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A vibration absorber of smart structures using adaptive networks in hierarchical fuzzy control ☆

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Abstract

The main goal of this paper is to develop a novel approach for achieving a high-performance active piezoelectric absorber of a smart panel using adaptive networks in hierarchical fuzzy control. Due to the adaptive capability of fuzzy inference systems, its applications to adaptive control and learning control are immediate. For this purpose, the adaptive network-based fuzzy inference system has been used to optimize the fuzzy IF-THEN rules and the membership functions to derive a more efficient fuzzy control. Furthermore, the study addresses the application of the concept of hierarchy for controlling fuzzy system to minimize the size of the rule base by eliminating "the curse of dimensionality". The computational complexity in the process can be reduced as a consequence of the rule-based size reduction, which has become one of the main concerns among system designers. The main advantage of the hierarchical structure is a great reduction of memory demand in the implementation. Consequently, the proposed controller in this research combines the strength of fuzzy systems, the ability to deal with uncertainties, with the advantage of neural nets, the ability to learn.

1. Introduction

Today's increasingly high speed and lightweight structures are subjected to extensive vibrations that can reduce structural life and contribute to mechanical failure. Piezoelectric transducers in

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conjunction with appropriate circuitry can be used as a mechanical energy dissipation device. Piezoelectric materials provide cheap, reliable, and non-intrusive means of actuating and sensing vibrations in flexible structures.

Ref. [1] was among the first to embed piezoelectric materials in composite laminated beams. Moreover, a structure contains an integrated distributed piezoelectric sensor and actuator as described in Refs. [2–9]. They show that the distributed piezoelectric sensing layer monitors the structural oscillation due to the direct piezoelectric effect and the distributed actuator layer suppresses the oscillation via the converse piezoelectric effect. The above discussion brings up another point by making frequent, simplifying assumptions; the problem at hand has become too uncertain to be of practical use. Moreover, the above literature review has not identified any examples of the application of the intelligent control theory in vibration absorber to treat uncertainties in the system.

When used in flexible structures, the piezoelectric materials are bonded to the body of the structure using strong adhesive material. A distinct characteristic of piezoelectric actuators or sensors is that they are spatially distributed over the surface that is being sensed and/or controlled. This property makes them different from the discrete actuators and sensors, which are often used in the control of flexible structures [10]. A research that introduces a class of resonant controllers that can be used to minimize structural vibration using collocated piezoelectric actuator–sensor pairs is indicated in Ref. [11]. All the papers considered above are limited to the vibration control of a laminated beam.

A flexible structure is a distributed parameter system of infinite order, but it must be approximated by a lower-order model and controlled by a finite-order controller because of limitations of the onboard computer, the inaccuracy of sensors, and noise in the system. The methodology that deals with model reduction schemes is shown in Refs. [12,13]. Hence, Chang et al. [12] presents a model reduction method and uncertainty modeling for the design of a low-order H_∞ robust controller for suppression of smart panel vibration. Moreover, the controller is designed to minimize the spatial H_2 norm of the closed-loop system to ensure average reduction of vibration throughout the entire structure proposed by Halim and Reza Moheimani [13]. That work also developed a dynamic model using modal analysis; it employed direct truncation to obtain a finite-dimensional model of the system.

In addition, control systems should be able to accommodate noisy input measurements and uncertainty in system parameter values. One promising strategy, the application of fuzzy control, possesses an inherent robustness and an ability to deal with linear and nonlinear structural behavior.

The application of the concepts of fuzzy set theory in vibration control has recently attracted increasing interest [14,15]. Fuzzy controllers afford a simple and robust framework for specific nonlinear control laws that accommodate uncertainty and imprecision. Therefore, Weng et al. [9] proposed a fuzzy logic algorithm for vibration suppression of a clamped-free beam with piezoelectric sensor/actuator. Similarly, Ofri et al. [16] also used a control strategy based on fuzzy logic theory for vibration damping of a large flexible space structure controlled by bonded piezoceramic actuators. In spite of this, the design of fuzzy controllers is often a time-consuming activity, definition of the controller structure; definition of rules and other parameters. At present, one of the currently important issues related to fuzzy logic systems is the reduction of the total number of rules and their corresponding computational demands. Unfortunately, all of the above papers never discuss the important issue such as rule-based size reduction.

In general, the fuzzy logic controllers use fuzzy inference with rules pre-constructed by an expert [17]. Therefore, the most important task is to form the rule base, which represents the experience and intuition of human experts. When the rule base of human experts is not available, an efficient control cannot be expected.

Adaptation is introduced in a fuzzy controller by exploiting the neural network ability to learn. On the other hand, fuzzy inference permits the use of highly structured local networks in the basic architecture. An adaptive controller differs from an ordinary controller in that the controller parameters are variable, and there is a mechanism for adjusting these parameters based on system performance. The adaptation law should pursue those values of the parameters for which stability and tracking converge [15,18].

The total number of rules is well known to be an exponential function of the number of system variables [17–21]. A fuzzy rule-based controller of a multi-dimensional system where n is large may not be effective. Realizing such a controller will require that the computer process a huge database; such processing is frequently accompanied by memory overload and increased computational time. However, all these papers only discussed the rule-based size reduction, no learning and optimization skills for fuzzy inference system were investigated.

A neuro-fuzzy training method learns fuzzy rule and terms by using training sets of data. After a system output is computed by forward propagation, an output error is evaluated. This error is then used to determine the fuzzy rule or membership function most suited for influencing the system behavior. In order to resolve the drawbacks of the fuzzy logic approach, Juang and Lin [22] proposed a recurrently adaptive fuzzy filter to deal with noisy speech processing. Similarly, Zhang and Gan [23] proposed a simplified fuzzy neural network (SFNN) to solve the nonlinear effect in the primary acoustic path of the active noise control system.

From the literature review, the researchers seldom discover the vibration control of smart structures for a plate. Therefore, this research investigates the potential of adaptive fuzzy control as applied to a smart panel. The fuzzy inference computational efficiency is improved by using the artificial neural network. For this purpose, the adaptive network-based fuzzy inference system has been used to optimize the fuzzy IF-THEN rules and the membership functions to derive a more efficient fuzzy control. Moreover, the rules are structured in a hierarchical way so that the total number of rules will be a linear function of system variables. In fuzzy control, the hierarchy is also effective in structuring the rules to make the fuzzy controller suitable for a relatively large system.

2. Dynamic model of the smart panels

This section describes a model of a plate with some gilded or embedded piezoelectric actuators and strain sensors. Consider an example of the geometry of such a system as that depicted in Fig. 1.

In Fig. 1, L, W, and H represent the physical dimensions of the panel with m actuators. Let the instantaneous transverse elastic displacement along the Z-axis be $w(x, y, t)$. For the convenience of the analysis assume that w is separable into its temporal and spatial components, and further assume the existence of a complete set of functions that allows w to be expanded in series

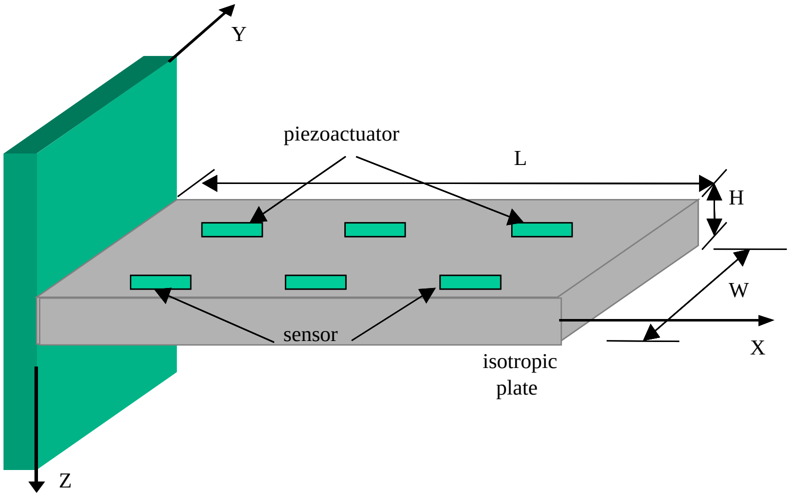

Fig. 1. Smart structures with piezoelectric actuators/sensors.

as follows:

$$w(x,y,t) = \sum_{j=1}^{n_s}\sum_{i=1}^{m_s} q_{ij}(t)\phi_i(x)\varphi_j(y) = \tilde{\Phi}^{\mathrm{T}} Q\tilde{\Psi},\ m_s, n_s \to \infty, \tag{1}$$

where m_s and n_s represent the mode numbers of the x and y direction for the plane. Moreover, $q_{ij}(t)$ are the generalized modal coordinates and $\phi_i(x)$, $\varphi_j(y)$ are mode shape functions that are dependent upon the boundary-value problem (i.e. free-free, pinned-pinned, clamped-free, etc.).

