Jurnal Mekanikal
June 2008, No. 25, 24 - 38

INTERACTIVE FRAMEWORK FOR DYNAMIC MODELLING AND ACTIVE VIBRATION CONTROL OF FLEXIBLE STRUCTURES

Intan Zaurah Mat Darus[1*], Siti Zaiton Mohd. Hashim[2] and M.O. Tokhi[3]

[1]Faculty of Mechanical Engineering,
[2]Faculty of Computer Science and Information Technology,
Universiti Teknologi Malaysia,
81310 Skudai, Johor Bahru, Malaysia

[3]Department of Automatic Control and Systems Engineering,
The University of Sheffield,
Sheffield, United Kingdom.

ABSTRACT

This paper presents the implementation of an interactive learning environment for dynamic simulation and active vibration control of flexible structures. The study attempts to facilitate the learning process of the subject area through the development of an interactive environment that can help users to simulate and visualise the behaviour of flexible structures with given physical characteristics, and to test and validate controller designs. Furthermore, the environment allows users to execute such processes repeatedly in a friendly and easy manner. Simulation algorithms based on finite difference scheme in characterizing the dynamic behaviour of flexible structures with different boundary conditions are incorporated. Controller-design strategies, parametric as well as non-parametric, are integrated within this framework. The design and implementation of the interactive learning system incorporating the simulation algorithms, modelling and control strategies, are developed using MATLAB. The environment allows the user to specify the boundary conditions and physical properties of the structure including the dimensions and material type, and provides the response of the structure to user-specified disturbances in the time and frequency domains. The result of the simulation is further utilized in the modelling and control of the specified flexible structure. The environment, thus developed, forms a useful interactive and user-friendly learning and education facility.

Keywords: *Interactive framework, flexible structure, modeling, active vibration control*

[*] Corresponding author: E-mail: intan@fkm.utm.my

1.0 INTRODUCTION

Soft computing comprises of a collection of methods that allows development of computationally intelligent systems, i.e. systems that are capable of imitating the human reasoning process as well as handling quantitative and qualitative knowledge. It is well known that an intelligent system can provide human like expertise such as domain knowledge, uncertain reasoning, and adaptation to a noisy and time-varying environment, which are important in tackling practical computing problems. Specifically, in modern control system design and analysis, there is a promising trend to employ some heuristic methods that can benefit from human experts, because the currently existing complex plants cannot be accurately described by rigorous mathematical models, and are, therefore, difficult to control using conventional model-based methods. Meanwhile, in practice, experienced operators are often able to obtain fairly satisfactory control quality. Soft computing is appropriate for creating knowledge-based intelligent systems. It has attracted the growing interest of researchers from various scientific and engineering communities in recent years [1].

The most popular members of the soft-computing methodologies are the optimisation algorithms such as genetic algorithms and particle swarm optimisation, neural networks, and fuzzy inference systems. Neural networks provide the mathematical power of the brain whereas the fuzzy logic based mechanisms employ the verbal power. The latter allows the linguistic manipulation of input-state-output data. The most interesting applications offer an appropriate combination of these approaches resulting in a hybrid system that operates on the linguistic descriptions of the variables and the numeric values through a parallel and fault tolerant architecture [2].

Flexible structures are utilised in a wide range of engineering systems: for example, civil engineering applications include skyscrapers and bridges; aerospace structures include propellers, aircraft fuselage and wings, satellite solar panels, and helicopter blades; and electro-mechanical systems include turbo generator shafts, engines, gas-turbine rotors, and electric transformer cores [3]. This is due to the advantages such structures offer in comparison to their rigid and bulky counterparts, namely, fast response, low energy consumption, reduced mass, and low cost [4].

However, flexible structure systems are known to exhibit an inherent property of vibration when subjected to disturbance forces, leading to component and/or structural damage [5]. Therefore, the purpose of vibration control in flexible structures is to dampen the response of the structure to external excitation. In all cases there are passive or active control solutions. Active vibration control consists of artificially generating cancelling sources to destructively interfere with the unwanted source and thus result in a reduction in the level of vibration at desired location(s) [5]. Owing to the broadband nature of the disturbances, it is vital that the control mechanism in an active vibration control (AVC) system realizes suitable frequency-dependent characteristics so that cancellation over a broad range of frequencies is achieved. The spectral contents of the disturbances as well as the characteristics of system components are, in general, subject to variation, giving rise to time-varying phenomena. This implies that the control mechanism is further required to be intelligent enough to track these variations so that the desired level of performance is achieved.

