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PCA-based neuro-fuzzy model for system identification of smart structures

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Abstract. This paper proposes an efficient system identification method for modeling nonlinear behavior of civil structures. This method is developed by integrating three different methodologies: principal component analysis (PCA), artificial neural networks, and fuzzy logic theory, hence named PANFIS (PCA-based adaptive neuro-fuzzy inference system). To evaluate this model, a 3-story building equipped with a magnetorheological (MR) damper subjected to a variety of earthquakes is investigated. To train the input-output function of the PANFIS model, an artificial earthquake is generated that contains a variety of characteristics of recorded earthquakes. The trained model is also validated using the1940 El-Centro, Kobe, Northridge, and Hachinohe earthquakes. The adaptive neuro-fuzzy inference system (ANFIS) is used as a baseline. It is demonstrated from the training and validation processes that the proposed PANFIS model is effective in modeling complex behavior of the smart building. It is also shown that the proposed PANFIS produces similar performance with the benchmark ANFIS model with significant reduction of computational loads.

Keywords: system identification; principal component analysis (PCA); fuzzy logic; neural network; adaptive neuro-fuzzy inference system (ANFIS); earthquake; magnetorheological damper; smart structures

1. Introduction

Smart control strategies constitute an important class of strategies used in the field of engineering (Housner *et al.* 1997, Spencer *et al.* 1997, Symans *et al.* 1999, Soong *et al.* 2002). The implementation of smart control devices such as magnetorheological (MR) dampers in structures has led to an increase in the buildings' ability to withstand destructive environmental forces such as strong winds and/or earthquake. However, it is challenging to model the structure integrated with nonlinear smart dampers. It is generally known that even if the structure is assumed to linearly behave, there are nonlinearities introduced due to the implementation of various actuators and smart dampers (Kim *et al.* 2009). Creating effective models for capturing nonlinear behavior of smart structures demands considerable amount of effort in terms of devising new models or using combinations of already available approaches as more efficient methods. With this in mind,

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this paper proposes a method that efficiently identifies nonlinear behavior of seismically excited buildings equipped with smart dampers.

System identification (SI) is an essential part for synthesis of smart structures because it produces mathematical models for control system design using data measured from the structures. SI is used to reliably predict how a structure behaves using the inputs and outputs measured from the structure under a variety of dynamic loading scenarios such as far- and near-field earthquakes. SI can be separated into two categories: parametric and nonparametric approaches (Bani-hani *et al*. 1999). Parametric approach identifies the properties of the structural system, including stiffness and damping elements that are intrinsically imbedded in the structure and its materials (Jalili-Kharaajoo 2004). The nonparametric SI method is used to train the input-output function of the structural system as a black box model (Filev 1991). It does not require accurate information about the structure. Thus, the nonparametric approach is easily applicable to nonlinear modeling of the structural system. This has successfully been performed with neural networks as well as fuzzy logic systems.

Fuzzy inference system, most commonly used as a nonparametric approach of modeling a system, uses fuzzy set theory to create a set of rules. It can be effective in dealing with nonlinearities and uncertainties of dynamic systems (Gu and Oyadiji 2008). Since the work of Zadeh (1965), fuzzy logic has been applied to many SI problems (Takagi and Sugeno 1985, Yan and Langari 1998, Kim *et al*. 2011). A number of studies on Takagi-Sugeno (TS) fuzzy models have been conducted in recent years, which deals with effective representations of nonlinear systems with the aid of fuzzy sets, fuzzy rules, and a set of local linear models (Filev 1991, Gopalakrishnan *et al.* 2010, Johansen and Babuska 2003). Fuzzy logic theory has been used mainly for nonlinear fuzzy control system design in the field of large-scale infrastructures (Guo *et al*. 2011, Kim *et al*. 2009, Mitchell *et al.* 2012). However, estimating the parameters of a fuzzy inference system requires many trials and errors.Hence, these fuzzy model parameters can be determined using neural networks.

Development of artificial neural networks (ANN) was inspired by the cognitive mechanism of the human brain (Wang *et al.* 2009). The ANN consists of linked nodes. Each node computes an output from its input. The node output is then used as another input for other nodes, and a link is created between each two nodes. ANNs improve the performance of each node by adjusting the parameters of the network, resulting in a more accurate model. Although ANN is effective in modeling nonlinear dynamic systems, it is challenging to design the ANN models in a transparent way because it is a black box modeling framework.

An integration of favorable features of both ANN and fuzzy logic models produces an effective nonlinear SI model, an adaptive neuro-fuzzy inference system (ANFIS). Its application for SI in civil engineering applications has been studied in many other researches; however, it still is a relatively new research topic (Gu and Oyadiji 2008, Gopalakrishnan 2010, Schurter *et al.* 2000, and Ozbulut *et al.* 2007, Hakim and Abdul-Razak 2013). An advantage of this modeling technique is its ability to create effectively a nonlinear function using adjustable parameters, including types of the membership functions (MF), the number of MFs, step size of the learning process, and number of epochs. However, the ANFIS modeling technique can be computationally expensive or time-consuming (Wang *et al.* 2009). It would be disadvantageous when dealing with real-time situations and/or with large sets of data. To resolve these issues, principal component analysis (PCA) is incorporated to the ANFIS model to reduce the computation load.

PCA, first introduced in a context of data fitting by Pearson (1901), has been mainly used as a method for dimensional reduction of measurement data in diverse fields such as psychology, biology, chemistry, economics, genetics, and geology among other areas (Jollife2002). Using this method, the contribution of each measurement to the variation of the whole data set can be determined. Such a process can be used to decrease the amount of data needed for further use by discarding redundant data or variables that are less important. There are some examples of implementation of PCA in the control and health monitoring field of civil engineering. Sharifi *et al*. (2010) applied PCA to sensor fault isolation and detection. Kuzniar and Waszczyszyn (2006) used PCA to identify natural periods from data measured from a building. Mujica *et al*. (2010) and Park *et al*. (2007) applied PCA to assess and detect damages in civil infrastructure.

The use of PCA as a means of data compression for an efficient training of ANFIS model significantly reduces computation time. Warne *et al*. (2004) proposed a hybrid PCA-ANFIS measurement system for monitoring product quality in the coating industry by inferring the ‘Anchorage’ of polymer-coated substrates. Avci and Turkoglu (2009) proposed an intelligent diagnosis system based on PCA and ANFIS for the heart valve diseases. Polat and Gundes (2007) suggest using PCA and ANFIS together to diagnose lymph disease.

However, to date, there has been minimal research regarding the application of PCA to the estimation of smart structures using the neuro-fuzzy modeling framework. Compression of various types of time series data using PCA for modeling nonlinear behavior of smart structures using ANFIS introduces a new challenge, which is addressed in this paper. PCA is implemented as a time series data compression method. Parts of the data are effectively removed during the compression process; however, the majority of the variation within the data is conserved for modeling purposes.