Furthermore,

$$w(x,y,t) = C_{\Phi\Psi}^{\mathrm{T}}\tilde{Q}, \tag{2}$$

where

$$C_{\Phi\Psi}^{\mathrm{T}} = [\,\phi_1\varphi_1 \quad \phi_1\varphi_2 \quad \cdots \quad \phi_1\varphi_n \quad \phi_2\varphi_1 \quad \phi_2\varphi_2 \quad \cdots \quad \phi_2\varphi_n \quad \cdots \quad \phi_m\varphi_n\,]$$

$$\tilde{Q}^{\mathrm{T}} = [\,q_{11} \quad q_{12} \quad \cdots \quad q_{1n} \quad q_{21} \quad q_{22} \quad \cdots \quad q_{2n} \quad q_{31} \quad \cdots \quad q_{mn}\,]$$

A model of the structure is derived by the modal analysis. This procedure demands that a solution to the partial differential equation (PDE) be found, to describe the dynamics of the flexible structures [24].

Furthermore, the equation of motion of a flat plate, based on the Kirchhoff theory [25], is

$$\Theta\nabla^4 w + \rho w_{tt} = 0, \tag{3}$$

where subscripts indicate partial differentiation, and where Θ is the flexural rigidity of the plate as defined by

$$\Theta = \frac{EH^3}{12(1-v^2)}, \tag{4}$$

where H is the thickness of the plate and v is the Poisson's ratio. The function $w(x, y, t)$ represents the transverse displacement of the point $(x, y, z = 0)$ and ∇^4 is the biharmonic operator and defined as $\nabla^4() = ()_{xxxx} + 2()_{xxyy} + ()_{yyyy}$. The partial differential equation can be solved independently for each mode using the orthogonal properties of its eigenfunctions.

To apply the Lagrangian formulation, the paper uses $\tilde{Q}$ and $\dot{\tilde{Q}}$ as our generalized coordinates in the expressions for the kinetic and potential energy. By carrying out some algebraic manipulations, it can obtain the dynamic equations,

$$M\ddot{\tilde{Q}} + D\dot{\tilde{Q}} + K\tilde{Q} = \tilde{u}. \tag{5}$$

The matrix equations are written in partitioned form to reflect the coupling between the elastic and electric field, where M is the inertia matrix, D is the damping matrix and is assumed to be diagonal. K is stiffness matrix. $\tilde{u}$ is the generalized force derived from the piezoactuator control force $\tilde{u}_c$ and the external disturbances $\tilde{u}_d$:

$$\tilde{u} = \tilde{u}_c + \tilde{u}_d. \tag{6}$$

In the following, the contribution of the external forces $\tilde{u}_d$ is assumed to be null and neglected. The equivalent generalized force due to the piezoactuator can be calculated as follows:

$$\tilde{u}_c = M\ddot{\tilde{Q}}_{m_{ij}} + D\dot{\tilde{Q}}_{m_{ij}} + K\tilde{Q}_{m_{ij}}, \tag{7}$$

where m are the number of piezoelectric actuators, and the subscript ij means the ith, jth mode on the x, y direction of the smart panel, respectively.

By introducing the numbers of actuators, Eq. (7) can be rewritten as

$$\tilde{u}_c = MU\ddot{\tilde{V}}(t) + DU\dot{\tilde{V}}(t) + KU\tilde{V}(t), \tag{8}$$

where U is a matrix [of size $(m_s \times n_s) \times m$] composed of $\tilde{u}_c$, and m_s and n_s are the number of modes taken into account in geometry eigenfunctions.

Hence

$$U = [\,\tilde{u}_1 \quad \tilde{u}_2 \quad \cdots \quad \tilde{u}_m\,]. \tag{9}$$

The vector $\tilde{V}$ is the applied actuating voltage profile and $\tilde{u}_i$ is a constant vector for each piezoactuator.

3. Modal analysis

The system of equation of motion presented in Eq. (5) is not suitable for system analysis because the order of degrees of freedom of the system is typically too high for the application of the finite element method. Multiplying the equation of motion (Eq. (5)) by the transformation matrix M^{-1} in modal coordinates yields

$$[I]\ddot{q}_{ij} + [2\xi_{ij}\omega_{n_{ij}}]\dot{q}_{ij} + [\omega_{n_{ij}}^2]q_{ij} = b_{ij}\tilde{V}, \tag{10}$$

where $\omega_{n_{ij}}$ and ξ_{ij} are the natural frequencies and the modal damping ratios for the ith, jth mode on the x, y direction of the smart panel, respectively. The control forces are provided by m number of actuators. In practice, dynamical models of a flexible structure as described in Eq. (10) have to be truncated to represent the system by a finite-dimensional model. The model can be truncated so as to include only the modes within the frequency bandwidth of interest. However, the truncation of the model produces additional error in the locations of the bandwidth zeros. This is due to the fact that the contribution of the out-of-bandwidth modes, i.e., high-frequency modes, is generally ignored in the truncation. Moreover, the decoupled structure equation (Eq. (10)) is given in modal coordinates in the following format:

$$
\begin{gathered}
\ddot{q}_{11} + 2\xi_{11}\omega_{n_{11}}\dot{q}_{11} + \omega_{n_{11}}^2 q_{11} = b_{11}\tilde{V},\\
\ddot{q}_{12} + 2\xi_{12}\omega_{n_{12}}\dot{q}_{12} + \omega_{n_{12}}^2 q_{12} = b_{12}\tilde{V},\\
\vdots\\
\ddot{q}_{1m_s} + 2\xi_{1m_s}\omega_{n_{1m_s}}\dot{q}_{1m_s} + \omega_{n_{1m_s}}^2 q_{1m_s} = b_{1m_s}\tilde{V},\\
\vdots\\
\ddot{q}_{n_s m_s} + 2\xi_{n_s m_s}\omega_{n_{n_s m_s}}\dot{q}_{n_s m_s} + \omega_{n_{n_s m_s}}^2 q_{n_s m_s} = b_{n_s m_s}\tilde{V}.
\end{gathered}
\tag{11}
$$

Eq. (11) is called the system equation of the structure. These equations are converted to the modal state space model without losing any characteristics of the modal structure. The modal state space is formulated using the parameters in Eq. (11) and the ith, jth mode are independently described as

$$
\begin{bmatrix} \dot{q}_{ij} \\ \ddot{q}_{ij} \end{bmatrix} = \begin{bmatrix} O & I \\ -\omega_{n_{ij}}^2 & -2\xi_{ij}\omega_{n_{ij}} \end{bmatrix} \begin{bmatrix} q_{ij} \\ \dot{q}_{ij} \end{bmatrix} + \begin{bmatrix} 0 \\ b_{ij} \end{bmatrix} \tilde{V}. \tag{12}
$$

The whole structure response, which is the superposition of all the modal responses, can be expressed as a combination of each modal state space variable as follows:

$$
\dot{x} = \begin{bmatrix} O & I \\ -W_c^2 & -2D_i W_c \end{bmatrix} x + \begin{bmatrix} 0 \\ B \end{bmatrix} \tilde{V}, \tag{13}
$$

where O and I are the zero and identity matrices with the appropriate sizes, respectively. Moreover, the state vector x is $[q_{11},\ q_{12},\ \ldots,\ q_{1n_s},\ q_{21},\ q_{22}, \ldots,\ q_{m_s n_s}]^{\mathrm{T}}$.

The number of modes considered in the truncated model in x and y direction is represented by m_s and n_s, respectively. If we order the vibration modes that are to be controlled as $n_{11},\ n_{12},\ \ldots, n_{1n_s},\ n_{21},\ n_{22}, \ldots, n_{m_s n_s}$, then it can define

$$
\begin{gathered}
D_i = \operatorname{diag}(\xi_{11}, \xi_{12}, \ldots, \xi_{1n_s}, \xi_{21}, \xi_{22}, \ldots, \xi_{m_s n_s}),\\
W_c = \operatorname{diag}(\omega_{11}, \omega_{12}, \ldots, \omega_{1n_s}, \omega_{21}, \omega_{22}, \ldots, \omega_{m_s n_s}),\\
B = \operatorname{diag}(b_{11}, b_{12}, \ldots, b_{1n_s}, b_{21}, b_{22}, \ldots, b_{m_s n_s}).
\end{gathered}
$$

4. Analysis of adaptive hierarchical fuzzy system

This section proposes a class of adaptive networks, which are functionally equivalent to fuzzy inference systems. The proposed architecture is referred to as ANFIS, standing for Adaptive-Network-Based Fuzzy Inference System. The main goals will be (1) increased decision-making speed, (2) optimization of the membership functions for a given loading situation, and (3) capability of making the control device adaptive.

