Direct Neuro-AVC Modelling And Control Strategy For Vibration Suppression Of A Flexible Plate Structure

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Abstract – **This paper investigates the development of a direct neuro-active vibration control (AVC) mechanism for vibration reduction of a flexible plate structure. A multi layer perceptron (MLP) neuro-controller is designed to characterise the ideal controller characteristic using an online adaptation and training mechanism. The effectiveness of the MLP neuro-controller is then verified within the AVC system. The neuro-AVC algorithm thus developed is implemented within a flexible plate simulation environment and its performance in the reduction of deflection at the centre of the plate is assessed. *The validation of the algorithm is presented in both* the time and frequency domains. Investigations reveal that the developed direct neuro-AVC controller perform very well in the suppression of vibration of a flexible plate structure.**

I. INTRODUCTION

Active vibration control (AVC) consists of generating cancelling source(s) to destructively interfere with the unwanted source and thus result in a reduction in the level of the vibration at desired location(s). This is realised by detecting and processing the vibration by a suitable controller so that when superimposed on the disturbances cancellation occurs [1]. In this paper, a neuro-AVC mechanism is developed by combining the ideas of neural networks and active vibration control. A neural network architecture based on multi-layer perceptron (MLP) network using the backpropagation-learning algorithm for training the network is introduced. A feedforward AVC structure is considered for optimum reduction of the vibration. An online adaptation and training mechanism allowing the neural network architecture to characterise the ideal (optimal) controller within the AVC system is developed. The neuro-adaptive active control system thus developed is implemented within a flexible plate simulation environment and its performance in the reduction of deflection at the centre of the plate is evaluated.

II. FLEXIBLE PLATE STRUCTURE

Plate structures are elements of practical importance in many engineering applications. Study of the natural modes, frequencies and the dynamic behaviour of flexible plates is a subject that has received considerable attention due to its technical importance, for the last decade. In addition to being a problem of academic interest, many applications of thin flat plates are found in industry. Examples include bridge decks, solar panels, and electronic circuit board design. The control of a vibrating plate is, however, a complex problem. This is due the highly non-linear dynamics of the system, which involve complex processes. Accordingly, there is a growing need for developing suitable modelling and control strategies for such systems. It is crucial to obtain an accurate model of a plate structure in order to control the vibration of the plate efficiently. An accurate model will lead to the realisation of satisfactory control.

Dynamic modelling and simulation of a flexible plate structure using finite difference methods have been reported by Mat Darus et al. [2], where a flat, square plate with all edges clamped has been considered. A simulation algorithm characterising the dynamic behaviour of the plate is developed through discretisation of the partial differential equation of the plate into several sections, where a linear relation for the deflection of each section is then developed using finite difference approximations. The simulation algorithm thus developed and validated will be used in this paper as test and verification platform in the investigations for development of neuro-AVC strategies for flexible plate structures.

III. ACTIVE VIBRATION CONTROL

The single-input-single-output feedforward AVC structure considered in this investigation is shown in Fig. 1. This structure has been considered in various noise and vibration control applications [3], [4], [5]. An unwanted (primary) point source introduces structural vibration into the plate system. This is detected by a detector located at a distanced r_e relative to the primary source, processed by a controller of suitable transfer characteristics and fed to a cancelling (secondary) point source located at a distance d relative to the primary source and a distance r_f relative to the detector. The secondary signal thus generated is superimposed on the primary signal so as to achieve vibration reduction at and in the vicinity of an observation point located at distances r_g and r_h relative to the primary and secondary sources, respectively.

An equivalent block diagram of the AVC structure is shown in Fig. 2, where E, F, G and H are transfer functions of the paths through the distances r_e, r_f, r_g and r_h, respectively. M, C and L are transfer characteristics of the detector, the controller and the secondary source, respectively. U_D and U_C are the primary and secondary signals at the source locations whereas Y_D and Y_C are the corresponding signals at the observation point, respectively. U_M is the detected signal and Y is the observed signal. The

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block diagram in Fig. 2 may be considered either in the time domain or the frequency domain [6].