The power of digital computation has had major positive influence on overall engineering fields. As early as 1974, an increasing interest in interactive computer programs may be noticed at almost all control institutes. Most of these programs are developed by the institutes themselves for educational purposes or as tools for researchers. There are several converging reasons for constructing an interactive system. In control theory specifically, the converging reasons are: (i) to instruct students on the aspects of modern control theory that need the use of computers, (ii) to create a library facility for control software and provide means by which results of one program can be used or analysed by another, (iii) to provide the possibility to compare methods, for example identification methods, and (iv) to save students' time by providing existing software which obviates time consuming calculations and graph plotting. Hough and Marlin [6] stated that the use of simulation is particularly effective in process control education because of the complex behaviour of control systems. More work on computer-based interactive learning, particularly in process control, has been reported by a number of researchers [7,8].

This paper presents the development of an interactive learning environment for dynamic simulation and active vibration control (AVC) of flexible structures. The study aims to facilitate the learning process of the subject area through the development of an interactive environment that can help users to simulate and visualise the behaviour of flexible structures with given physical characteristics, as well as to test and validate controller designs. Furthermore, it allows users to execute such processes repeatedly in a friendly and easy manner.

Adaptive systems are designed to modify their behaviour in accordance with the changing properties of controlled processes and their signals. An adaptive mechanism is characterised by two complementary processes, namely, identification and control. In the process of identification a suitable model is developed that exhibits the same input/output characteristics as the controlled process (plant). In the process of control a control process is determined, implemented and tested on the plant on the basis of the identified model and control/performance objective [4].

The finite difference (FD) method is utilised to develop simulation algorithms characterising the dynamic behaviour of one-dimensional (1D) and two-dimensional (2D) flexible structures [9, 10]. The design and implementation of an interactive system incorporating the simulation algorithms, the modelling and active vibration control strategies, and graphical user interface are described using MATLAB. The environment allows the user to specify the boundary conditions and physical properties of the structure, and provides the response of the structure to user-specified disturbances in the time and frequency domains and in 2D and 3D views. The result of the simulation is then utilized in the modelling stage, and then in the development of suitable controllers for the flexible structure. Several parametric and non-parametric controller design strategies are investigated for vibration suppression of the flexible structure. The performance of the controller is described in time and frequency domains for analysis and further study.

2.0 DESIGN OF A HYBRID NEURO – FUZZY AVC

A schematic diagram of the geometric arrangement of a single-input-single-output (SISO) feedforward AVC structure considered in this study is shown in Figure 1. An unwanted (primary) point source introduces structural vibration into a flexible structure system and in this case a flexible plate system. This is detected by a detector, processed by a controller of suitable transfer characteristics, and fed to a cancelling (secondary) point source. The secondary signal thus generated is superimposed on the primary signal so as to achieve vibration reduction in the vicinity of an observation point on the plate.

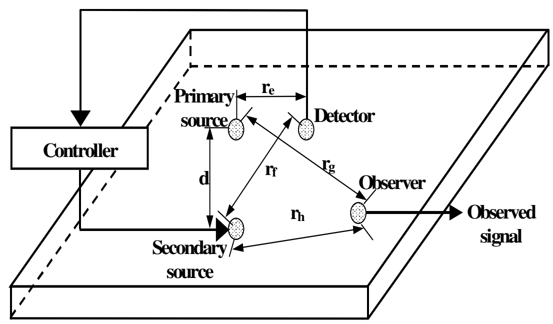


Figure 1: Schematic diagram of the AVC structure

The objective in Figure 1 is to achieve optimum vibration suppression at the observation point. This is equivalent to the minimum variance design criterion in a stochastic environment. This requires that the primary and secondary signals at the observation point are to be equal in amplitudes and to have a phase difference of 180° relative to one another. Synthesising the controller on the basis of this objective yields [11]:

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

where Q_0 and Q_1 represent the equivalent transfer characteristics of the system, with input at the detector and output at the observer, when the secondary source is off and on, respectively.

Equation (1) is the required controller design rule, which can easily be implemented on-line on a digital processor. This leads to a self-tuning AVC algorithm, comprising of the processes of identification and control. The process of identification involves obtaining Q_0 and Q_1 using a suitable identification technique whereas the process of control involves designing the controller according to equation (1) and implementing this in real-time.

An online design and implementation of a soft computing controller such as a hybrid Neuro–Fuzzy or also known as an adaptive neuro fuzzy inference system (ANFIS) controller can be devised to allow for variations due to characteristics of the system components. For optimum reduction of the vibration at the observation point in Figure 1, the controller characteristics given by equation (1) can be realized by obtaining the inverse of the system shown in Figure 2.