The design of fuzzy controllers is often a time-consuming activity, which depends on knowledge acquisition, definition of the controller structure, definition of rules and other parameters. At present, one of the currently important issues related to fuzzy logic systems is the reduction of the total number of rules and their corresponding computational demands. The paper addresses the concept of a hierarchy in fuzzy control system shown in Ref. [26]. An attempt is made to reduce the size of the inference engine of a large-scale system.

Furthermore, a hierarchical fuzzy control structure is used where the most influential parameters are chosen as the system variables in the first level, the next most important parameters are chosen as the system variables in the second level, and so on. In many practical problems, they may have the knowledge that some variables are more important than others. Hence, Raju et al. [20] proposed a methodology to analyze the sensitivity of the system output with respect to small perturbations in the input variable. The way to determine a ranking of importance is using the sensitivity method.

The first-level rule set gives a basic control action, while the higher level rule sets initiate fine tuning control action based on the base (gross) control action. In general, the first-level rule set depends upon only a few important system variables, while the higher-level rule sets rely on more system variables. Each controller takes aim at the global behavior of the reference fuzzy logic controller (FLC), regardless of the missing information about the other inputs.

Consider the hierarchical fuzzy system shown in Fig. 2. The main advantage of the hierarchical structure of Fig. 2 is a great reduction of memory demand in the off-line implementation. In a general way, an n-input FLC can be realized using n_p two-input FLC, where n_p are all possible permutations of n written in groups of two. Nevertheless, all considerations also apply to a more general n-input controller.

Hence, we suppose that r fuzzy sets A_i^p are defined for each variable x_i, where $i = 1, \ldots, n$ and $p = 1, \ldots, r$. The membership function of the ith fuzzy consequents $f_{1,1}(x_1, x_2)$ is the sum of the MF's of all the reference rules consequents that have $x_1 = A_1^p$ and $x_2 = A_2^q$ as antecedents at the first level of the hierarchical fuzzy system. Similar considerations hold for the other fuzzy controllers FLC$_i$. All the output fuzzy variables are defined on the same universe, even if each of them has its own term set.

Therefore, the hierarchical fuzzy system can be derived as follows. The fuzzy system in the first level (Level 1) of Fig. 2 is the Takagi-Sugeno-Kang (TSK) fuzzy system [19,20].

FLC$_{1,1}$—the fuzzy algorithm is

If x_1 is A_1^p **and** x_2 is A_2^q, **then** $y_{1,1}$ is $f_{1,1}(x_1, x_2)$ where

$$f_{1,1}(x_1, x_2) = y_{1,1} = \frac{\sum_{p=1}^{r}\sum_{q=1}^{r} h_{1,1}^{pq}(x_1, x_2)[\mu_{A_1^p}(x_1)\mu_{A_2^q}(x_2)]}{\sum_{p=1}^{r}\sum_{q=1}^{r}[\mu_{A_1^p}(x_1)\mu_{A_2^q}(x_2)]}. \tag{14}$$

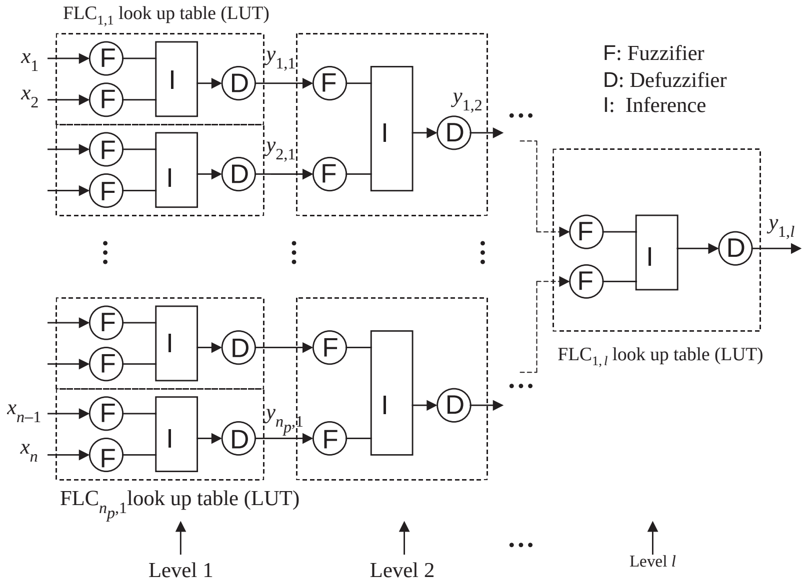

Fig. 2. Proposed hierarchical fuzzy logic controller.

In the above Eq. (14), $y_{1,1}$ indicates the fuzzy logic controller 1 ($\mathrm{FLC}_{1,1}$) of the first level and $h_{1,1}^{pq}(x_1, x_2)$ are linear or nonlinear functions.

$$\vdots$$

$\mathrm{FLC}_{n_p,1}$—the fuzzy algorithm is

If x_{n-1} is A_{n-1}^p **and** x_n is A_n^q, **then** $y_{n_p,1}$ is $f_{n_p,1}(x_{n-1}, x_n)$ where

$$f_{n_p,1}(x_{n-1}, x_n) = y_{n_p,1} = \frac{\sum_{p=1}^{r}\sum_{q=1}^{r} h_{n_p,1}^{pq}(x_{n-1}, x_n)[\mu_{A_{n-1}^p}(x_{n-1})\mu_{A_n^q}(x_n)]}{\sum_{p=1}^{r}\sum_{q=1}^{r}[\mu_{A_{n-1}^p}(x_{n-1})\mu_{A_n^q}(x_n)]}. \tag{15}$$

In general, the sequence fuzzy logic controller n_p at level l is the fuzzy system

$$f_{n_p,l}(y_{n_p-1,l-1}, y_{n_p,l-1}) = y_{n_p,l} = \frac{\sum_{p=1}^{r}\sum_{q=1}^{r} h_{n_p,l}^{pq}(y_{n_p-1,l-1}, y_{n_p,l-1})[\mu_{A_{n_p}^p}(y_{n_p-1,l-1})\mu_{A_{n_p}^q}(y_{n_p,l-1})]}{\sum_{p=1}^{r}\sum_{q=1}^{r}[\mu_{A_{n_p}^p}(y_{n_p-1,l-1})\mu_{A_{n_p}^q}(y_{n_p,l-1})]}, \tag{16}$$

where $h_{n_p,l}^{pq}$ are linear or nonlinear functions.

In the hierarchy, the first level gives an approximate output $y_{1,1}$, which is then modified by the second-level rule set. The second-level variables include the approximate output $y_{1,1}$ of the first level and system variables as shown in (14). This process is repeated in succeeding levels of hierarchy [20]. At each ith level, one or more system variables may be considered in addition to the output of the previous level in the development of the ith level. In such a case, $y_{1,1}, y_{2,1}, \ldots, y_{1,2}, \ldots, y_{1,l}$, correspond to physical variables of the system. If this is not the case, the $y_{1,1}, y_{2,1}, \ldots$ can still be interpreted as the "internal state variables" of the system. This is analogous to the states in the state-space representation of systems, where a state characterizes some key feature of the system but does not necessarily correspond to any physical variable. However, if we put all variables in the first level, the structure is the same as the conventional one. That means the conventional rule based fuzzy controller is a special case of the hierarchical one.

4.1. The fuzzy control structure of the system

The ultimate goal of controller design for a structure is to regulate the structure vibration to a desired level by properly driving an actuator.

This section applies the hierarchical fuzzy controller to control the vibrations in a flexible structure using piezoelectric actuators. Typically, the response of a plate is dominated by the lower (1st, 2nd, 3rd…) modes. Consequently, in an approximate dynamic model, few flexible retained modes are chosen for the system. In the proposed hierarchical fuzzy control structure, the first-level rules are those associated with the first flexible mode, and its derivatives are collected to generate the first-level hierarchy. The second most dominant mode and its derivative are selected as inputs to the second-level hierarchy, and so on. Clearly, the size of the rule base is differently reduced depending on the number of flexible modes that can be fused, when they are put into a hierarchical structure, and in what order.