2. PCA-based adaptive neuro-fuzzy inference system (PANFIS)

PANFIS is an integrated model of PCA, ANN and fuzzy inference systems. It is a nonlinear learning model that uses a least-squares method as well as back-propagation methods to train the fuzzy inference system’s MFs and its associated parameters using the PCA-based compressed input and output data sets.

2.1 Takagi-Sugeno fuzzy model

Takagi-Sugeno (TS) fuzzy model is the backbone for the proposed PANFIS control system. In 1985, Takagi and Sugeno proposed an effective way for modeling complex nonlinear dynamic systems by introducing linear equations in consequent parts of a fuzzy model, which is called TS fuzzy model (Takagi and Sugeno 1985). It has led to the reduction of computational costs because it does not need any defuzzification procedures. The fuzzy inference system used in the PANFIS model is of the TS fuzzy model form. It typically takes the following form

$$\begin{aligned} &R_j : IF\ u_{FZ}^1\ is\ P_{1,j}\ and\ u_{FZ}^2\ is\ P_{2,j} \ldots and\ u_{FZ}^i\ is\ P_{i,j} \\ &Then\ z_{FZ} = f_j\left(u_{FZ}^1, \ldots, u_{FZ}^i\right),\ j = 1, 2, \ldots, N_r \end{aligned} \tag{1}$$

where R_j is the j^{th} fuzzy rule, N_r is the number of fuzzy rules, $P_{i,j}$ are fuzzy sets centered at the operating j^{th} point, and u_{FZ}^i are premise variables that can be either input or output values. The equation of the consequent part $z_{FZ} = f_j(u^1_{FZ},\dots,u^i_{FZ})$ can be any linear equation. Note that the Eq. (1) represents the j^{th} local linear subsystem of a nonlinear system, i.e., a linear system model that is operated in only a limited region. All of the local subsystems are integrated by blending operating regions of each local subsystem using the fuzzy interpolation method as a global nonlinear system

$$y_{FZ} = \frac{\sum_{j=1}^{N_r} W_j\left(u^i_{FZ}\right)\left[f_j\left(u^1_{FZ},\dots,u^i_{FZ}\right)\right]}{\sum_{j=1}^{N_r} W_j\left(u^i_{FZ}\right)} \tag{2}$$

where $W_j\left(u^i_{FZ}\right) = \prod_{i=1}^{n} \mu_{P_{i,j}}\left(u^i_{FZ}\right)$ and $\mu_{P_{i,j}}\left(u^i_{FZ}\right)$ is the grade of membership of u^i_{FZ} in $P_{i,j}$. These parameters are optimized by the back propagation neural network. A typical architecture of fuzzy rules for a model with *n* membership functions for each input and n^2 rules are shown in Fig. 1.

Optimization of the parameters of the model is the main challenge in the application of a fuzzy model. Therefore, incorporating neural networks to create an adaptive neuro-fuzzy inference system allows for these parameters to be optimized during computation, which is explained below.

2.2 ANFIS architecture

The architecture of a typical ANFIS model is as in Fig. 2. This figure represents two inputs and one output architecture with *n* MFs for each input, which is only for illustrative purposes and the model used has two MFs for each input.

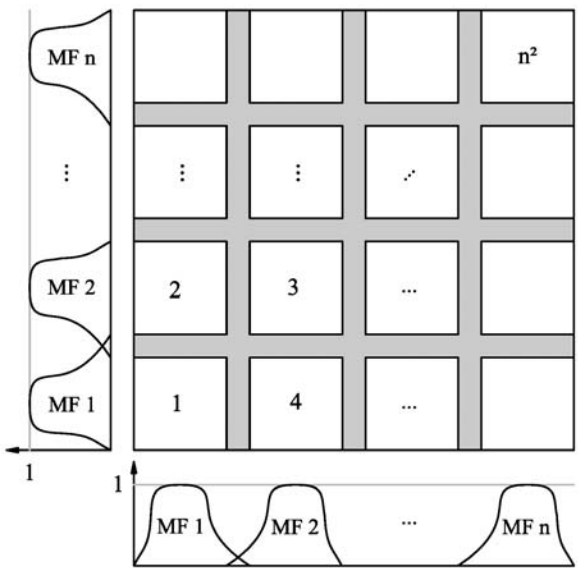


Fig. 1 Typical fuzzy rules layout

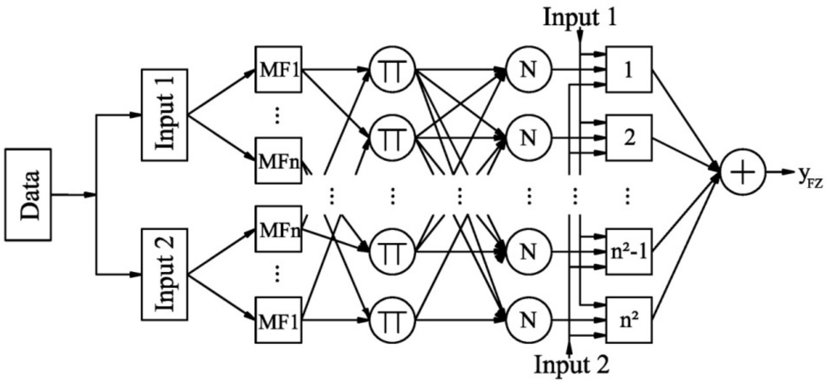


Fig. 2 ANFIS architecture with n MFs for each of the two inputs

Each layer has particular tasks to complete before the data moves to the next layer. In the first layer (layer 1), the function of the node is represented by

$$F_{FZ}^{1,j} = \mu_{P_{i,j}}\left(u_{FZ}^{i}\right) \tag{3}$$

The Gaussian MF used in the examples of this paper has the following form

$$\mu_{P_{i,j}}\left(u_{FZ}^{i}\right) = \exp\left(-\left(u-a_1\right)^2 \big/ 2a_2^2\right) \tag{4}$$

where a_1 and a_2 are adjustable parameters of the Gaussian function. This MF is applied to each input in layer 1. The second layer (layer 2) then outputs the product of all inputs of layer 2, known as the firing strengths

$$F_{FZ}^{2,j} = \mu_{P_{i,j}}\left(u_{FZ}^{1}\right) \times \mu_{P_{i,j}}\left(u_{FZ}^{2}\right) \ldots \mu_{P_{i,j}}\left(u_{FZ}^{i}\right) \tag{5}$$

The third layer (layer 3) takes a ratio of layer 2 firing strengths in order to normalize the layer 2 outputs $F_{FZ}^{2,j}$ as following

$$F_{FZ}^{3,j} = F_{FZ}^{2,j} \Big/ \prod\nolimits_{i=1}^{n} \mu_{P_{i,j}}\left(u_{FZ}^{i}\right) \tag{6}$$