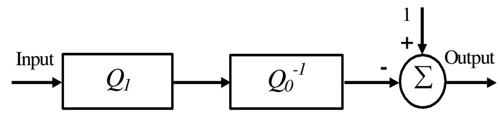


Figure 2: Inverse of the optimum controller characteristics

In this manner, an inverse modelling approach can be adopted to obtain the corresponding soft computing controllers. To allow non-linear dynamics of the system be incorporated within the design, it is proposed to train suitable Neural Networks and hybrid Neuro-Fuzzy networks to characterize the system models Q_0^{-1} and Q_1. Thus, the corresponding hybrid controllers for optimum vibration reduction can be trained as shown in Figure 3, with a suitable input signal covering the dynamic range of interest of the system. An AVC system design and implementation approach according to the procedure above can accordingly be formulated as follows:

1. With C = 0, train a hybrid Neuro–Fuzzy network to characterise the inverse of the system between the detection and observation points. This gives characterisation of Q_0^{-1}.
2. With C = 1, train a hybrid Neuro–Fuzzy network to characterise the system between the detection and observation points. This gives characterisation of Q_1.
3. Train hybrid a Neuro–Fuzzy network according to Figure 3 to characterise the inverse of the system in Figure 2. This gives the required hybrid Neuro–Fuzzy controller.
4. Implement the hybrid Neuro–Fuzzy controller within the AVC system.

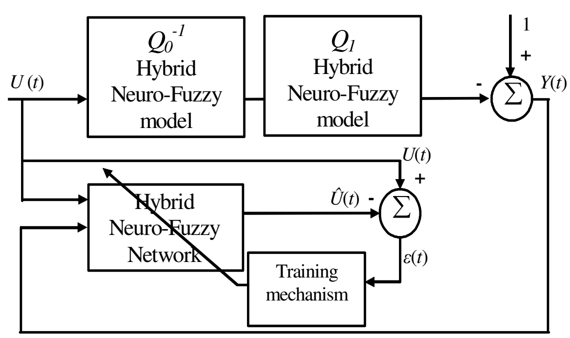


Figure 3: Training the hybrid Neuro–Fuzzy AVC controller

To assess and verify the hybrid Neuro–Fuzzy AVC algorithm the simulation environment, characterising the feedforward AVC structure described in Figure 1, was utilised. A uniformly distributed white noise was used as the primary source. This type of input is chosen to ensure that the dynamic range of interest of the simulated plate system is captured. The hybrid Neuro–Fuzzy structure with first-order Sugeno model containing 36 rules was considered. Gaussian membership functions with product inference rule were used at the fuzzification level. The fuzzifier outputs the firing strengths for each rule. The vector of firing strengths is normalized. The resulting vector is defuzzified by utilizing the first-order Sugeno model. At the identification of the flexible plate, the fuzzifier possessed two inputs, the rule base contained 36 rules and the defuzzifier had one output. Figures 4 and 5 show the performance of the hybrid Neuro–Fuzzy in characterising Q_0^{-1} and Q_1 respectively. It is noted that the network gave a very good output prediction with a mean square error of $8.6723\text{x}10^{-15}$ and $8.2250\text{x}10^{-15}$ in characterising Q_0^{-1} and Q_1 respectively.

To obtain the hybrid Neuro–Fuzzy AVC controller, another first-order Sugeno model structure containing 36 rules was considered. The bell-shaped membership functions with product inference rule were used at the fuzzification level. In this process the fuzzifier outputs the firing strengths for each rule. The vector of firing strengths is normalized. The resulting vector is defuzzified by utilizing the first-order Sugeno model. To characterise the controller, a hybrid Neuro–Fuzzy network with the fuzzifier possessing two inputs, the rule base containing 36 rules, and the defuzzifier comprising one output was trained.

During the training the network achieved a very good output prediction with a mean-squared error of $8.7122\text{x}10^{-15}$. The performance of the hybrid Neuro–Fuzzy network thus trained is shown in Figure 6. The corresponding correlation test functions were found to be within the 95% confidence intervals, indicating an adequate fitted model.

The hybrid Neuro–Fuzzy controller thus obtained was implemented within the AVC system and its performance assessed in vibration reduction of the plate structure using uniformly distributed white noise input applied to the plate as primary source. Figure 7 shows the performance of the hybrid Neuro–Fuzzy AVC system in suppressing the vibration of the plate at the observation point when the primary source was uniformly distributed white noise. The first three resonance modes of the system are at 10.737 rad/s, 36.815 rad/s and 59.825 rad/s. It is noted that, with the uniformly distributed white noise input, the spectral attenuation achieved at the resonance modes with hybrid Neuro–Fuzzy controller are 15.2360dB, 27.2721dB, and 10.7773dB for the first, second and third modes respectively.