Since the lower modes dominate the plate vibration action, the experiment uses only two modes of x and y directions. To implement the proposed technique, the system is decomposed into four subsystems: the first subsystem takes q_{xf1} (the first vibration mode of x-direction) and $\dot{q}_{xf1}$ as local variables, while the second subsystem takes q_{xf2} and $\dot{q}_{xf2}$ as local variables, etc. The third and fourth subsystem is for the first and second vibrational mode of y-direction. Hence, in the proposed hierarchical fuzzy control structure, the first subsystem rules are those associated with the first flexible mode, and its derivatives are used to generate the first-level hierarchy. The second most dominant mode and its derivative are selected as inputs to another fuzzy controller at the same level, and so on.

The fuzzy logic controller $\mathrm{FLC}_{1,1}$ takes q_{xf1} and $\dot{q}_{xf1}$ as inputs to generate the local control action $u_{1,1}$, while fuzzy logic controller $\mathrm{FLC}_{2,1}$ takes q_{xf2} and $\dot{q}_{xf2}$ to generate another control action $u_{2,1}$. Similarly, fuzzy logic controller $\mathrm{FLC}_{3,1}$ takes q_{yf1} and $\dot{q}_{yf1}$ as inputs to generate the local control action $u_{3,1}$ while $\mathrm{FLC}_{4,1}$ takes q_{yf2} and $\dot{q}_{yf2}$ to generate another control action $u_{4,1}$. Thus, at the local level, each subsystem is designed separately. The fuzzy logic rule base for each subsystem is designed based on the dynamic response of each mode when a control force is activated on the flexible structure system. These are then summed to form the total control force for feeding back to the plate.

4.2. A priori design of the membership functions and fuzzy rule base

In fuzzy logic control, it is necessary to determine the universe of discourse to give the semantics of a fuzzy variable, i.e. its membership function. A priori selection of membership functions and fuzzy rules is performed for the guidelines of the proceeding section. In this study, the vibration states and their rate variables are the inputs, and the voltage applied to the voltage amplifier is the output. Since adaptive-network-based fuzzy inference system handles smooth membership functions better than trapezoidal ones, bell-shaped functions are employed to convert these input and output variables into linguistic control variables. Usually we choose $\mu_{A_i}(x)$ to be bell shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{A_i}(x) = \exp\left\{-\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}\right\}, \tag{17}$$

where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label A_i. In this paper, linguistic variables corresponding to *large negative* (LN), *small negative* (SN), *zero* (ZE), *small positive* (SP), *large positive* (LP) are used to represent the domain knowledge.

4.3. Adaptive learning schemes for fuzzy models

An algorithm that uses the Takagi and Sugeno inference system then optimizes the controller. This computes the fuzzy output for each rule as a linear combination of input variable membership values plus a constant term. By employing a hybrid learning procedure, the proposed architecture can refine fuzzy if-then rules obtained from human experts to describe the input–output behavior of a complex system.

An adaptive network, as its name implies, is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, part or all of the nodes are adaptive, which means their outputs depend on the parameters pertaining to these nodes, and the learning rule specifies how these parameters should be changed to minimize a prescribed error measure.

The structure of an adaptive network-based fuzzy inference system is shown in Fig. 3. Fig. 3 shows a two input with 25 rules. Five membership functions are associated with each input (vibration modes and their derivatives), so the input space is partitioned into 25 fuzzy subspaces, each of which is governed by a fuzzy if-then rules. The premise part of a rule delineates a fuzzy subspace, while the consequent part specifies the output within this fuzzy subspace.

Moreover, Fig. 4 gives a graphical representation of the idea for local training of fuzzy models on each hierarchical level with the following notations: LC-local criterion; LA-learning algorithm. As seen from this figure, each local fuzzy controller $\mathrm{FLC}_{i,j}$ is trained separated by using its own local criterion $\mathrm{LC}_{i,j}$. Since the number of model inputs two is usually small, the local learning scheme leads to a significant reduction in both calculation time and complexity. Therefore, the local learning could be a proper way to cope with the high-dimensionality problem in simulation of real-life processes.

4.3.1. Design of hierarchical fuzzy systems through training

The main idea in the learning procedure is to update the membership function and fuzzy rule by using the information from the training patterns, i.e., sets of input–output outcomes. We are given a number of input–output pairs $(x_0^s; y_0^s = g(x_0^s))$, $s = 1, 2, \ldots$, where the input points x_0^s cannot be arbitrarily chosen. Therefore, the task of this section is to design a hierarchical fuzzy system that

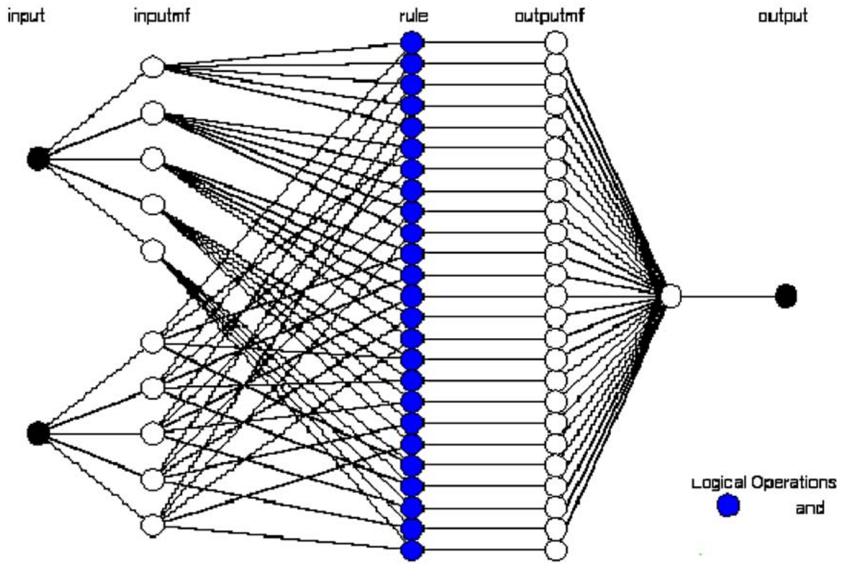

Fig. 3. Structure of an adaptive network-based fuzzy inference system.

matches the input–output pairs $(x_0^s; y_0^s)$ in some sense. For simplicity and without loss of much generality, let us discuss the fuzzy logic controller 1 ($FLC_{1,1}$) of the first level $f_{1,1}$ only. The training algorithm for each local fuzzy model on the hierarchical level is shown in the following steps:

Step 1: Let us discuss the $f_{1,1}$ in Eq. (14) and choose $h_{1,1}^{pq}(x_1, x_2)$ to be a constant $\bar{y}_{1,1}^{pq}$. Therefore, the structure of the fuzzy system $f_{1,1}$ is shown in the following:

$$f_{1,1}(x_1, x_2) = y_{1,1} = \frac{\sum_{p=1}^{r}\sum_{q=1}^{r} \bar{y}_{1,1}^{pq}[\mu_{A_1^p}(x_1)\mu_{A_2^q}(x_2)]}{\sum_{p=1}^{r}\sum_{q=1}^{r}[\mu_{A_1^p}(x_1)\mu_{A_2^q}(x_2)]}, \tag{18}$$

where the membership function $\mu_{A_1^p}(x_1)$ and $\mu_{A_2^q}(x_2)$ are fixed (may be chosen as the bell-shaped functions or the other qualified candidate functions) and the free parameters are $\bar{y}_{1,1}^{pq}$. Moreover, $\bar{y}_{1,1}^{pq}(0)$ are the initial parameters that can be chosen according to the linguistic information. If no linguistic information is available, $\bar{y}_{1,1}^{pq}(0)$ may be chosen uniformly across the domain of $f_{1,1}$. Our goal is to determine these free parameters such that the matching error

$$e^s = \tfrac{1}{2}[f(x_0^s) - y_0^s]^2 \tag{19}$$

is minimized.

Step 2: We use the gradient descent algorithm to determine the parameters. Specifically, to determine $\bar{y}_{1,1}^{pq}$, we use the training algorithm [21]

$$\bar{y}_{1,1}^{pq}(k+1) = \bar{y}_{1,1}^{pq}(k) - \eta_1 \left.\frac{\partial e^s}{\partial \bar{y}_{1,1}^{pq}}\right|_k, \tag{20}$$

where $k = 0, 1, 2, \ldots$ is the training index, η_1 is a constant step-size, and $p, q = 1, \ldots, r$.