The fourth layer (layer 4) then applies a node function to the normalized firing strengths

$$F_{FZ}^{4,j} = F_{FZ}^{3,j} \times f_j = F_{FZ}^{3,j}\left[f_j\left(u_{FZ}^{1}, \ldots, u_{FZ}^{i}\right)\right] \tag{7}$$

The last layer summates the layer inputs

$$F_{FZ}^{5} = \frac{\sum_j \prod_{i=1}^{n} \mu_{P_{i,j}}\left(u_{FZ}^{i}\right)\left[f_j\left(u_{FZ}^{1}, \ldots, u_{FZ}^{i}\right)\right]}{\sum_j \prod_{i=1}^{n} \mu_{P_{i,j}}\left(u_{FZ}^{i}\right)} \tag{8}$$

The output of the system F_{FZ}^{5} is then used in a hybrid learning algorithm. The key parameters for this simulation include the number of iterations or epochs, the number of MFs and their type, as well as the step size of the function or algorithm. Types of MFs can vary from a generalized bell function, Gaussian functions, sigmoidal functions, trapezoidal function, as well as other forms. Each change of variables will yield different output results (Filev 1991 and Kim *et al*. 2011). The fuzzy inference system sets up rules based on the number of MFs used in simulation.

For a system with n MFs for each input, fuzzy rules are set up as shown in Fig. 1, where y_{FZ} corresponds to F_{FZ}^{5}. Each number in layer 4 of Fig. 2 represents one of the n^2 fuzzy regions that are created with n MFs in the ANFIS model. The fuzzy region is defined by the premise, and the output is generated through the consequent.

Although ANFIS is very effective in modeling complex nonlinear systems, it requires much computational effort. Such a problem can be addressed through the integration of principal component analysis.

2.3 Principal component analysis (PCA)

PCA was introduced by Pearson (1901) in the context of data fitting and was developed independently by Hotelling (Jollife 2002). Hotelling method of derivation of principal components using Lagrange multipliers and eigenvalue/eigenvector analysis is explained in this section.

Suppose $\mathbf{V}_{obs.}$ is a matrix representing N observations of p random variables, organized as p rows and N columns, where the mean of random variable i is subtracted from each element of row i. Covariance matrix for this matrix of measurement data $\mathbf{V}_{obs.}$ can be constructed as

$$\mathbf{C}_{\mathbf{V}_{obs.}} = \frac{1}{N}\mathbf{V}_{obs.}\mathbf{V}_{obs.}^{T} \tag{9}$$

where each element $c_{i,j},\ i, j = 1,\ldots, p$ of the covariance matrix $\mathbf{C}_{\mathbf{V}_{obs.}}$, is the covariance between i^{th} and j^{th} variables. Element $c_{i,j}, i = j$ of the covariance matrix is the covariance between i^{th} and i^{th} variable which is the same as the variance of the i^{th} variable. It is often desirable to find a linear transformation of observation matrix $\mathbf{V}_{obs.}$, with the following form

$$\mathbf{V}_{tran.} = \mathbf{Q}\mathbf{V}_{obs.} \tag{10}$$

which results in the maximum variances between linear combinations of p random variables among all other permissible linear combinations of them. $\mathbf{Q}$ is a transformation matrix. It is desirable for the transformation matrix $\mathbf{Q}$ to be a unit norm matrix, that is $\mathbf{Q}^{T}\mathbf{Q} = \mathbf{I}$. In other words, the goal is to find $\mathbf{Q}$, with the constraint $\mathbf{Q}^{T}\mathbf{Q} = \mathbf{I}$, such that the covariance matrix $\mathbf{C}_{\mathbf{V}_{tran.}}$ of the transformed set of data $\mathbf{V}_{tran.}$ is maximized,

$$\underset{\mathbf{Q}}{Max}\left\{\mathbf{C}_{\mathbf{V}_{tran.}}\right\} \tag{11}$$

The function to be maximized, $\mathbf{C}_{\mathbf{V}_{tran.}}$ can also be written as

$$\mathbf{C}_{\mathbf{V}_{tran.}} = \left(1/N\right)\mathbf{Q}\mathbf{C}_{\mathbf{V}_{obs.}}\mathbf{Q}^{T} \tag{12}$$

By employing a constraint condition, the objective function is formulated as follows

$$\left(1/N\right)\mathbf{Q}\mathbf{C}_{\mathbf{v}_{obs.}}\mathbf{Q}^T - \lambda(\mathbf{Q}^T\mathbf{Q}-\mathbf{I}) \tag{12}$$

where λ is the Lagrange multiplier. Differentiating with respect to $\mathbf{Q}$ gives

$$\left(\left(1/N\right)\mathbf{C}_{\mathbf{v}_{obs.}} - \lambda\mathbf{I}\right)\mathbf{Q} = \mathbf{0} \tag{13}$$

where $\mathbf{I}$ is an $p \times p$ identity matrix, λ is an eigenvalue of the covariance matrix of the original data, and $\mathbf{Q}$ is found to be the corresponding matrix of eigenvectors of all the eigenvalues λ. Therefore, the eigenvectors of $\mathbf{C}_{\mathbf{v}_{obs.}}$ (i.e., $\mathbf{Q}$) transforms $\mathbf{C}_{\mathbf{v}_{obs.}}$ to a covariance matrix: the off-diagonal elements are zero and the diagonal elements have the maximum value. It is possible to examine each row as observations of random variables in terms of their contribution (corresponding element in matrix of eigenvectors, $\mathbf{Q}$) to the covariance matrix. The variables with larger eigenvectors contribute more to the variation of the measurements. Therefore, it is possible to discard variables that contribute less than a threshold and decrease the dimensions of data needed for further analysis.

2.4 PCA-based ANFIS system identification

In the context of structural system identification, complex behaviour of structures can be estimated using black box modeling framework using measured data. The measured data can include inputs and outputs to the structure. The input data may contain time series of earthquake signals and forces of control devices such as smart dampers. The output data may contain structural responses such as accelerations and displacements. In practice, the amount of measurement data for long periods can be huge. Hence, sometimes it is difficult to apply signal processing techniques (e.g., vibration analysis, system identification, structural health monitoring, control system designs, among others) to the lengthy data sets. Therefore, it is crucial to decrease the number of data points in these input-output time series. This can lead to a significant reduction in training time of ANFIS models or other machine learning techniques. With this in mind, PCA is applied to the set of input and output data to reduce the number of data.

