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Smart pattern recognition of structural systems

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Abstract. Structural Control relies, with a great deal, on the ability of the control algorithm to identify the current state of the system, at any given point in time. When such algorithms are designed to perform in a smart manner, several smart technologies/devices are called upon to perform tasks that involve pattern recognition and control. Smart pattern recognition is proposed to replace/enhance traditional state identification techniques, which require the extensive manipulation of intricate mathematical equations. Smart pattern recognition techniques attempt to emulate the behavior of the human brain when performing abstract pattern identification. Since these techniques are largely heuristic in nature, it is reasonable to ensure their reliability under real life situations. In this paper, a neural network pattern recognition scheme is explored. The pattern identification of three structural systems is considered. The first is a single bay three-story frame. Both the second and the third models are variations on benchmark problems, previously published for control strategy evaluation purposes. A Neural Network was developed and trained to identify the deformed shape of structural systems under earthquake excitation. The network was trained, for each individual model system, then tested under the effect of a different set of earthquake records. The proposed smart pattern identification scheme is considered an integral component of a Smart Structural System. The Reliability assessment of such component represents an important stage in the evaluation of an overall reliability measure of Smart Structural Systems. Several studies are currently underway aiming at the identification of a reliability measure for such smart pattern recognition technique.

Keywords: neural networks; pattern recognition; semi active; smart; structural control.

1. Introduction

Smart structural systems have, recently, been introduced as a viable alternative for conventional systems, especially in responding to highly uncertain loading conditions. Smart systems rely on smart components and/or techniques that circumvent the need for accurate system identification. Structural properties, which are required for any conventional solution, are not necessary in the case of a smart system. In addition, the time required to evaluate the response and accordingly any control action is greatly reduced, which is a major factor due to the nature of such loading conditions, i.e., winds and earthquakes. In this paper, a smart pattern recognition scheme is explored. The proposed scheme is designed to identify an abstract deflected shape of any structural system. This technique is an integral component of a smart structural system that is capable of indentifying its current deformed state, using the proposed pattern recognition technique. This information is then communicated to a smart structural controller that evaluates the required control action, which is then applied through a set of

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smart actuators. It is obvious that pattern recognition, as introduced above, would act as the driving force for the overall system. Since smart structural systems are employed, the exact evaluation of the structure's time history is not required. Rather an abstract evaluation of the deformed shape is enough to drive a smart control strategy which is known to rely on heuristics rather than specifics. As mentioned earlier, such smart technologies would require much less mathematical manipulation and accordingly less time to evaluate a control action and/or suppress undesired deformations and/or vibrations. Thus, the proposed technique, when integrated with a smart structural control system would provide a viable solution for designing earthquake resistant structures.

Pattern classification and/or recognition have been recently employed in several applications relating to damage detection and system identification (Adeli and Jiang 2006, Farrar and Sohn 2000, Lakshmanan, *et al.* 2008 and Reda Taha and Lucero 2005). In damage detection and structural health monitoring, researchers have implemented pattern classification techniques in identifying changes in structural parameters due to damage initiation (Farrar and Sohn 2000, Lakshmanan, *et al.* 2008, Masri, *et al.* 2000 and Reda Taha and Lucero 2005). System identification using pattern classification techniques could be performed in the time domain and/or in the frequency domain (Loh, *et al*. 2000 and Poon and Chang 2007). Pattern calssification techniques could be further classified into parametric (Loh, *et al*. 2000 and Poon and Chang 2007). and nonparametric techniques (Hung, *et al.* 2003 and Alimoradi, *et al.* 2005). There are several pattern classification techniques, both parametric and nonparametric, that have been successfully employed in structural identification, damage detection and strcutural health monitoring. Statistical pattern calssification has been recently introduced as a powerful tool in identifying damage initiation through the statistical analysis of measured data (Farrar and Sohn 2000 and Sohn, *et al.* 2001). Several nonparametric techniques have been successfully employed in identifying healthy structures and accordingly picking up any changed behavior of the same structures due to intiation of damage. Neural networks (Masri, *et al.* 2000 and Lakshmanan, *et al.* 2008), fuzzy inference systems (FIS) (Alimoradi, *et al*. 2005 and Reda Taha and Lucero 2005) and the enhancement of nonparamteric techniques by integrating powerful analytical tools such as wavelet neural networks and fuzzy wavelet neural networks (Adeli and Jiang 2006 and Hung, *et al.* 2003) have all shown several successful applications.