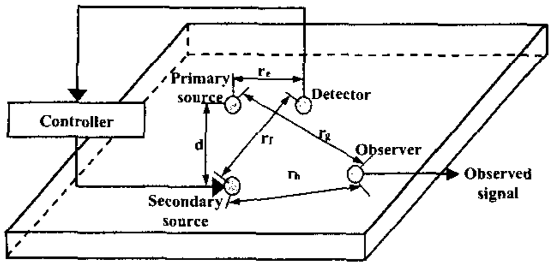

Fig. 1: Active vibration control structure.

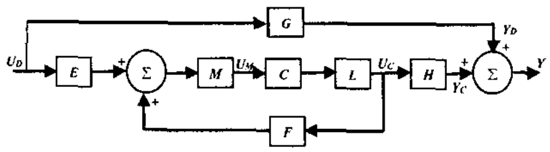

Fig. 2: Block diagram for AVC.

The objective in Fig. 1 is to force the observed signal, Y to zero. To design an AVC system so that the controller characteristics are updated in accordance with changes in the system such that the required performance is achieved and maintained, a self-tuning strategy, allowing online design and implementation of the controller can be utilised [6], [7].

For online design of the controller, the system can be considered with the detected signal, U_M, as input and the observed signal, Y, as output. Thus, owing to the state of the secondary source let the system behaviour be characterised by two subsystems, namely, when the secondary source is off, with equivalent transfer function denoted as Q_0, and when the secondary source is on, with an equivalent transfer function denoted as Q_1;

$$Q_0 = \left.\frac{Y}{U_M}\right|_{U_C=0} \tag{1}$$

$$Q_1 = \left.\frac{Y}{U_M}\right|_{U_C\neq 0} \tag{2}$$

Thus, synthesising the controller within the system and using Q_0 and Q_1 yields [5]:

$$C = \left[1 - \frac{Q_1}{Q_0}\right]^{-1} \tag{3}$$

This is the required optimal controller design rule given in terms of the transfer characteristics Q_0 and Q_1, which can be measured/estimated online.

IV. DIRECT NEURO-AVC

To allow for variations due to characteristics of system components be accounted for an online design and implementation of a neuro-controller can be devised. Consider the AVC system in Fig. 1 and Fig. 2. For optimum reduction of the vibration at the observation point, the controller characteristics given in (3) can be restated as:

$$C = \left[1 - Q_1 Q_0^{-1}\right]^{-1} \tag{4}$$

This can be realized by obtaining the inverse of the system shown in Fig. 3. In this manner, an inverse modelling approach can be adopted to obtain the corresponding neuro-controller. To allow non-linear dynamics of the system be incorporated within the design, it is proposed to train suitable neural networks to characterize the system models Q_0^{-1} and Q_1. This can be achieved according to the descriptions shown in Fig. 4 and Fig. 5. Thus, the corresponding neuro-controller, for optimum reduction of the vibration, can be trained as shown in Fig. 6, with a suitable input signal covering the dynamic range of interest of the system.

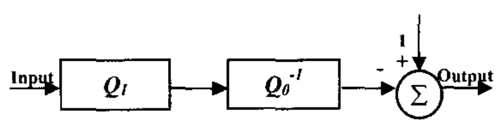

Fig. 3: Inverse of the optimum controller characteristics.

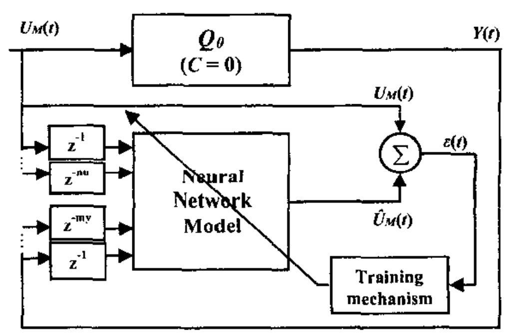

Fig. 4: Training a neural network to model the inverse plane Q_0^{-1}.

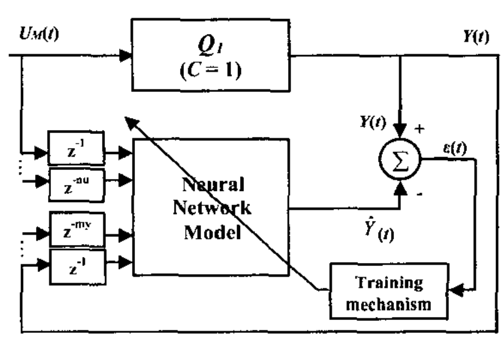

Fig. 5: Training a neural network to model the plane Q_1.