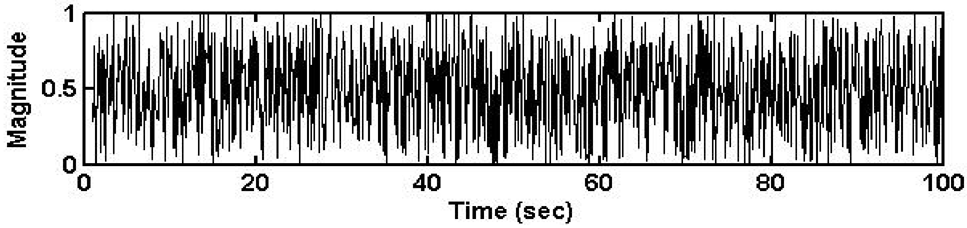
Ground acceleration constitutes an important part of the inputs to the smart structure. It would be effective in increasing the computational efficiency by applying only a short duration of ground acceleration with large variations to the modelling process. These large variations may result in a broad range of behavior of the structure, which then helps to perform a more accurate and efficient system identification.

To find a short duration of earthquake signal with maximum variations among other durations, it is proposed to divide earthquake acceleration $\ddot{\mathbf{x}}_g(t),\ t \in [0,T]$ to N_t number of time series $\mathbf{v}_i(t),\ t \in \left[(i-1)T/N_t, (i)T/N_t\right],\ i = 1,\ldots,N_t$ with equal lengths called segments, where each segment is small enough for favourable training time and large enough for reasonably accurate training of the ANFIS model. Then, PCA can be applied to the following matrix of the time series segments

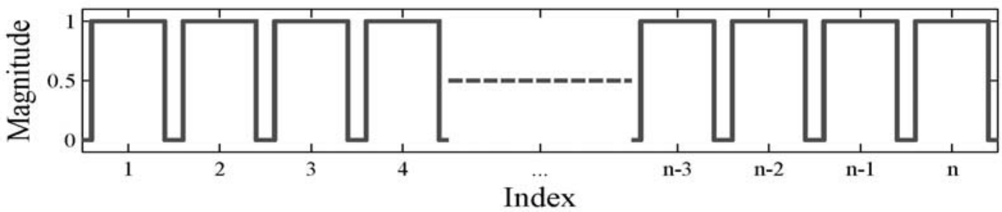
$$\mathbf{v} = \left[\ \mathbf{v}_1(0,T/N_t)\ \mathbf{v}_2(T/N_t, 2T/N_t) \ldots \mathbf{v}_N(\left(N_t-1\right)T/N_t, T)\ \right] \tag{14}$$

to find principal components of the time series with the length of T/N_t .Fig. 3 represents a conceptual example on the application of PCA to times series. Any signal (Fig. 3(a)) can be divided into n segments with equal lengths using the window functions (applied point by point) and then the PCA is applied to the selected signals. The PCA coefficients show where the important signal component is located within the whole data sets: indices of 1, 4, and $n-3$.

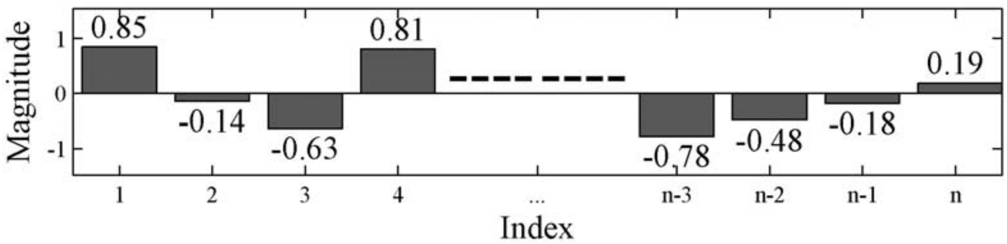
The higher PCA coefficients represent that the dynamic signals have the broader range of variations, which means that the signal includes the better information. Hence the signal with the highest PCA components is selected in this study. As shown in the concept example in Fig. 3, the indices of 1, 4, and n-3 have the higher PCA values than other indices. Thus, the application of the first index component to identifiers would produce the better identification results. Hence, instead of training the ANFIS model using the entire data sets, the ANFIS is developed using the selected time series with the high values of PCA coefficients and the corresponding input-output segments. Therefore, the architecture of PANFIS can be proposed as Fig. 4. It should be noticed that PCA is applied to the earthquake time series to find the major contributing part to make the training data set smaller. In the following section, the effectiveness of the PANFIS modeling is demonstrated with examples. The application of such a strategy to smart structures under a variety of earthquakes will be described with examples in the following section.



(a) An illustrative times series



(b) Window functions



(c) PCA coefficient for each segment

Fig. 3 Conceptual example on the application of PCA to times series

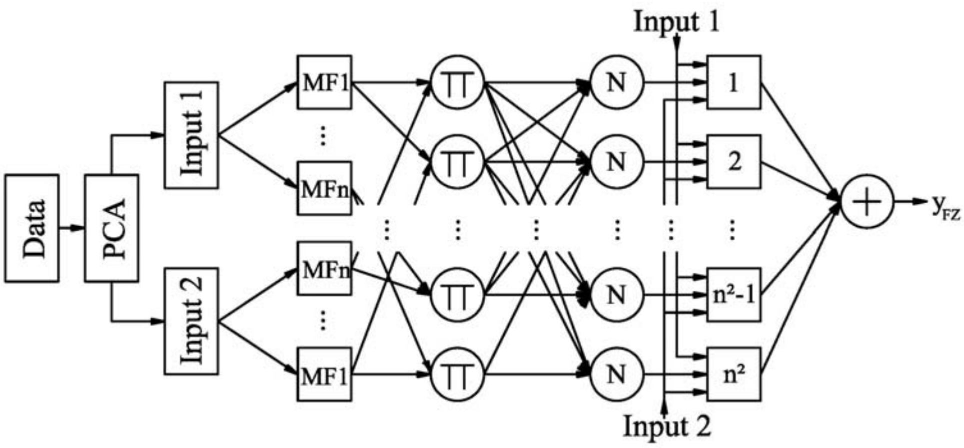


Fig. 4 PANFIS architecture

3. Example

To demonstrate the effectiveness of the PCA-based adaptive neuro-fuzzy inference system (PANFIS) approach, a three-story building employing a magnetorheological (MR) damper is investigated.

3.1 Magnetorheological (MR) damper

In recent years, smart structures have emerged from many engineering fields because the performance of structural systems can be improved without either significantly increasing the mass of the structure or requiring high cost of control power. They may be called intelligent structures, adaptive structures, active structures, and the related technologies adaptronics, structronics, etc. The reason to use these terminologies is that a smart structure is an integration of actuators, sensors, control units, and signal processing units with a structural system. The materials that are commonly used to implement the smart structure: piezoelectrics, shape memory alloys, electrostrictive, magnetostrictive materials, polymer gels, magnetorheological fluid, etc. (Hurlebaus and Gaul 2006).

Semiactive control systems have been applied to large structures because the semiactive control strategies combine favorable features of both active and passive control systems. Semiactive control devices include variable-orifice dampers, variable-stiffness devices, variable-friction dampers, controllable-fluid dampers, shape memory alloy actuators, piezoelectrics, etc. (Hurlebaus and Gaul 2006). In particular, one of the controllable-fluid dampers, magnetorheological (MR) damper has attracted attention in recent years because it has many useful characteristics.