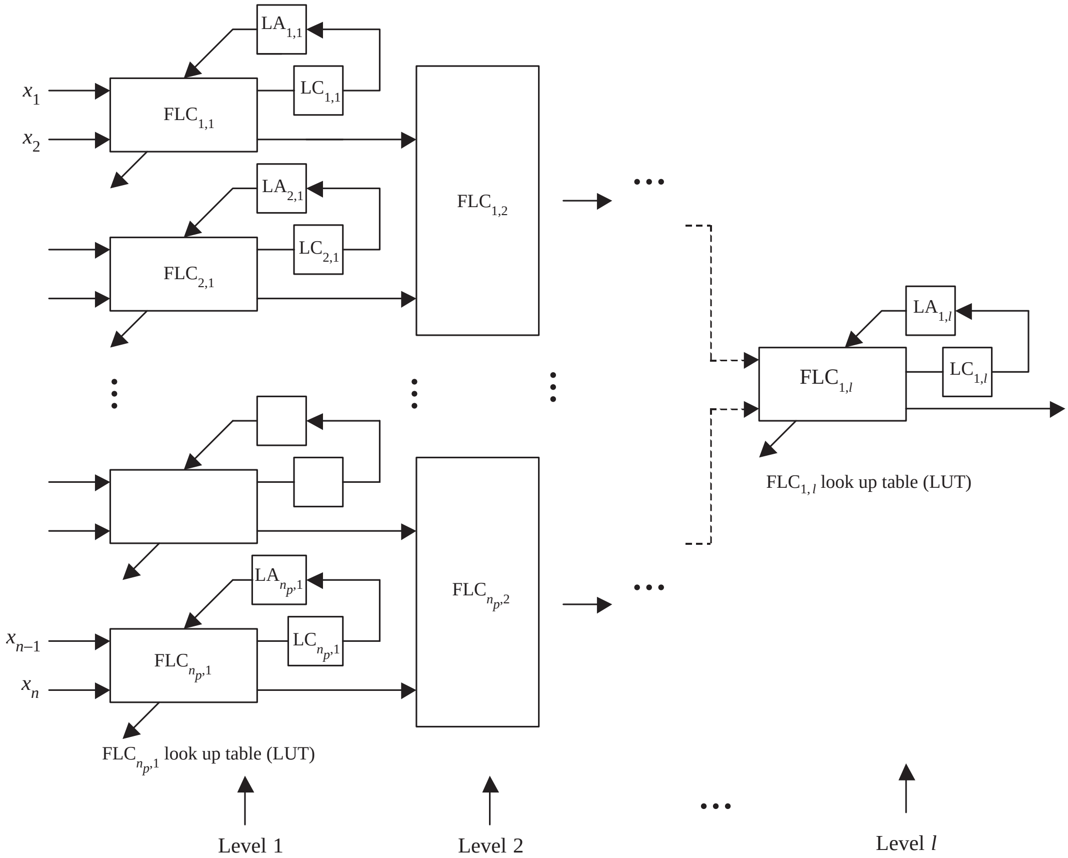

Fig. 4. Structure of local learning by hierarchical fuzzy.

Step 3: For a given input–output pair $(x_0^s; y_0^s)$, $s = 1, 2, \ldots$, and kth stage of training, $k = 0, 1, \ldots$, update the parameters from $\bar{y}_{1,1}^{pq}(k)$ to $\bar{y}_{1,1}^{pq}(k+1)$ according to Eq. (20).

Step 4: Go to Step 3 with $k = k + 1$ until the error $|f(x_0^s) - y_0^s|$ is less than a pre-specified small number ε, or until k equals a pre-specified maximum training step.

Step 5: Go to step 3 with $s = s + 1$.

The fuzzy system is trained automatically until the specified tolerance level is achieved. The inference process of the system is shown in the *Rule View* of the window of the *Fuzzy Logic Toolbox* in *MATLAB*. Fig. 5 displays the Rule View window for an exemplary input. Furthermore, Fig. 6 indicates the 3D plot for the rule surface.

4.3.2. The composite control of the system

A hierarchical fuzzy approach is pursued which allows the adaptation of a composite control strategy. The total (final) control action of the hierarchical fuzzy controller is composed of the control actions due to different level rule sets; that is

$$u_F = \sum_{i=1}^{L} k_i u_i, \tag{21}$$

where L is the total number of levels in the hierarchy and u_F is the final control action. u_i is the control action obtained by consulting the ith level rule set. k_i is the corresponding weight parameters. Furthermore, the weighting factor (output scaling factor) is self-regulated during the control process, and can optimize the gain for the hierarchical fuzzy controller. To avoid initiating an undesirable control action, the final control actions should mainly depend upon the first level rule set when system parameter perturbation occurs [19]. For simplicity, the first level output will govern the control action since it consists of the dominant modes in this research. Specifically, the final control action is illustrated, $u_F = u_{1,1} + u_{2,1} + u_{3,1} + u_{4,1}$, in this specific example.

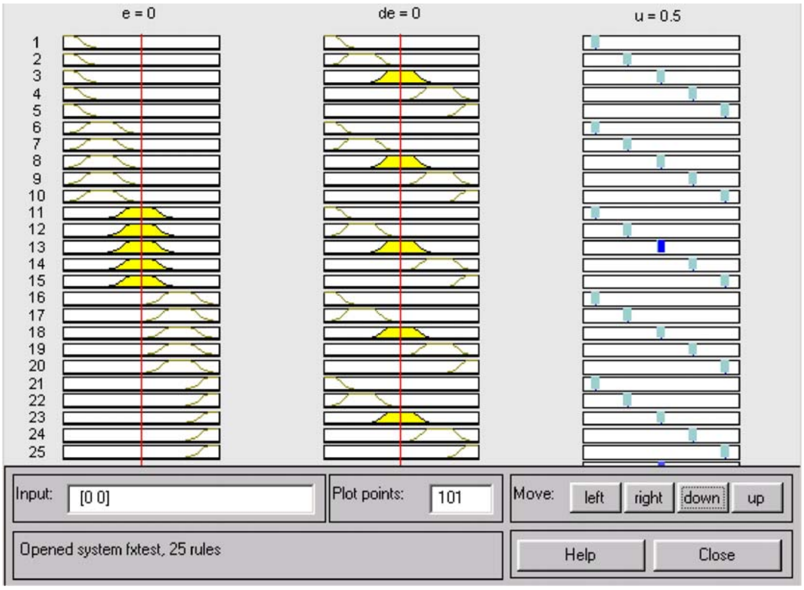

Fig. 5. The rule view of the system.

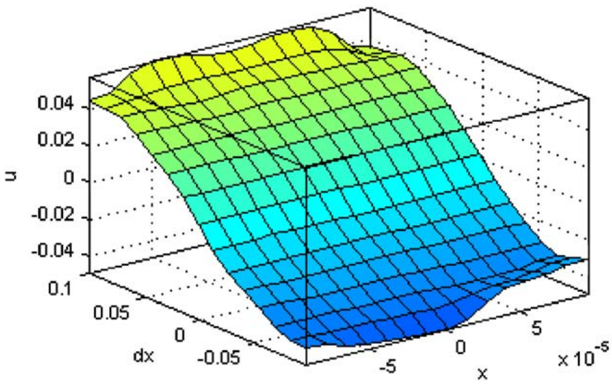

Fig. 6. A 3D plot for the rule surface.

The overall hierarchical fuzzy controller is to be implemented according to the block diagram of Fig. 4. The main advantages of the hierarchical structure in Fig. 4 are a great reduction of memory demand in the off-line implementation.

5. Experimental implementation

This section applies the hierarchical fuzzy controller to control the vibrations of a flexible structure using piezoelectric actuators.

