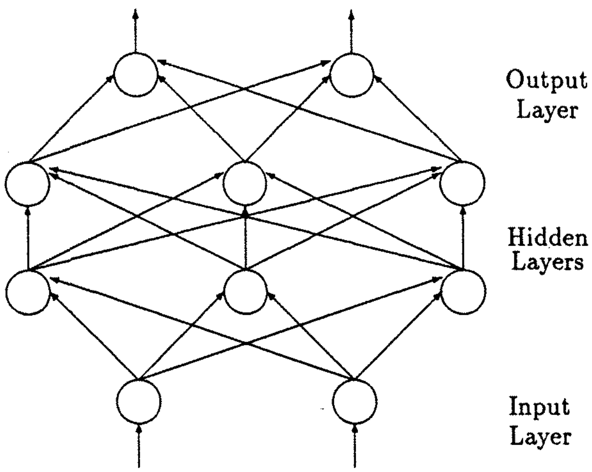

Figure 1: Typical Neural Networks Structure

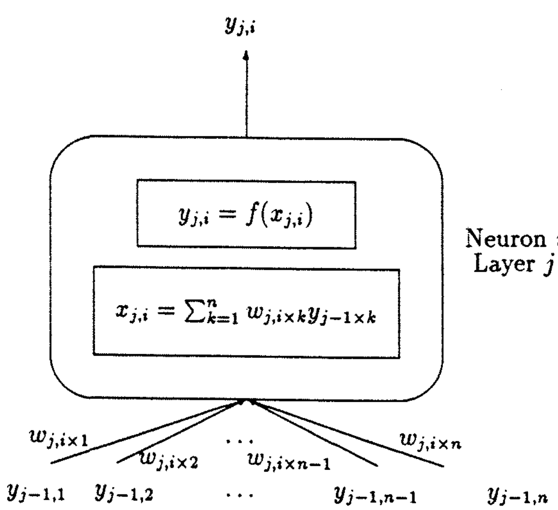

Figure 2: General Neuron Model

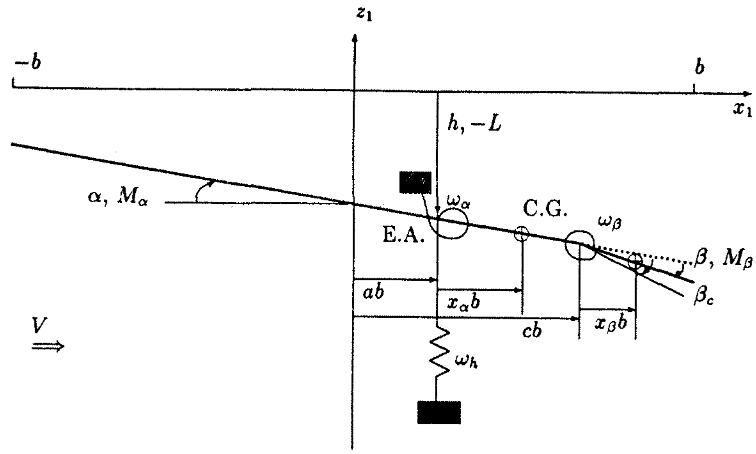

Figure 3: Aeroelastic Model under Study

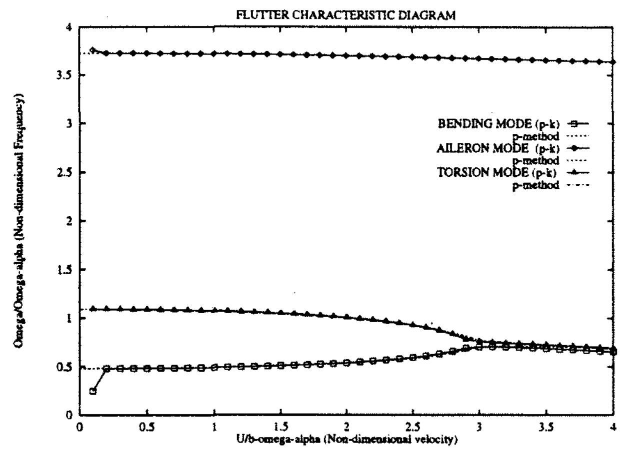

Figure 4: Flutter Characteristics Diagram (Frequency Diagram)

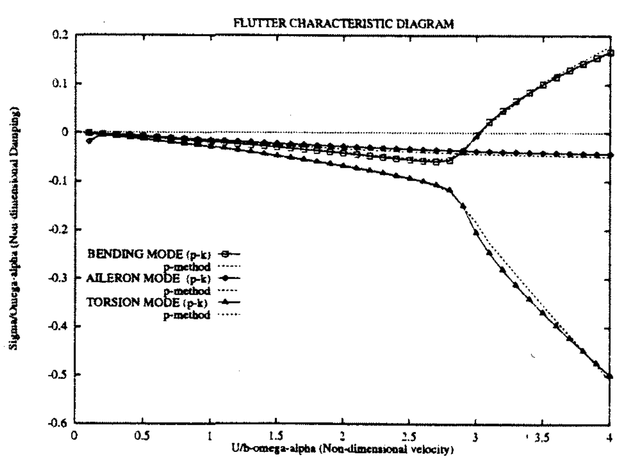

Figure 5: Flutter Characteristics Diagram (Damping Diagram)