It can be seen clearly that the hybrid Neuro–Fuzzy AVC controller has performed significantly well in both modelling and vibration suppression of the flexible plate. It is noted that with suitable choice of the input data structure the system data can faithfully be predicted with a very small prediction error. It is also noted that a good model prediction is crucial and will lead to a good controller design.

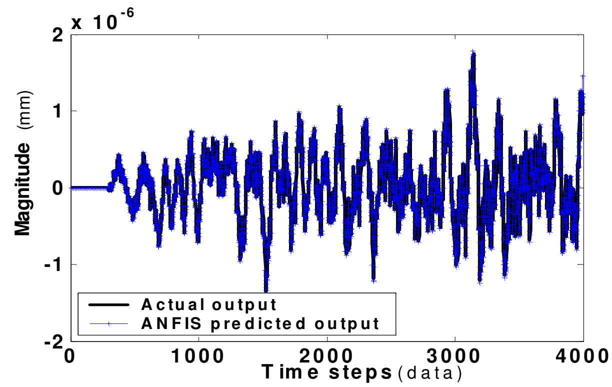


Figure 4: Performance of the hybrid neuro-fuzzy network in characterising Q_0^{-1}

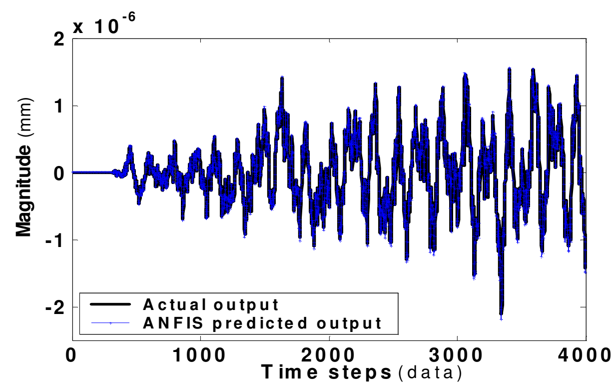


Figure 5: Performance of the hybrid neuro-fuzzy network in characterising Q_1

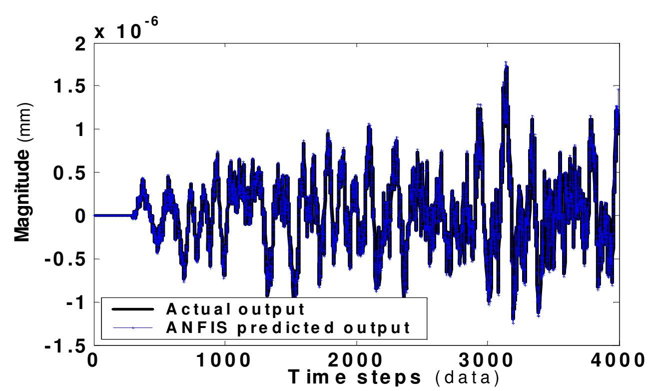
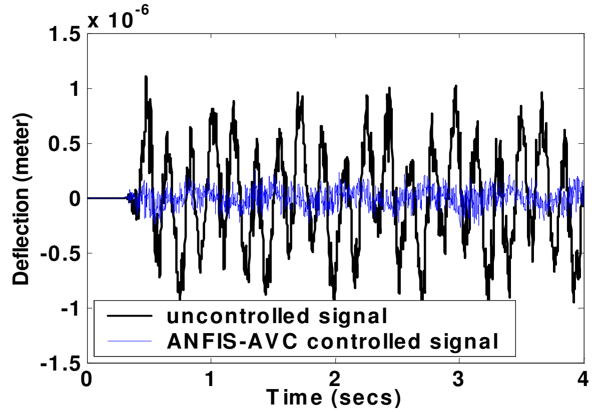
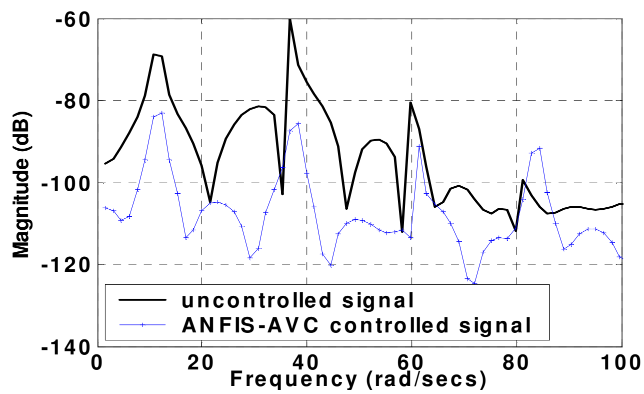