In general MR dampers consists of a hydraulic cylinder, magnetic coils, and MR fluids that typically contain micron-sized magnetically polarizable particles floating within oil-type fluids as shown in Fig. 5. The MR damper can be operated as a passive damper; however, when a magnetic field is applied to the MR fluid, the fluid changes into a semi-solid state in a few milliseconds. This is one of the most unique aspects of the MR damper compared to active systems: the active control system malfunction might occur if some control feedback components, e.g., wires and sensors, are broken for some reasons during severe earthquake event; while a semiactive system can still be operated as a passive damping system even when the control feedback components are not functioning properly. Its characteristics are summarized in (Kim *et al*. 2009).

To fully exploit the behavior of MR dampers, a mathematical model is needed that portrays the nonlinear behavior of the MR damper. However, this is challenging because the MR damper is a highly nonlinear hysteretic device. The MR damper force $f_{MR}(t)$ predicted by the modified Bouc-Wen model is governed by the following differential equations (Spencer *et al*. 1997)

$$f_{MR} = c_a \dot{u}_b + k_a (u_a - u_{a_0}) \tag{15}$$

$$\dot{z}_{BW} = -\gamma |\dot{u}_a - \dot{u}_b| z_{BW} |z_{BW}|^{n-1} - \beta(\dot{u}_a - \dot{u}_b)|z_{BW}|^n + A(\dot{u}_a - \dot{u}_b) \tag{16}$$

$$\dot{u}_b = \frac{1}{(c_a + c_b)} \{\alpha z_{BW} + c_b \dot{u}_a + k_b (u_a + u_b)\} \tag{17}$$

$$\alpha = \alpha_a + \alpha_b u_{MR} \tag{18}$$

$$c_a = c_{a_1} + c_{a_2} u_{MR} \tag{19}$$

$$c_b = c_{b_1} + c_{b_2} u_{MR} \tag{20}$$

$$\dot{u}_{MR} = -\eta (u_{MR} - v_{MR}) \tag{21}$$

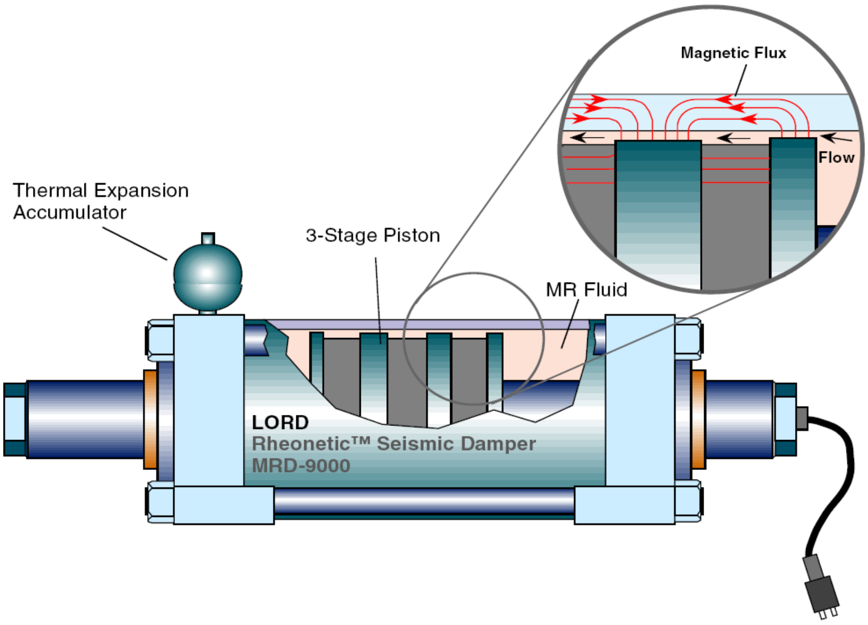


Fig. 5 Schematic of the prototype 20-ton large-scale MR damper (Yang *et al.* 2002)

where z_{BW} and α called evolutionary variables, describe the hysteretic behavior of the MR damper; c_b is the viscous damping parameter at high velocities; c_a is the viscous damping parameter for the force roll-off at low velocities; $\alpha_a, \alpha_b, c_{b_1}, c_{b_2}$, c_{a_1} and c_{a_2} are parameters that account for the dependence of the MR damper force on the voltage applied to the current driver; k_b controls the stiffness at large velocities; k_a represents the accumulator stiffness; u_{a_0} is the initial displacement of the spring stiffness k_a; γ, β and A are adjustable shape parameters of the hysteresis loops, i.e., the linearity in the unloading and the transition between pre-yielding and post-yielding regions; v_{MR} and u_{MR} are input and output voltages of a first-order filter, respectively and η is the time constant of the first-order filter. The structure itself is assumed to behave linearly; however the addition of the MR damper introduces nonlinearities which necessitate developing a mathematical model to portray this behavior which is usually the key part in the design of semiactive control systems.

3.2 Integrated structure-MR damper system

The equation of motion of a structure employing MR dampers is given by

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = \mathbf{\Gamma}\mathbf{f}_{MR}(t, \mathbf{x}_i, \dot{\mathbf{x}}_i, v_{MR_i}) - \mathbf{M}\mathbf{\Lambda}\ddot{x}_g \tag{22}$$

where $\ddot{x}_g$ denotes the ground acceleration, $\mathbf{M}$ the mass matrix, $\mathbf{K}$ the stiffness matrix, $\mathbf{C}$ the damping matrix, and the vector $\mathbf{x}$ the displacement relative to the ground, $\dot{\mathbf{x}}$ the velocity, $\ddot{\mathbf{x}}$ the acceleration; $\mathbf{x}_i$ and $\dot{\mathbf{x}}_i$ are the displacement and the velocity at the i^{th} floor level relative to the ground, respectively, v_{MR_i} is the voltage level to be applied, and $\mathbf{\Gamma}$ and $\mathbf{\Lambda}$ are location vectors of control forces and disturbance signal, respectively. The second order differential equation can be converted into a state space model

$$\begin{aligned} \dot{\mathbf{z}} &= \mathbf{A}\mathbf{z} + \mathbf{B}\mathbf{f}_{MR}(t, \mathbf{x}_i, \dot{\mathbf{x}}_i, v_i) - \mathbf{E}\ddot{x}_g \\ \mathbf{y} &= \mathbf{C}\mathbf{z} + \mathbf{D}\mathbf{f}_{MR}(t, \mathbf{x}_i, \dot{\mathbf{x}}_i, v_i) + \mathbf{n} \end{aligned} \tag{23}$$

in which the following parameters are used

$$\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C} \end{bmatrix} \tag{24}$$

$$\mathbf{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{M}^{-1}\mathbf{F} \end{bmatrix} \tag{25}$$

$$\mathbf{C} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C} \end{bmatrix} \tag{26}$$

$$\mathbf{D} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{M}^{-1}\mathbf{F} \end{bmatrix} \tag{27}$$

$$\mathbf{E} = \begin{bmatrix} \mathbf{0} \\ \mathbf{F} \end{bmatrix} \tag{28}$$

where $\mathbf{F}$ is the location matrix of Chevron braces within the building structure, $\mathbf{n}$ is the noise vector, $\mathbf{x}_i$ and $\dot{\mathbf{x}}_i$ are the displacement and the velocity at the i^{th} floor level of the three-storybuilding structure, respectively. Properties of the three-story building structure are adopted from Dyke *et al.* (1996).