An experimental device was designed and established to verify both the development and the design of the controller. A smart structure with a piezoelectric actuator is set up in the Sensor and Control Laboratory at the Department of Mechanical Engineering at Ching Yun University. Fig. 7 schematically depicts the control experiment. Fig. 8 shows the experimental apparatus. In order to simplify the implementation, the experimental structure is a uniform panel with a rectangular cross section and pinned at both ends. A strip-benders-type BM500/120/6 piezoelectric actuator and four strain gauges are attached to both sides of the plate, to serve as an actuator and sensor, respectively. Because the PZT effect is a dual effect, bending elements are successfully used as vibration and force sensors as well as small electrical generators. The BMT 60 three-pole amplifier has been designed to drive large capacitance, low voltage PZT benders with maximum bilateral displacement over a wide range of frequencies up to their mechanical resonance. The high-voltage BMT 60 three-pole amplifier (provided by Piezomechanik), capable of driving highly capacitive loads, was used to supply the necessary voltage to the actuating

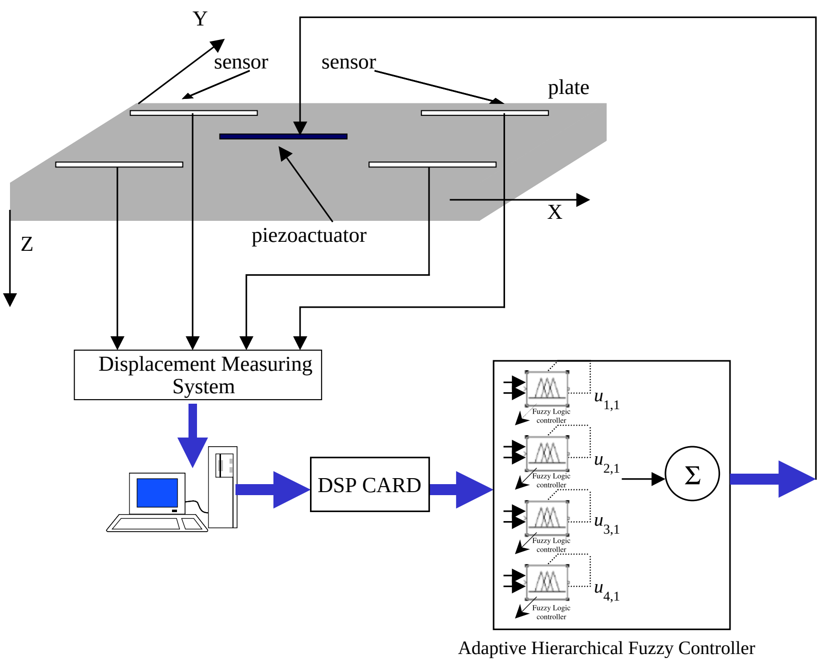

Fig. 7. Schematic diagram of the control experiment.

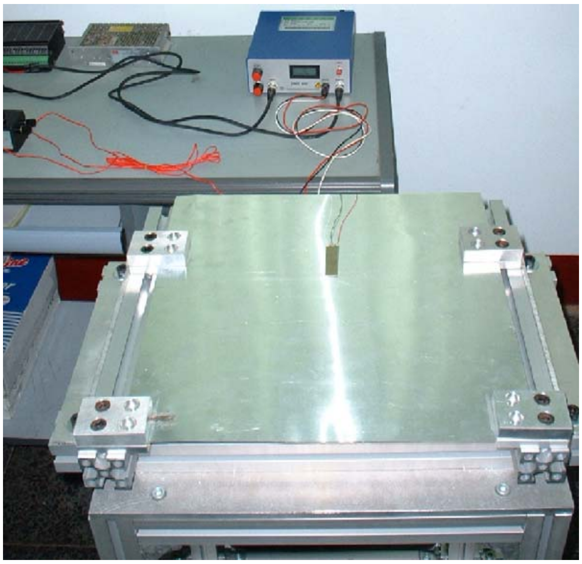

Fig. 8. Experimental apparatus.

piezoelectric patch. The BMT 60 amplifiers drive low-voltage benders in the electrically pre-stressed mode and provide the required voltages. Moreover, a testing platform fabricated from aluminum was designed as a special module that can operate with arbitrary mechanical boundary conditions (simply supported, clamped, and others). The controller was implemented using a 200PCI instruNet and LabView.

In various practical situations, only a limited number of modes are excited and the objective of active damping is to stabilize these "effective modes". Therefore, the implementation uses only two modes of x and y directions. The measurement methodology of the vibration mode and its derivative can be obtained from Lin and Lewis [26]. Moreover, the controllability of the effective modes on the effective modes depends on the function of the modal shape, which corresponds to the location of the actuator. Hence, the controllability can be improved by relocating the actuator. Additionally, in the training algorithm, the input–output pairs to train the local fuzzy model are obtained from several time histories of fuzzy-controlled responses. Running the original fuzzy controller for several different simulated input excitation time histories collected the training data, i.e. by examining the desired input–output data and/or by trial and error. The input–output pairs were then imposed by using each set of values (mode, mode velocity, local control force).

6. Results and discussions

A number of tests were performed on a simply supported smart plate to evaluate the merit of the concepts presented. The dynamic characteristics of two differently sized panels were assessed.

The panel was square, and the second was rectangular. The common properties of the test panels are:

Young's modulus $= 3.185 \times 10^{10}\,\text{N/m}^2$;
Poisson's coefficient $= 0.36$;
Density $= 1.03 \times 10^{10}\,\text{kg/m}^3$.

6.1. Case A. reduction of the vibration of square panel using adaptive hierarchical fuzzy control

In this test, the dimensions of the square panel were *400 × 400 × 5 mm* ($L \times W \times H$). Two hierarchical fuzzy controllers (pre- and post learning) are assumed to be independent to reduce the complexity of the problem. According to the fuzzy inference system by the Mandani model, it was arbitrary to chose the initial membership functions and set up the rule base. This is defined as the pre-learning fuzzy controller. Then, using an algorithm that is shown in Section 4 and defined as post-learning fuzzy controller optimizes the controller.

For a system described in the previous section, the overall structural response will be a sum of the response contributed from the excitation force and the response contributed from the control force. Here, Fig. 9 plots the measured midpoint of the panel and the impulse excitation frequency responses under the open-loop and closed-loop, respectively. It can be observed that the controller has a resonant structure, as expected. The resonant responses of the lower modes reduced considerably once the active controller was introduced. The modal resonant magnitudes have been reduced up to 57.45 dB at the resonant frequency 1000 rad/s. Fig. 10 makes a comparison of

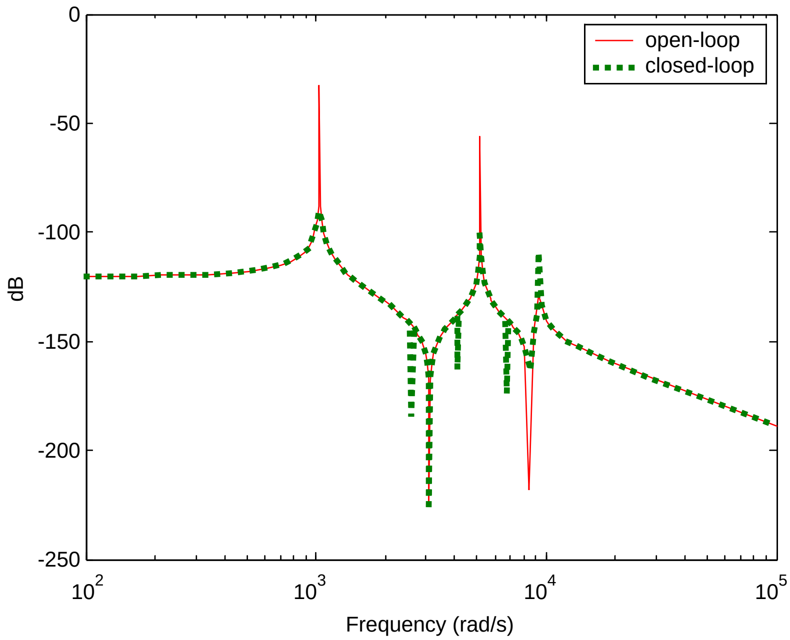

Fig. 9. Frequency response for square panel.

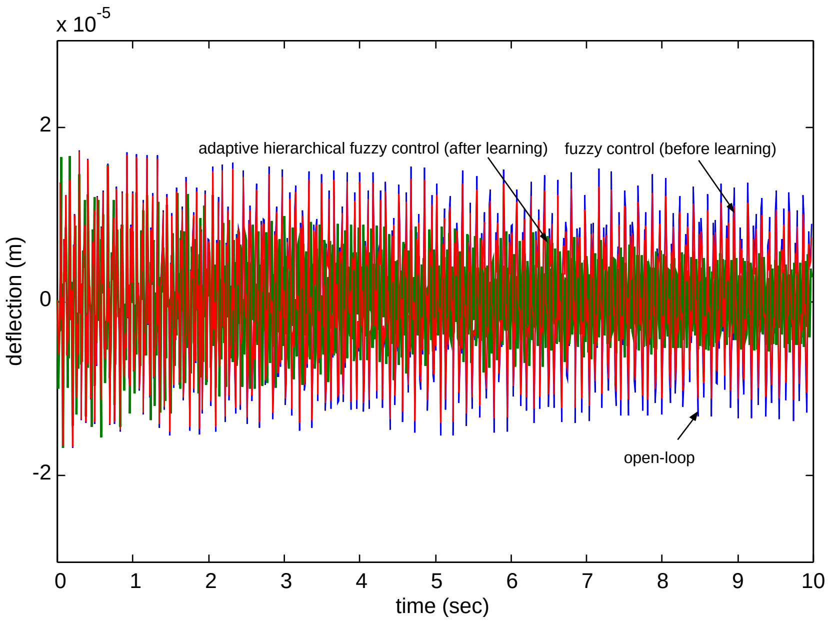

Fig. 10. Vibrational Displacement of the square panel ($x = 0.1\,\mathrm{L}, y = 0.1\,\mathrm{W}$).

the controlled and uncontrolled vibrational displacement subjected to initial impulse excitation for specified panel point ($x = 0.1\,\mathrm{L}, y = 0.1\,\mathrm{W}$). Similarly, Figs. 11 and 12 also demonstrates the vibrational displacement response for each specified point by various controllers, respectively. From Figs. 10 to 12, the improvement in the performance of the pre-learning fuzzy controller is not significant and the systems still oscillate. Therefore, a hierarchical fuzzy control through training is urgently desired. Consequently, these figures show the adaptive hierarchical fuzzy controller's effectiveness in minimizing the structure's vibration in the time domain. The settling time of the position response has been reduced considerably by the control action.