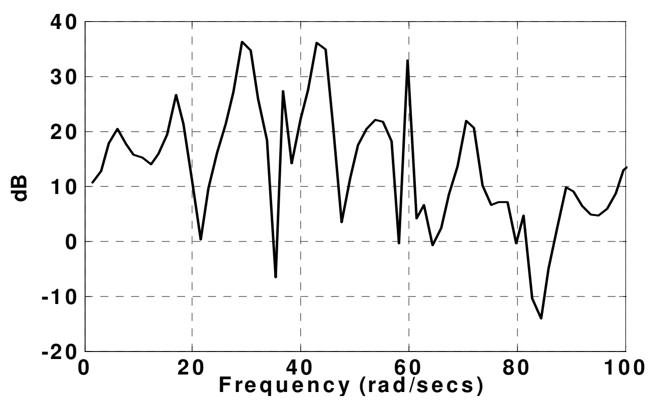
Figure 6: Performance of the hybrid neuro-fuzzy network in inverse modelling of the system



a) Time domain



(b) Spectral density



(c) Spectral attenuation

Figure 7: Performance of the system with uniformly distributed white noise input

3.0 DESIGN OF THE INTERACTIVE LEARNING ENVIRONMENT

This section discusses the design of the system by highlighting the main components of the interactive environment. A flowchart of the system is shown in Figure 8, and the corresponding system inputs are described in Figure 9.

The system comprises of three main sub-menus, where each sub-menu represents the process that takes place in the design of controller in the AVC of a specified flexible structure. The controller design law is well described in the literatures [3, 4, 5]. The sub-menus are simulation, identification and control stage. Each is discussed below.

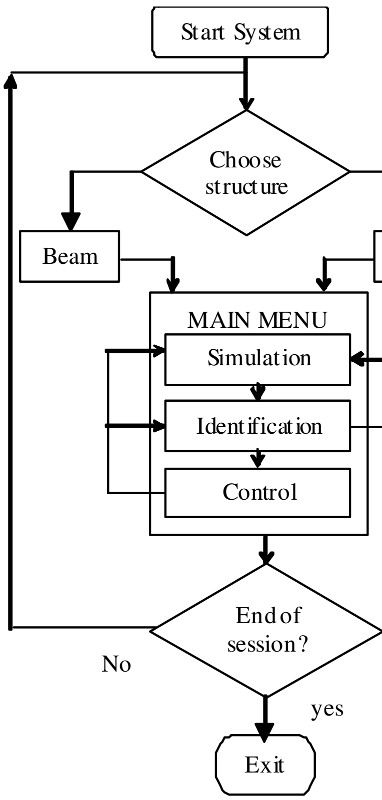


Figure 8: Flowchart of the system

3.1 Simulation

A flowchart and corresponding interface for the simulation process are shown in Figures 10 and 11 respectively. In this process, the input parameters are taken from the user, where the user can specify and attempt various inputs, shown in Figure 9. The output response is displayed in time and frequency domains, and in 3D view, as shown in Figure 11.