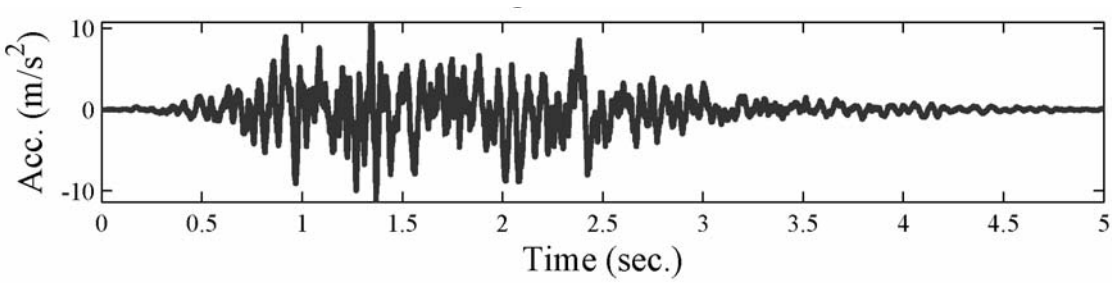
3.3 Simulation

To demonstrate the effectiveness of the PANFIS model, a set of input-output data is generated from a building equipped with an MR damper. MR damping forces and an artificial earthquake are used as input signals while the structural response is the output. In system identification, it is critically important to generate input signals for training the system model such that the input data include a broad range of spectrums. Hence the MR damping forces are produced using a random voltage generator so that much voltage information is included in the data set of the applied MR damper forces. As the 2nd input signal, the artificial earthquake is developed such that the stochastic signal has a spectral density defined by the Kanai-Tajimi spectrum (Yang *et al.* 1987). Although the proposed modeling framework can be applied to any type of signals such as accelerations, velocities, and displacement (or drift), the output in this study is the acceleration. The reason is that accelerometer is relatively cheap and is easy to install into large-scale civil infrastructural systems. Furthermore, accelerometers provide absolute measurement values, not relative one. This acceleration-based prediction model will be useful to implement output feedback controllers into large civil structures, i.e. acceleration feedback control systems. Note that many structural control systems are implemented using acceleration responses (Schurter and Roschke 2001).

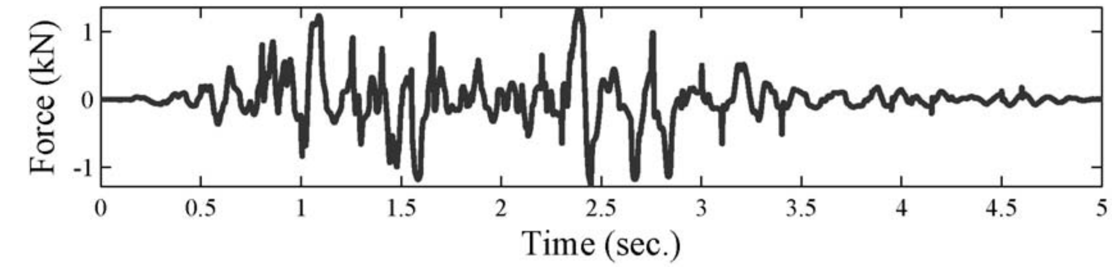
Once the set of input and output data is generated, the approach proposed in Section 2.2 is then applied, i.e., PCA is first used to compress the five-seconds-long artificial earthquake signal to a one-second-long signal using a window function. The performance of the proposed PCA algorithm may change depending on the width of the window function. Hence it is recommended that the window width should be optimized. Furthermore, the use of adaptive window functions would improve the robustness of the proposed algorithm in detecting some sudden peak in the structural responses during very short periods such as impulse loading. The segments of the signal along with the corresponding PCA coefficients are illustrated in Fig. 6. It should be noted that the sum of squares of the PCA coefficients is equal to one. In this paper, the two components (b) and (c) of artificial earthquake shown in Fig. 7 are used with the corresponding MR damper forces and acceleration responses to train the ANFIS model, reducing the computation load significantly.

The architecture of the PANFIS model is determined via trial-and-error strategies: the number of MFs is chosen to be two for both earthquake and MR damper force. Gaussian MFs are used as the design variables. Maximum number of epochs is 150 and the step size is chosen as 0.001. Although the architecture of the PANFIS model can be optimized through an optimization procedure, it is beyond the scope of the present paper.

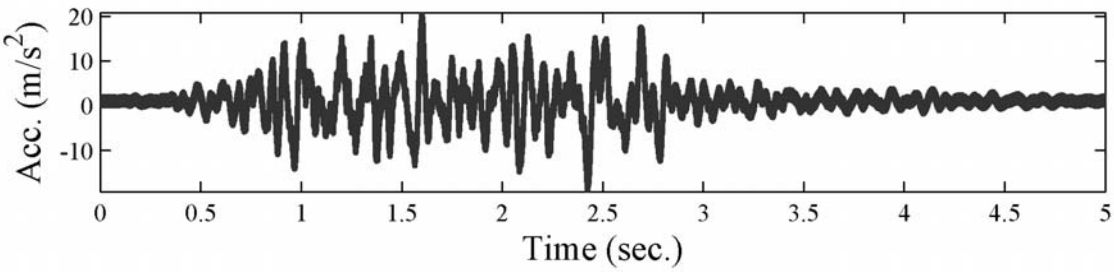
Fig. 8 compares the dynamic response of the original simulation model with that of the trained PANFIS model. Notice that the original simulation model is an analytical model of the building equipped with an MR damper subjected to the artificial earthquake signal. As seen, overall good agreements between the original data and the identified PANFIS model is found. The modeling errors are quantified using indices defined later. As previously discussed, the performance of the PANFIS model can be improved by increasing input parameters, which can also significantly increase computation time, however.