Furthermore, Table 1 presents the normalized Root-Mean-Square (RMS) vibrational displacement under open-loop, pre-learning fuzzy control, and a hierarchical fuzzy control using adaptive networks at various positions of the panel subjected to impulse excitation. Evidently, a fuzzy control using adaptive networks yields a more significant improvement in displacement reduction over that obtained by using traditional fuzzy control techniques. The reduction in vibrational displacement is maximal in the middle of the panel. Consequently, the hierarchical fuzzy control using adaptive networks was designed to minimize the deflection in the middle of the plate as well as at the other point, ensuring that the structural vibration of the entire structure is suppressed.

6.2. Case B. Reduction of the vibration of rectangular panel using adaptive hierarchical fuzzy control

The dimensions of the rectangular panel were $400 \times 250 \times 5\,mm$ ($L \times W \times H$). Fig. 13 plots the measured displacement and voltage frequency responses. The frequency responses (at the voltage

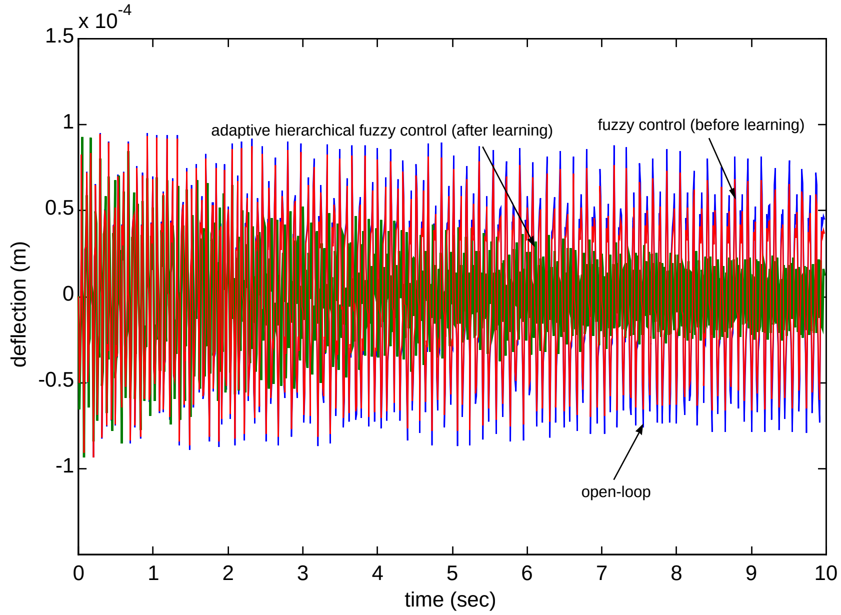

Fig. 11. Vibrational Displacement of the square panel ($x = 0.3\,\mathrm{L}, y = 0.3\,\mathrm{W}$).

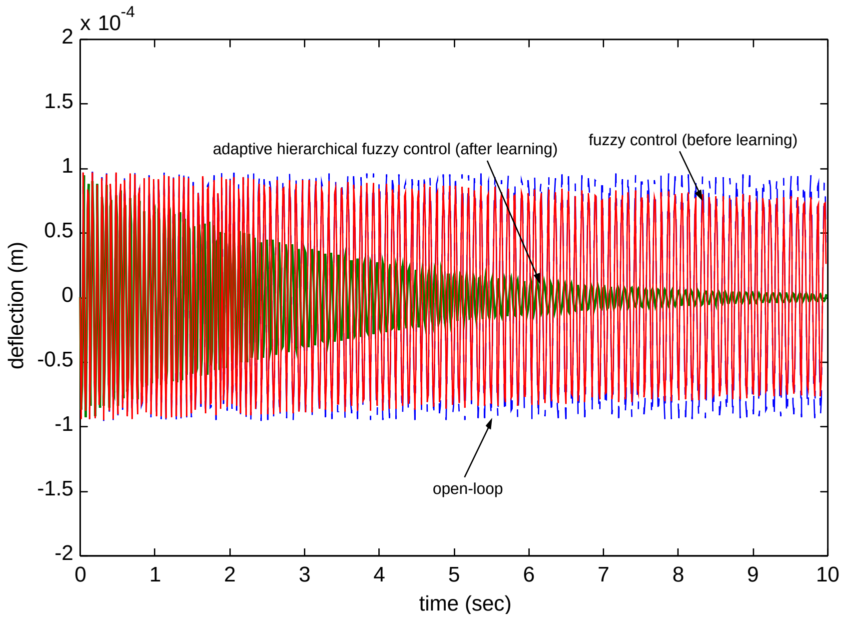

Fig. 12. Vibrational Displacement of the square panel ($x = 0.5\,\mathrm{L}, y = 0.5\,\mathrm{W}$).

Table 1
Normalized RMS vibrational displacements of a square panel

Point Controller	$x = 0.1$ L $y = 0.1$ W	$x = 0.3$ L $y = 0.3$ W	$x = 0.5$ L $y = 0.5$ W	$x = 0.7$ L $y = 0.7$ W	$x = 0.9$ L $y = 0.9$ W
Open-loop	7.93e–5	4.83e–4	6.75e–4	4.83e–4	7.93e–5
Pre-learning fuzzy control	7.24e–5	4.40e–4	6.14e–4	4.40e–4	7.24e–5
Hierarchical fuzzy control using adaptive networks	5.36e–5	2.70e–5	2.80e–5	2.70e–5	5.36e–5
Reduction (%)	32%	44.1%	58.6%	44.1%	32%

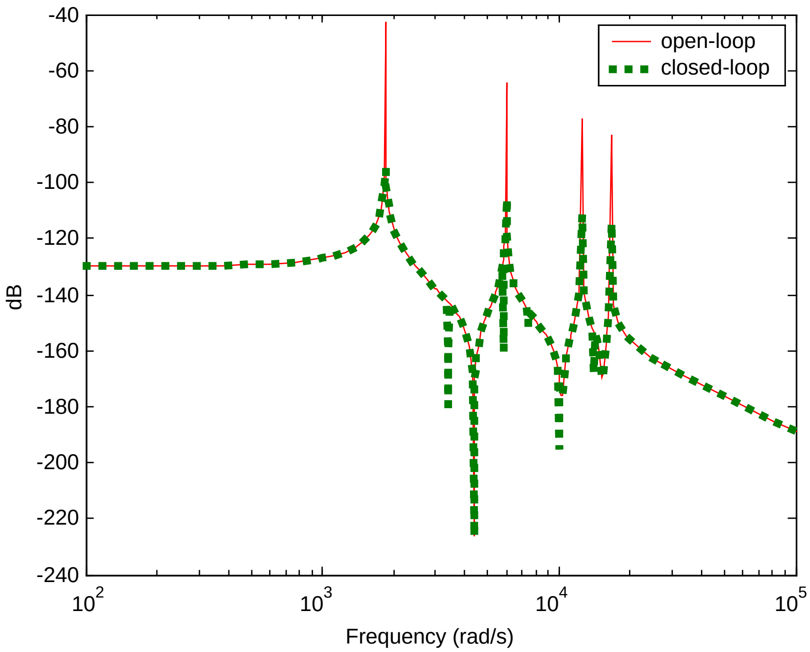

Fig. 13. Frequency response for rectangular panel.