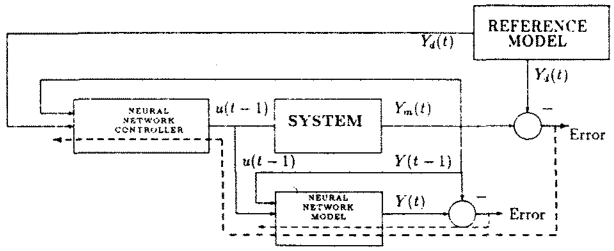

Figure 6: Indirect Adaptive Control Scheme [15][31]

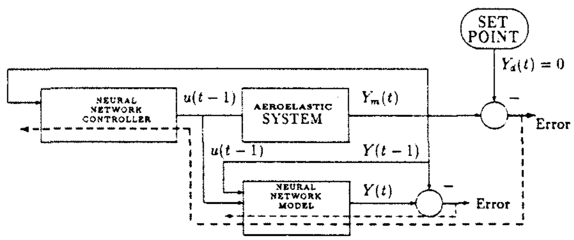

Figure 7: Aeroservoelastic Systems using Indirect Adaptive Control

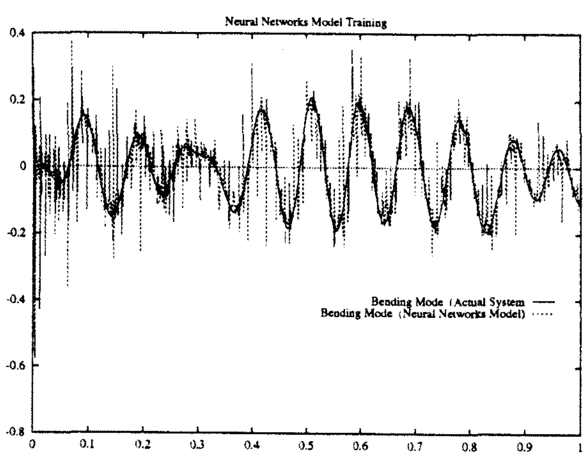

Figure 8: Neural Networks Model Performance

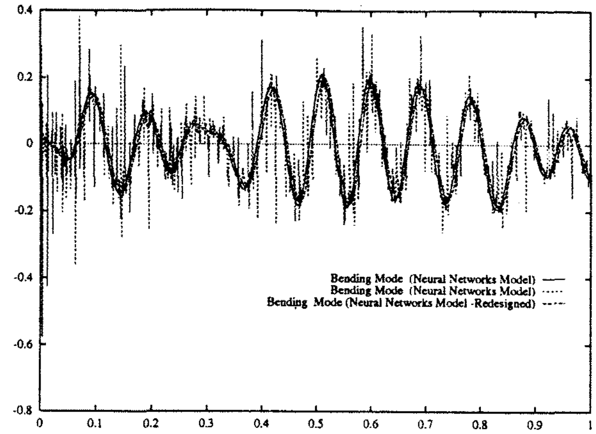

Figure 9: Neural Networks Model (redesign) Performance

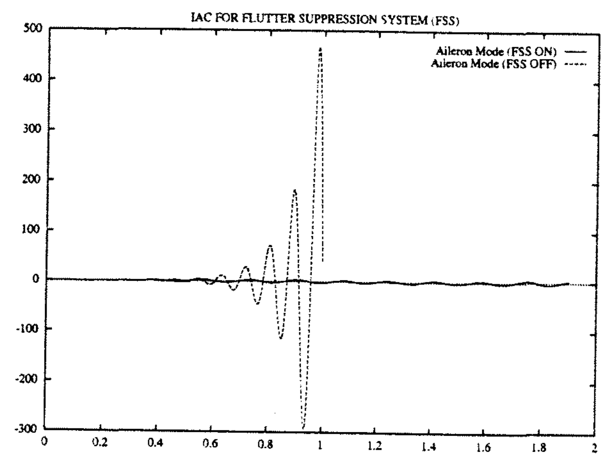

Figure 10: Flutter Suppression using Indirect Adaptive Control (Aileron Mode)

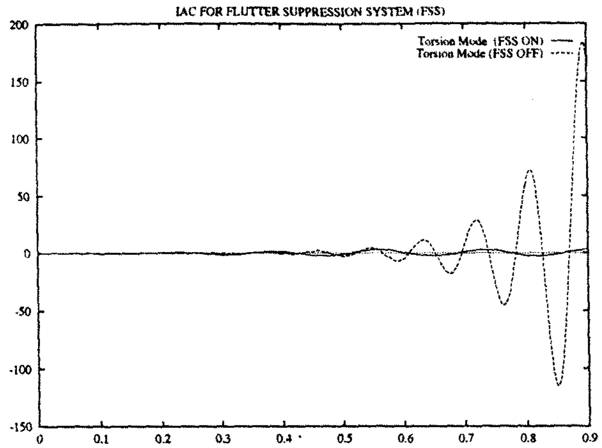

Figure 11: Flutter Suppression using Indirect Adaptive Control (Torsion Mode)