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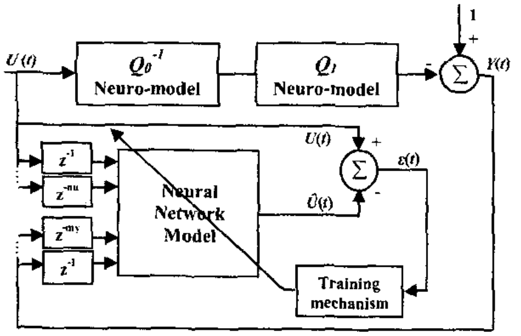


Fig. 6: Training the neuro-controller.

An AVC system design and implementation approach according to the procedure above can accordingly be formulated as follows.

Direct Neuro-AVC Algorithm:

i) With $C = 0$, train a neural network to characterise the inverse of the system between the detection and observation points. This gives characterisation of Q_0^{-1}.

ii) With C = 1, train a neural network to characterise the system between the detection and observation points. This gives the characterisation of Q_1.

iii) Train a neural network according to Fig. 6 to characterise the inverse of the system in Fig. 3 This gives the required neuro-controller.

iv) Implement the neuro-controller within the AVC system.

V. IMPLEMENTATION AND RESULTS

To assess and verify the direct neuro-AVC algorithm a simulation environment, characterising the feedforward AVC structure described in Fig. 2, was utilised. A uniformly distributed white noise was used as the primary source. This type of input is chosen to ensure that all the dynamic range of interest of the simulated plate system is captured. An MLP network with two hidden layers, each having 12 tansigmoid neurons, and one output layer with linear neuron was trained to characterise Q_0^{-1}. The input, U_M, and output, Y, when $C=0$ from the plate algorithm were used as training data. The network input vector of format:

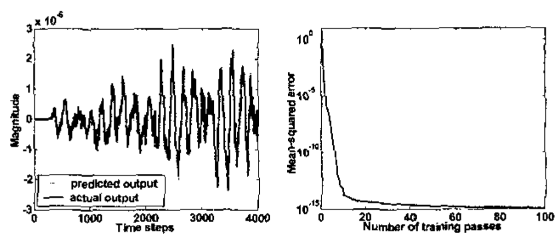
$$X(t) = [y(t-1),\ldots,y(t-n);u(t-1),\ldots,u(t-m)]^T \qquad (5)$$

was used with $m = n = 12$. The one-step-ahead (OSA) prediction technique was used to train the network. Fig. 7 shows the network prediction. It is noted that the network gave a very good output prediction with a mean square error of 1.1416×10^{-15}.

A further MLP network with two hidden layers each having 12 tansigmoid neurons and one output layer with a linear neuron was trained to characterise Q_1. The input, U_M, and output, Y, when $C=1$ from the plate algorithm were used as training data. The network input vector of the same format as in (5) was used with $m = n = 14$. The OSA prediction technique was used to train the network. Fig. 8 shows the network prediction. It is noted that the network gave a very good output prediction with a mean square error of 3.1285×10^{-15}.

To realise the neuro-AVC controller, another MLP network with two hidden layers, each having 20 tansigmoid neurons, and one output layer with a linear neuron was trained according to the scheme in Fig. 6 using the Q_0^{-1} and Q_1 networks obtained above. The network input vector of the format as in (5) was used with $m = n = 16$. During the training the network achieved a very good output prediction with a mean-squared error of 2.0093×10^{-17} with the OSA prediction. The performance of the MLP neural network thus trained is shown in Fig. 9. The corresponding correlation test functions were found to be within the 95% confidence intervals, indicating an adequate fitted model.