of the actuator required to deflect the plate) under open-loop control and closed-loop control are presented, respectively. Similar to case A, the resonant responses of the lower modes also reduced considerably once the active controller was implemented. The modal resonant magnitudes have been reduced up to 52.43 dB at the resonant frequency 1850 rad/s. Hence, the controller reduces resonant responses of the structure by increasing the system damping at resonant frequencies. Furthermore, Figs. 14–16 show that the vibrational displacement barely affects the performance of the pre-learning fuzzy controller. Similar to the above case A, the improvement in the performance of the pre-learning fuzzy controller is not significant and the systems still oscillate. Moreover, these figures also clearly demonstrate the effect of the proposed adaptive hierarchical fuzzy controller in reducing the vibration of the panel, the deflection having been reduced by the action of the controller for various dimensions of the panel. Such a controller suppressed the

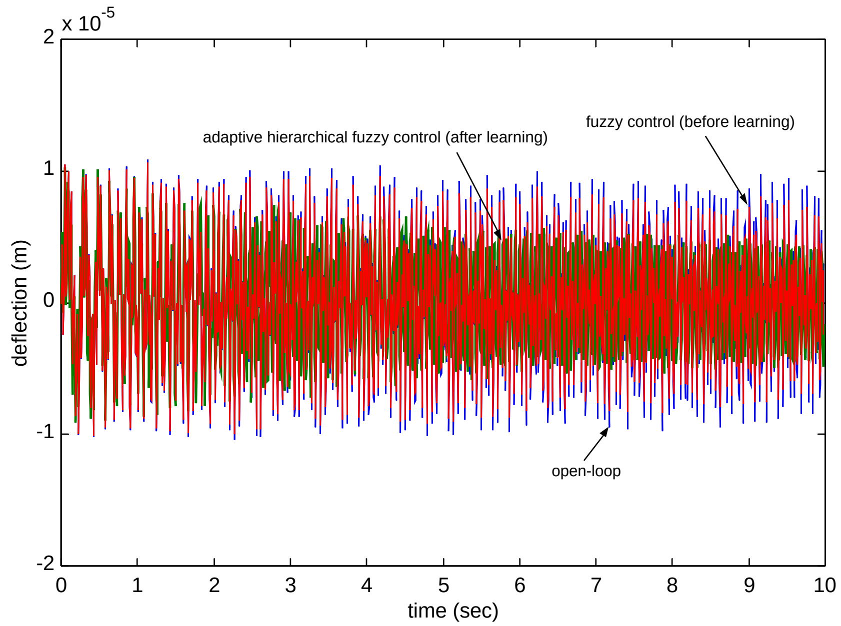

Fig. 14. Vibrational Displacement for rectangular panel ($x = 0.1\,\mathrm{L}, y = 0.1\,\mathrm{W}$).

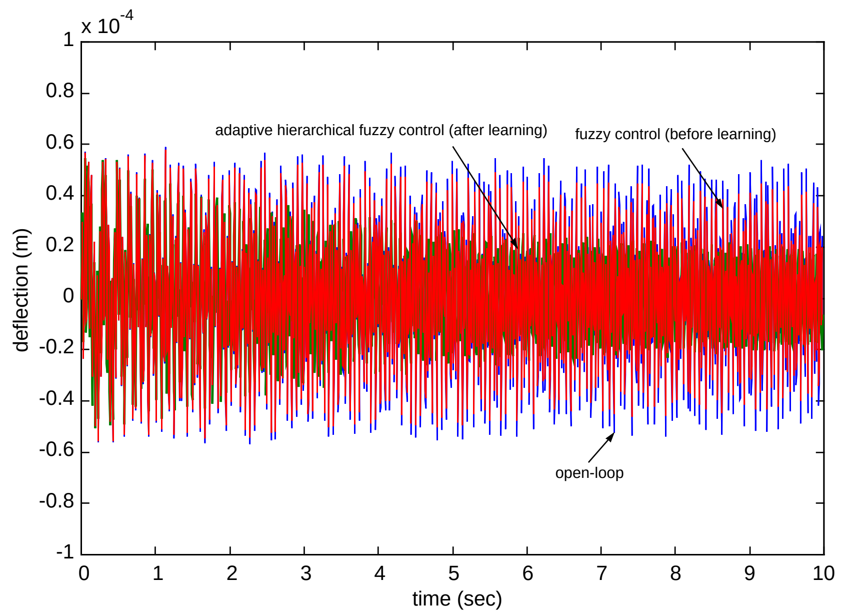

Fig. 15. Vibrational Displacement for rectangular panel ($x = 0.3\,\mathrm{L}, y = 0.3\,\mathrm{W}$).

transverse vibration of the entire structure by the hierarchical fuzzy through training techniques. However, the vibration of each point is dynamically related to the vibrations at each point over the structure. A controller must therefore be designed to minimize the structural vibrations of the

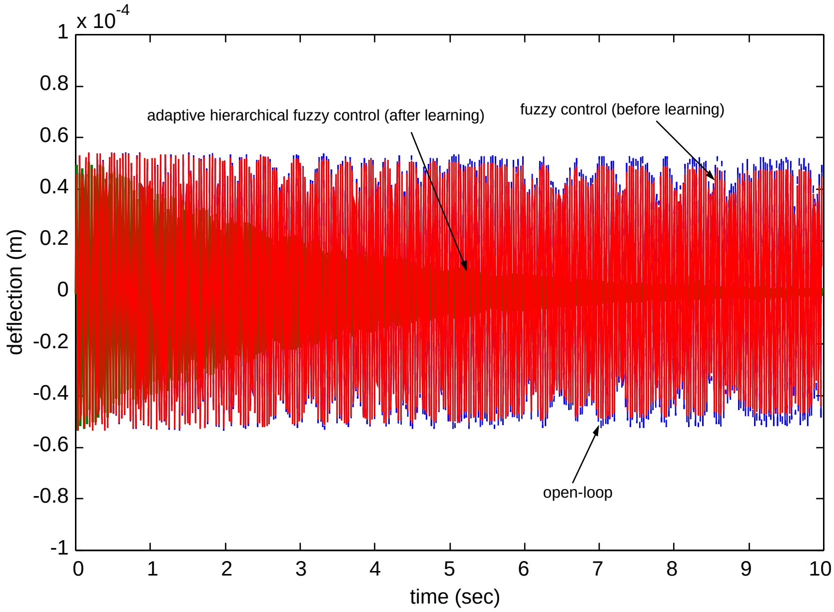

Fig. 16. Vibrational Displacement for rectangular panel ($x = 0.5\,L, y = 0.5\,W$).

Table 2
Normalized RMS vibrational displacements of a rectangular panel

Point Controller	$x = 0.1\,L$ $y = 0.1\,W$	$x = 0.3\,L$ $y = 0.3\,W$	$x = 0.5\,L$ $y = 0.5\,W$	$x = 0.7\,L$ $y = 0.7\,W$	$x = 0.9\,L$ $y = 0.9\,W$
Open-loop	5.03e–5	2.88e–5	3.77e–5	2.88e–5	5.03e–5
Pre-learning fuzzy control	4.58e–5	2.56e–5	3.08e–5	2.56e–5	4.58e–5
Hierarchical fuzzy control using adaptive networks	3.52e–6	1.57e–5	1.61e–5	1.57e–5	3.52e–6
Reduction (%)	30%	45.4%	57.3%	45.4%	30%

entire structure, rather than just a limited number of points. Table 2 reveals that the proposed fuzzy control system reduces the displacement due to vibration of an uncontrolled by approximately around 30–57% at each specified point. Implementing the hierarchical fuzzy control using adaptive networks scheme for the square panel, as well as the rectangular panel, also greatly improved the performance of the dynamic system. The proposed fuzzy control method is quite useful in terms of reliability and robustness.

7. Conclusions

In this paper, a new active piezoelectric absorber of a smart panel was investigated. A methodology for designing adaptive hierarchical fuzzy controllers was studied with system performance being measured and expressed by some fuzzy variables. Based on this approach, adaptive network of fuzzy inference system was constructed. This methodology was used to adjust the parameters of the hierarchical fuzzy controller to achieve better performance even in the case of unexpected changes in system parameters. The advantage of its use is the high speed by which the value of the control force is inferred from the monitored state of the smart structure. More generally, the coupling of fuzzy inference with artificial neural networks seems to be a promising research area for smart structure research. Furthermore, a hierarchical fuzzy logic structure is derived for a multi-input FLC, leading to the implementation of faster controllers with reduced memory demand. Consequently, it appears that the hierarchical fuzzy control method is quite useful as regards reliability and robustness. Future work will involve the active-passive piezoelectric absorber for structural vibration control.

Acknowledgments

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