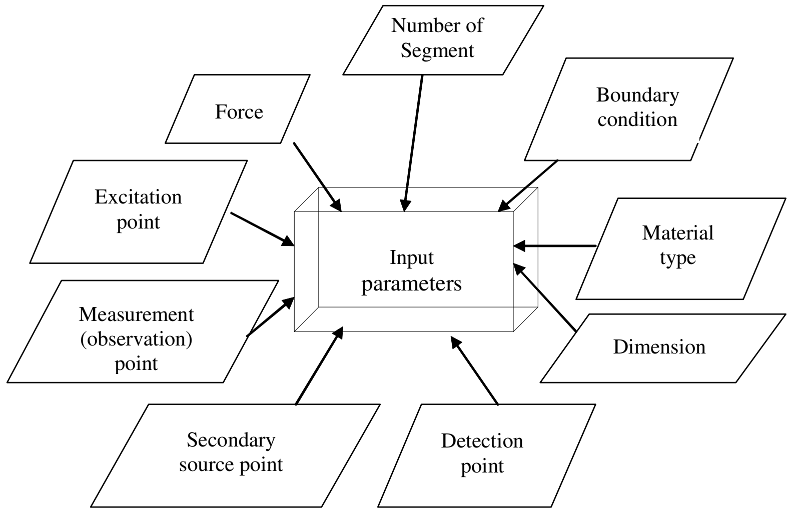


Figure 9: System inputs

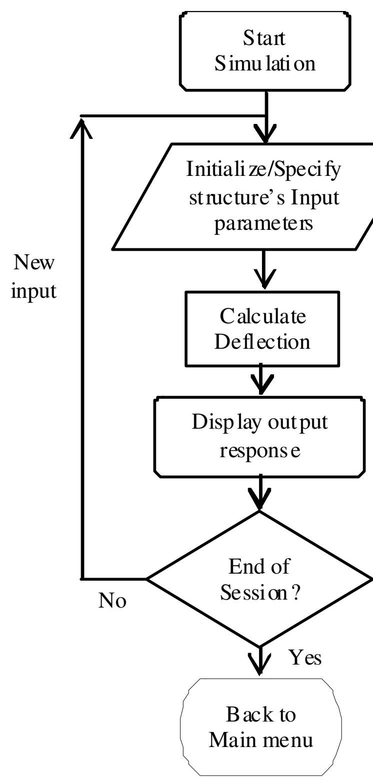


Figure 10: Flowchart of sub-menu

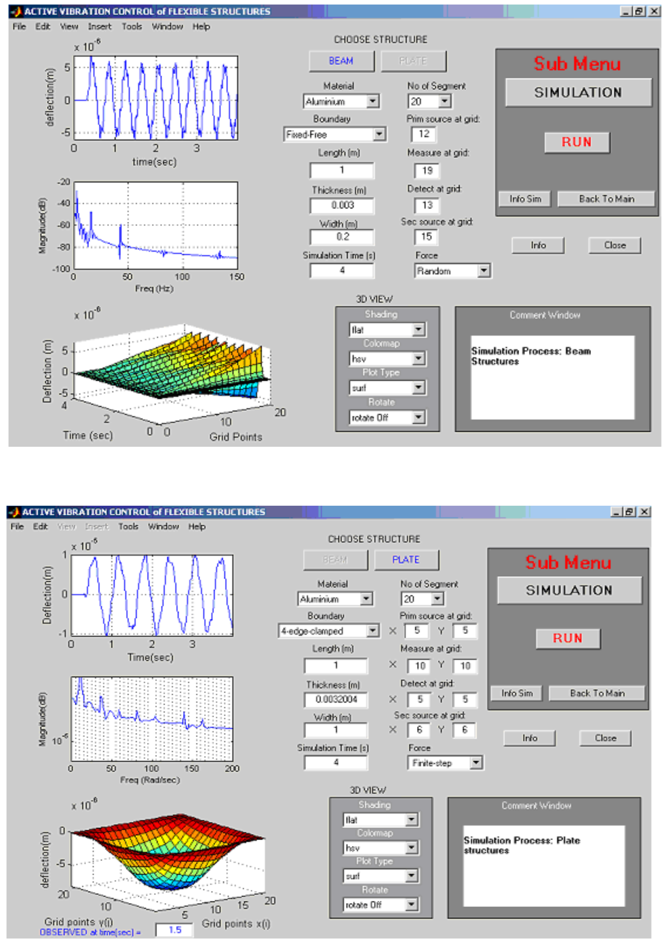


Figure 11: Interface of sub-menu simulation for beam and plate structures respectively

3.2 Identification

A flowchart of the identification process and the corresponding interface are shown in Figures 12 and 13 respectively. In this process, a suitable model is developed that exhibits the same input/output characteristics as the controlled process (plant) [5]. A number of techniques have been devised by researchers to determine models that best describe input-output behaviour of a system. Parametric and non-parametric identification are two major classes of system modelling techniques. Identification consists of determination of the numerical values of the structural parameters which minimize the distance between the system to be identified and its model. The parametric methods investigated in this study involve recursive least square (RLS) and genetic algorithms (GAs). On the other hand, non-parametric models utilised here are neural network (NN) and hybrid neuro–fuzzy or also known as adaptive neuro-based fuzzy inference system

(ANFIS) [12, 13, 14]. The models obtained are validated using several techniques such as calculating mean squared error and correlation tests [15].