(a) Artificial earthquake

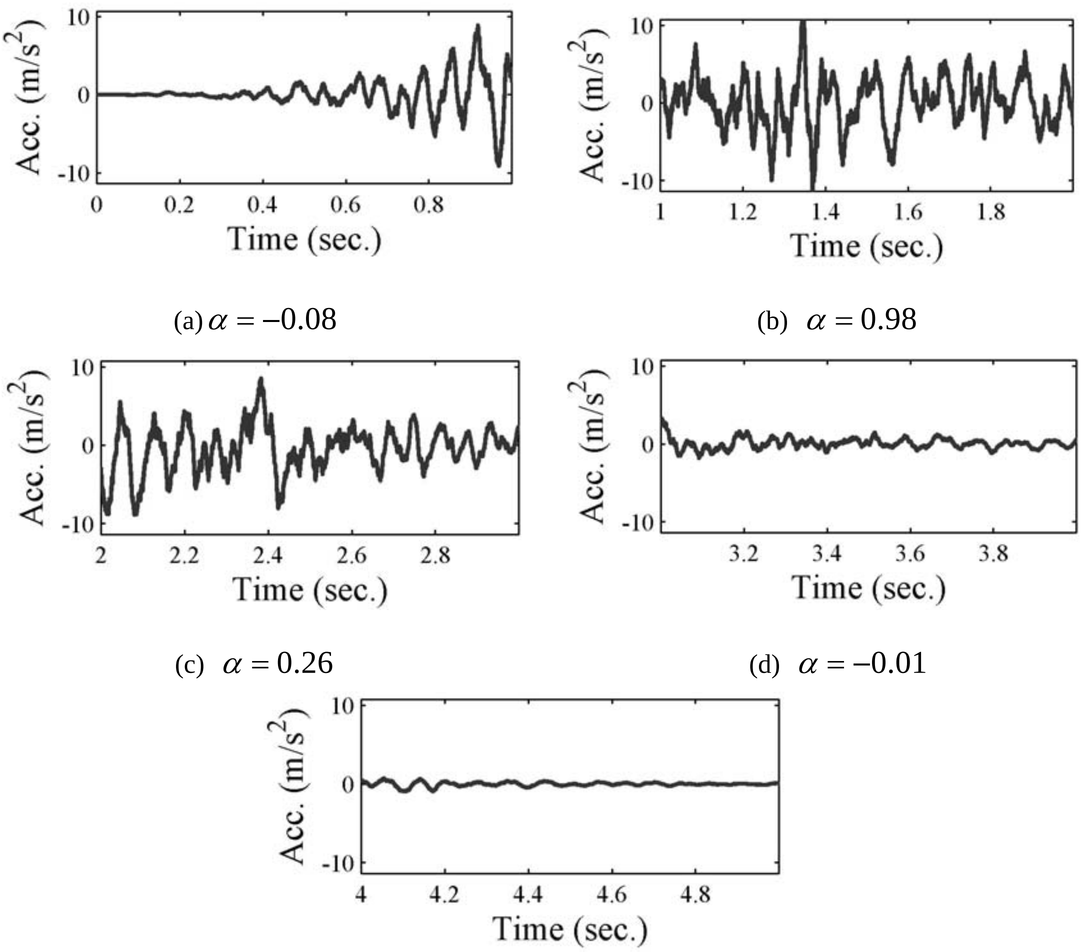


(b) MR damping forces



(c) Structural responses

Fig. 6 A set of input and output for training the PANFIS model



(a) $\alpha = -0.08$

(b) $\alpha = 0.98$

(c) $\alpha = 0.26$

(d) $\alpha = -0.01$

(e) $\alpha = -0.01$

Fig. 7 Five segments of the artificial earthquake with corresponding PCA coefficients

It is necessary to validate the trained model using data that are not used for training the model so that the trained model can be used for a range of possible earthquakes. The selected earthquakes include El-Centro, Kobe, Hachinohe, and Northridge. Because the benchmark smart building used in this study is a 1/5 scale model structure, all the real earthquakes that were used for both training and validating were reproduced at five times the recorded rate (Chung *et al.* 1989, Dyke *et al.* 1998). However, it should be noted that this proposed approach can be applied to any type of signals by adjusting the width of the window functions. Figs. 9-12 show comparisons of the actual accelerations at the third story level and the predicted responses obtained from the PANFIS for the validating earthquakes. It is clear from the figures that the validated responses correlate well with the actual accelerations, meaning that the proposed PANFIS model is effective in modeling the nonlinear dynamic response to various earthquake signals. The accuracy of the identified model can be improved by increasing either the number of MFs or the step size. However, these increased parameters (i.e., overtraining) may not be an efficient approach for validating the developed model using other data sets.