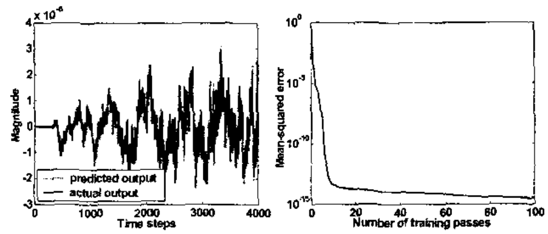
The direct neuro-AVC thus obtained was implemented within the AVC system of the plate and its performance assessed using uniformly distributed white noise input applied to the plate as primary source. Fig. 10 shows the performance of the direct neuro-AVC controller in suppressing the vibration of the system at the observation point. The first five resonance modes of the system are 10.737 rad/s, 36.815 rad/s, 59.825 rad/s, 81.301 rad/s and 102.776 rad/s. It is noted that the spectral attenuation achieved at the resonance modes with direct neuro-controller were 15.2dB, 18.43dB, 9.27dB, 15.51dB and 1.8dB for the first, second, third, fourth and fifth modes respectively.



(a) The actual and predicted output.

(b) Error between the actual and predicted output.

Fig. 7: Performance of the MLP neural network in characterising Q_0^{-1}.



(a) The actual and predicted output.

(b) Error between the actual and predicted output.

Fig. 8: Performance of the MLP neural network in characterising Q_1.

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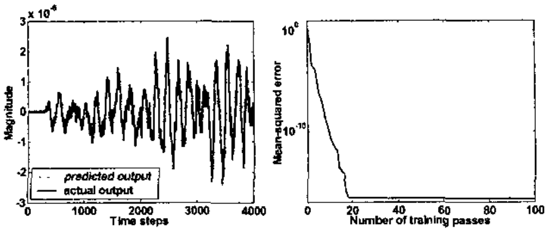

(a) The actual and predicted output.

(b) Error between the actual and predicted output.

Fig. 9: Performance of the MLP neural network in characterising the controller.

VI. CONCLUSION

The development of a neuro-adaptive AVC strategy based on a direct neuro-modelling and control scheme has been presented and verified in the reduction of vibration of a flexible plate structure. The MLP neural network with advanced backpropagation training algorithm has been introduced and the capability of the network in characterising highly nonlinear dynamic systems has been investigated. OSA predictions have been used as training method and model validity tests using correlation tests have been carried out. It has been shown that with suitable choice of the input data structure the system data can faithfully be predicted with a very minimal prediction error. The online design and implementation of the AVC system has been achieved through neuro-modelling of the two subsystems, Q_I and Q_0 and the design of the neuro controller. The control strategy has been tested within AVC system and a significant level of reduction of vibration has been achieved.

The significance of the neuro-control strategy has been clearly demonstrated through the level of performance accomplished in the suppression of vibration of a flexible plate structure.

VII. REFERENCES

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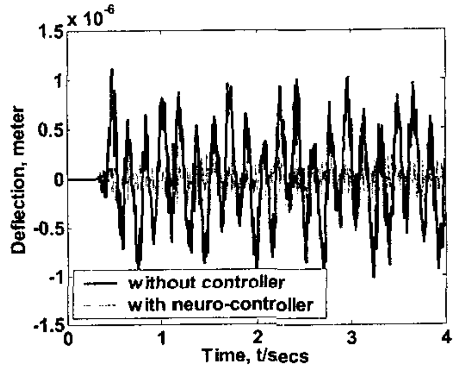
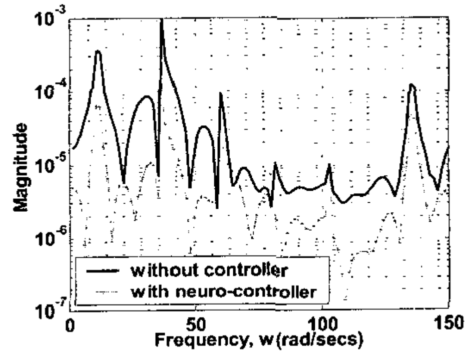
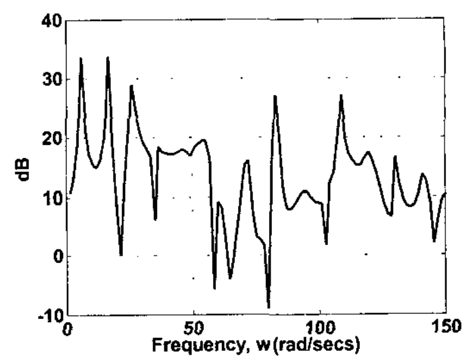


(a) Time domain.



(b) Spectral density.



(c) Spectral attenuation.

Fig. 10: Performance of the system with uniformly distributed white noise input

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