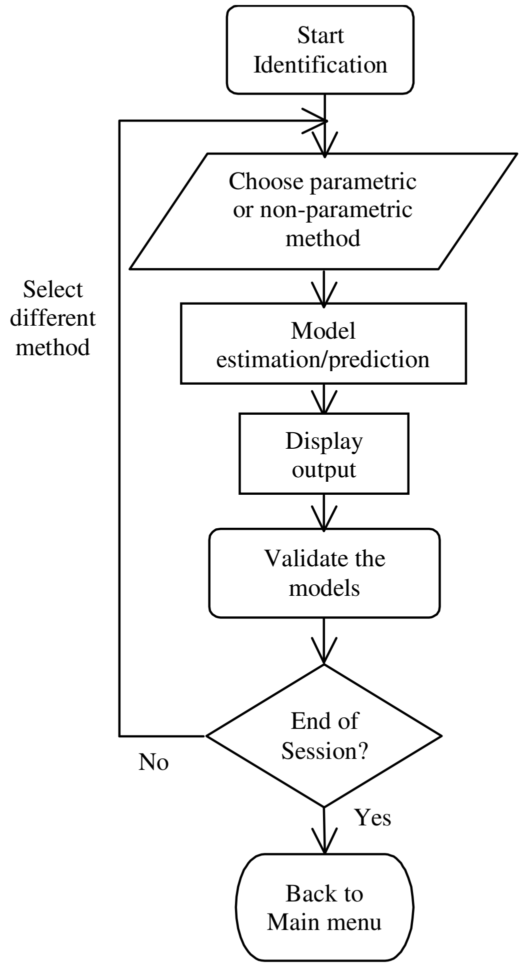


Figure 12: Flowchart of sub-menu system identification

3.3 Control

A flowchart and corresponding interface for the control process are shown in Figures 14 and 15 respectively. In this process, the controller transfer function is calculated based on the identified model parameters obtained in the parametric identification stage. For non-parametric approach, the controller is designed based on the networks obtained through the training process [13]. In this sub-menu, the controller is designed based on the method chosen in the system identification stage. The output response is displayed in time and frequency domains, and in 3D for both conditions, before and after the controller is applied.

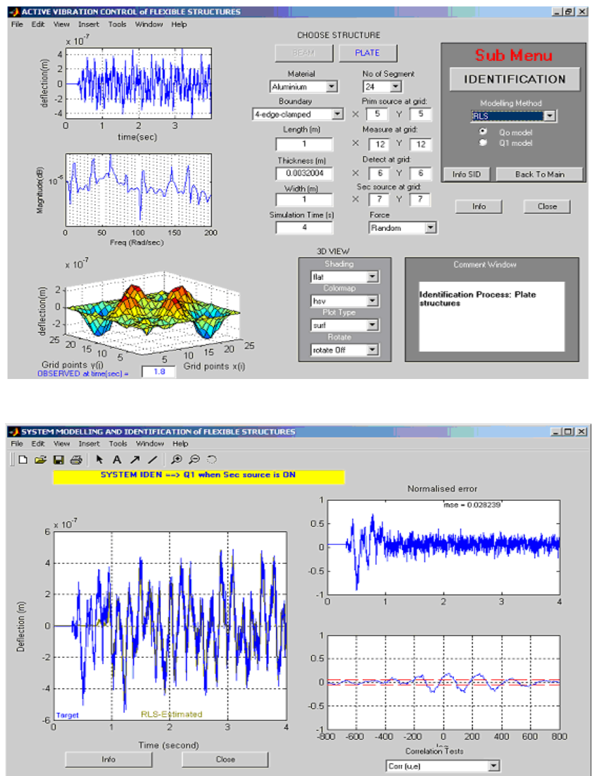


Figure 13: Interface of sub-menu system identification

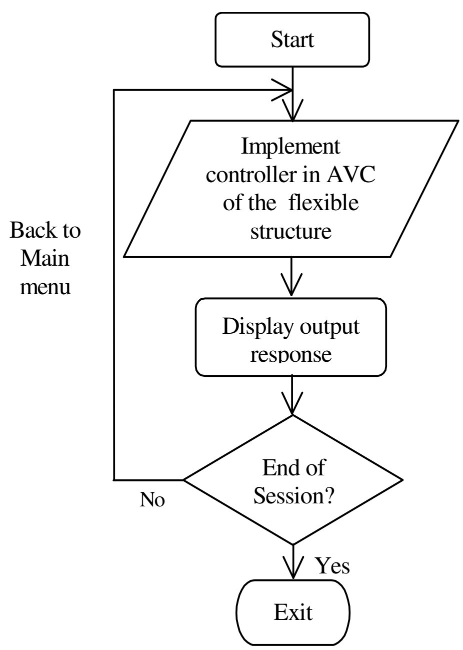


Figure 14: Flowchart of sub-menu control

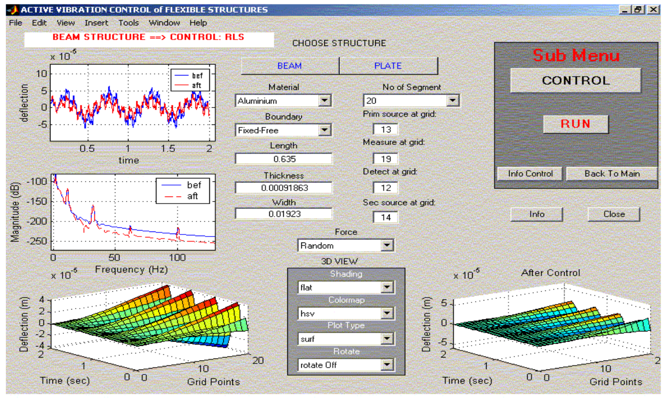


Figure 15: Interface of sub-menu control

4.0 CONCLUSIONS

The development of a hybrid Neuro–Fuzzy Active Vibration Control strategy based on a direct Neuro–Fuzzy modelling and control scheme has been presented and verified for the suppression of vibration of a flexible plate structure. The adaptive neural network with fuzzy inference system algorithm has been introduced. The capability of the network in characterising highly nonlinear dynamic systems has been demonstrated. The online design and implementation of the AVC system has been achieved through the Neuro–Fuzzy modelling of the two subsystems, Q_1 and Q_0 and the design of the hybrid Neuro–Fuzzy controller. The control strategy has been tested within an AVC system of flexible plate structure and a significant level of vibration reduction has been achieved.