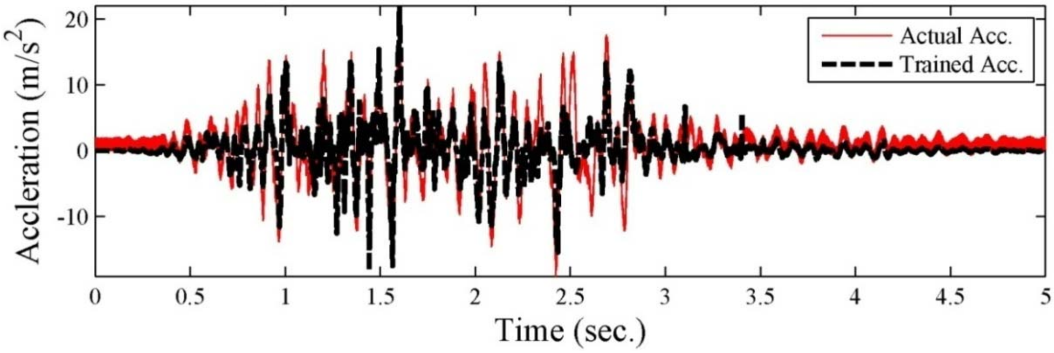


Fig. 8 Training: Artificial earthquake

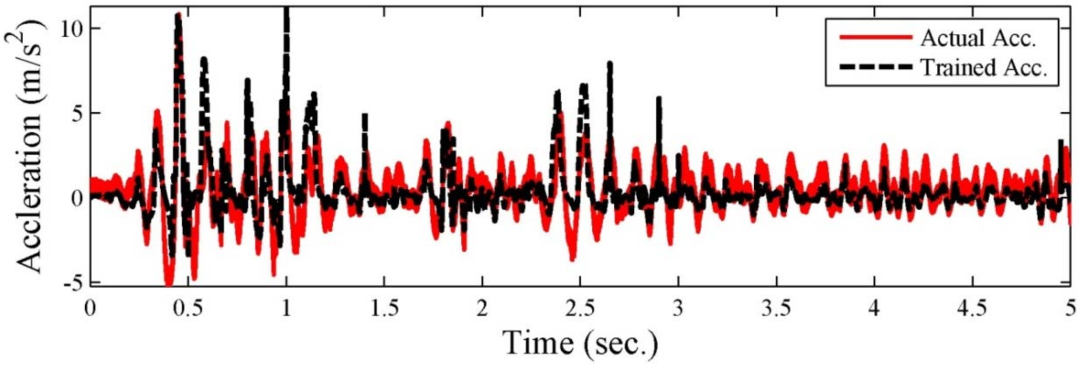


Fig. 9 Validation: El-Centro earthquake

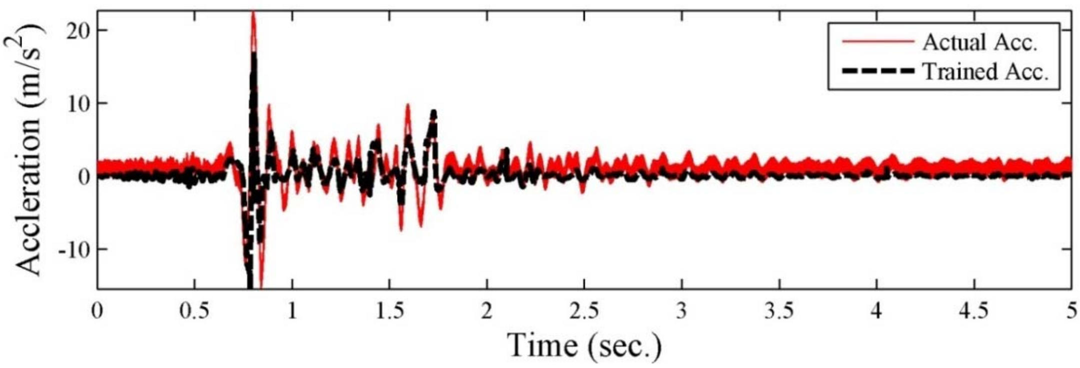


Fig. 10 Validation: Northridge earthquake

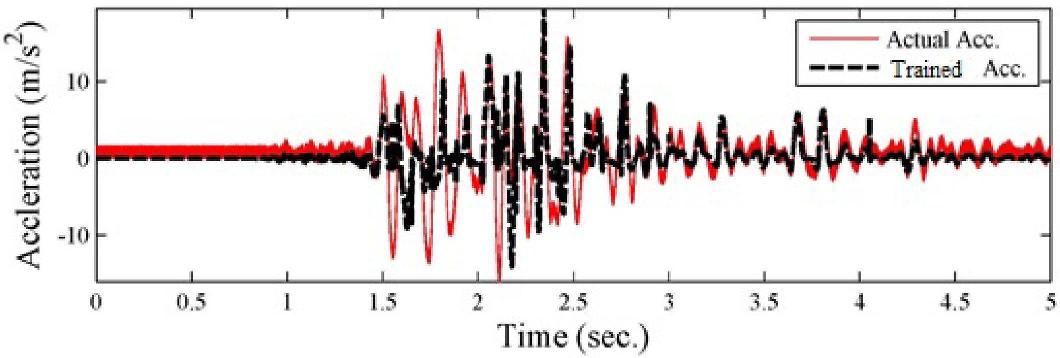


Fig. 11 Validation: Kobe earthquake

In order to quantify the error and the relationship between the predicted response and the actual response of the structure, six indices are introduced. The first index J_1 is the maximum error of the estimated data

$$J_1 = Max\left(\left|\hat{y} - \tilde{y}\right|\right) \tag{29}$$

where $\hat{y}$ is the estimation and $\tilde{y}$ is the actual structural response data. The next index, J_2 is the minimum error of the predicted data

$$J_2 = Min\left(\left|\hat{y} - \tilde{y}\right|\right) \tag{30}$$

Root-mean-square error (RMSE) index J_3 is defined as

$$J_3 = RMSE = \sqrt{\frac{\left(\hat{y} - \tilde{y}\right)^2}{N}} \tag{31}$$

J_4 is also used for evaluating the fitting rate of the predicted data as follows. Note that if the PANFIS model produces the same responses as the simulation model, the fitting rate J_4 will be 100%.

$$J_4 = \left(1 - \frac{\mathrm{var}\left(\left|\hat{y} - \tilde{y}\right|\right)}{\mathrm{var}\left(\left|\tilde{y}\right|\right)}\right) \tag{32}$$

The training time is considered as another index J_5

$$J_5 \equiv \text{training time in minutes} \tag{33}$$

To compare the validation results of ANFIS and PANFIS, J_6 is defined. It is simply the absolute value of the difference between the fitting rate index J_4 of the ANFIS and PANFIS results

Table 1 Training results of ANFIS and PANFIS

System	Number of MFs for each input	J_1 (m/s^2)	J_2 (m/s^2)	J_3 (m/s^2)	J_4 (%)	J_5 (min.)	J_6 (%)
ANFIS	2	16.78	0	2.973	73.22	2.068	1.68
PANFIS	2	16.87	1.131×10^{-5}	3.058	74.90	0.7265	

Table 2 Validation of the trained models

Index	El-Centro		Northridge		Kobe		Hachinohe	
	ANFIS	PANFIS	ANFIS	PANFIS	ANFIS	PANFIS	ANFIS	PANFIS
J_1	7.814	7.574	33.50	25.97	21.49	19.24	7.567	7.284
J_2	7.137	0.025	35.17	5.281	21.22	43.68	60.91	4.845
J_3	1.301	1.249	1.785	1.969	3.278	3.445	1.054	0.736
J_4	66.86	69.38	62.31	64.33	45.69	44.79	58.58	67.38
J_5	2.068	0.727	2.068	0.727	2.068	0.727	2.068	0.727
J_6	3.769		3.14		2.01		13.06	

$$J_6 = \left| J_4^{ANFIS} - J_4^{PANFIS} \right| \tag{34}$$

The evaluations of the training results are provided in Table 1. It is evident from J_4 and J_5 that the accuracy of the PANFIS model is close to that of ANFIS, while PANFIS's training time is 35.13% of ANFIS's, proving to be an efficient method.

The validation errors arefor ANFIS and PANFIS models also provided in Table 2. It shows that the PANFIS model performs slightly better than ANFIS with a significant decrease in computation time (approximately 64.87% less than ANFIS).

4. Conclusions

In this paper, an efficient PCA-based adaptive neuro-fuzzy inference system (PANFIS) is proposed for a fast nonlinear system identification of seismically excited building structures equipped with magnetorheological (MR) dampers. To fully exploit their advantages, Takagi-Sugeno fuzzy model, principal component analysis, and artificial neural networks are integrated to create the PANFIS system. The proposed model yields accurate results for the system identification of smart structures with significantly reduced time of computation compared to ANFIS. To train the input-output mapping function of the PANFIS model, an artificial earthquake signal and an MR damper force signal are used as a disturbance input signal and a control input, respectively, while the acceleration response is used as output data. Furthermore, a variety of other earthquake records, MR damping forces, and their associated responses are used to validate the trained model. This approach can be applied to an integrated model of a building employing nonlinear MR damping devices without decoupling the identification procedure of the highly nonlinear MR damper from that of the primary building. It is demonstrated through the simulation results that the proposed PANFIS model is effective in identifying the nonlinear behavior of the seismically excited building-MR damper system while significantly decreasing the training time.

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