An interactive learning environment for dynamic simulation and Active Vibration Control of flexible structures has been developed. The FD method has been used to discretise the governing partial differential equation formulation of the dynamics of the structures. The design and implementation of the interactive system incorporates three stages involved in AVC of flexible structures, namely simulation, modelling, and control. Both parametric and non-parametric approaches in modelling the system have been investigated. The models obtained were further utilised for controller design. The environment thus developed forms a useful interactive and user-friendly learning and education facility in studying the dynamic features of 1D and 2D structures as well as their control aspects.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to the Universiti Teknologi Malaysia (UTM) and MOSTI for their continuous support in the research work. This research was fully supported by a research grant using Vote No. 78197.

REFERENCES

1. Lin, C.-T. and Lee, C.S.G., 1996. *Neural Fuzzy Systems*: *A Neuro-Fuzzy Synergism to Intelligent Systems*, Upper Saddle River, NJ, Prentice-Hall.
2. Efe, M.O. and Kaynak, O., 2000. A comparative study of soft-computing methodologies in identification of robotic manipulators, *Robotics and Autonomous Systems*, vol. 30, pp. 221–230.
3. Hossain, M.A., 1996. *Digital signal processing and parallel processing for real-time adaptive active vibration control*, PhD thesis, Department of Automatic Control and Systems Engineering, University of Sheffield, UK
4. Tokhi, M.O. and Veres, S.M., 2002. *Active sound and vibration control: Theory and application*, Institution of Electrical Engineers, London.
5. Tokhi, M.O. and Leitch, R.R., 1992. *Active noise control*, Clarendon Press, Oxford.
6. Hough, M. and Marlin, T., 2000. Web-based interactive learning modules for process control, *Computers and Chemical Engineering,* 24, pp. 1485-149.
7. Book, W.J., Koeppen, K. and Rouse, M., 2002. Virtual access hydraulic experiment for system dynamics and controls education, *Journal of Mechatronics*, 12, pp 261-270.
8. Jovan, V. and Petrovcic, J., 1996. Process laboratory – a necessary resource in control engineering education, *Journal of Computers Chemical Engineering*, 20, (13), pp S1335-S1340.
9. Mohd. Hashim, S.Z., Mat Darus, I.Z. and Tokhi, M.O., 2002. An interactive environment for simulation and control of flexible structures, *ACTIVE 2002: International Symposium on Active Control of Sound and Vibration*, Southampton, UK, 15-17 July.
10. Mat Darus, I.Z. and Tokhi, M.O., 2001. Dynamic modelling and simulation of a 2D structure using finite difference methods, *Inter-Active2001: IEE International On-line Conference on Active Control of Sound and Vibration*, November.
11. Tokhi, M.O. and Hossain, M.A., 1994. Self-tuning active vibration control in flexible beam structures, *Proceedings of IMechE-I: Journal of Systems and Control Engineering*, vol. 208, issue 14, pp. 263–277.
12. Mat Darus, I.Z., Tokhi, M.O. and Mohd. Hashim, S.Z., 2004. Modelling and control of a flexible structure using adaptive neuro-fuzzy inference system algorithm, *Proceedings of the IEEE International Conference on Mechatronic*, ICM, Istanbul, Turkey, 3 – 5 June.
13. Mat Darus, I.Z. and Tokhi, M.O., 2005. Soft Computing-based active vibration control of flexible structure, *Journal of Engineering Application of Artificial Intelligent,* 18, pp. 93-114, Science Direct, Elsevier Ltd.
14. Mat Darus, I.Z. and Tokhi, M.O., 2006. Parametric and Non-Parametric Identification of a Two Dimensional Flexible Structure, *Journal of Low Frequency Noise, Vibration and Active Control*, vol. 25, no. 2, June, pp. 119-143(25), Multi-Science Publishing Co Ltd.
15. Billings, S.A. and Voon, W.S.F., 1986. Correlation based model validity tests for non-linear systems, *International Journal of Control*, 15, (6), pp. 601-615.