Smart Pattern Recognition is classified as a nonparametric pattern identification technique where heuristic methods are employed in identifying the pattern of a structural system. Smart structural systems employ technologies and/or devices that are capable of emulating the human thinking process, rather than engaging in the setup and evaluation of complicated mathematical models (Connor 2003, Soong 1987, 1990, Spencer and Sain 1998 and Utku 1998). The deformed shape of any structural system, i.e., its pattern, would probably reflect the best smart approach necessary to reposition the system into its original configuration (Hassan and Ayyub 1997, Hassan 2005, 2006). It is well known that the deformed shape of any linear system could be expressed in terms of the linear combination of its free un-damped mode shapes (Connor 2003 and Clough and Penzein 1975). It is also well documented that most structural systems could be fairly expressed by employing the first three free un-damped mode shapes (Clough and Penzein 1975). Therefore, a smart procedure could be developed, employing linear superposition of the first three un-damped mode shapes for a given structure. Such system would be capable of identifying the current pattern of a structural system at any given point in time. As a result, necessary corrective action could be evaluated and suggested. The actual evaluation of a corrective action is also expected to be performed by employing a smart control algorithm.

In this paper, pattern recognition is employed in a different context than what was cited from the literature. Pattern recognition is used in identifying an abstract deformed shape of a structural system in an attempt to integrate such information with a smart structural controller. The pattern classification could be employed in suggesting a suitable control strategy and/or an optimum scheme for actuator firing. The objective of this paper is to explore the applicability of Neural Network technologies in real-time identification of the deformed shape of structural systems. Three structural systems are presented for the development and testing of such classification schemes. Three earthquake records are considered for this task, the first for training purposes and the other two for checking and validation purposes. Because of the heuristic nature of such an approach, its reliability under real life conditions is a major concern (Hassan 2005). The development of a reliability measure, for a neural network pattern identifier, is currently underway. Such a reliability measure would serve as a guide to evaluate the expected performance of such a technique when employed in a real Smart Structural System.

2. Structural models

Three structural system models are employed, in this study, in order to demonstrate the applicability of the proposed techniques on a range of systems. The systems include a single-bay three-story rigid frame, which is referred to hereafter as Model-1, a four-bay three-story rigid frame with the last bay simply connected, referred to hereafter as Model-2 and a four-bay three-story rigid frame with all bays rigidly connected, referred to hereafter as Model-3. Model-2 is actually one of the benchmark problems developed in (Ohtori, *et al.* 2004) for testing emerging control strategies. Model-1 is simply one of the four bays, using the same size, dimensions and design. Model-3 is an alternate design for Model-2, which include all bays to be rigidly connected. Figs. 1, 2 and 3 show the dimensions and design sections for all three structural models.

All structural models have a 30 ft bay and a 13 ft high floor level. In plan, the system has four bays in the N-S direction and six bays in the E-W direction for Models 2 and 3. Model 1 has one bay in the N-S direction and six bays in the E-W direction. The systems are assumed to be under a horizontal earthquake excitation in the N-S direction where a moment-resisting rigid frame is employed in

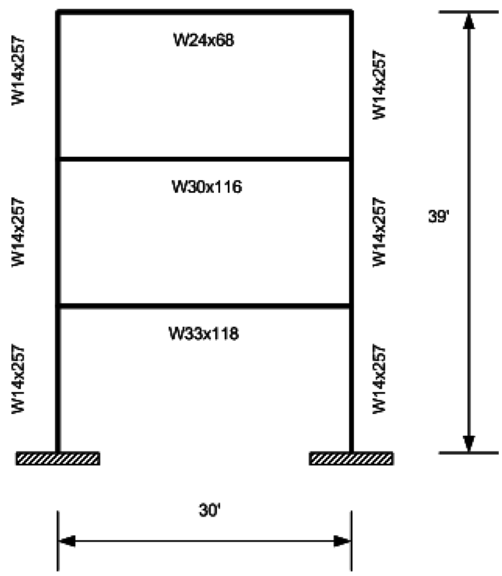

Fig. 1 Single-bay 3-story frame (Model-1)

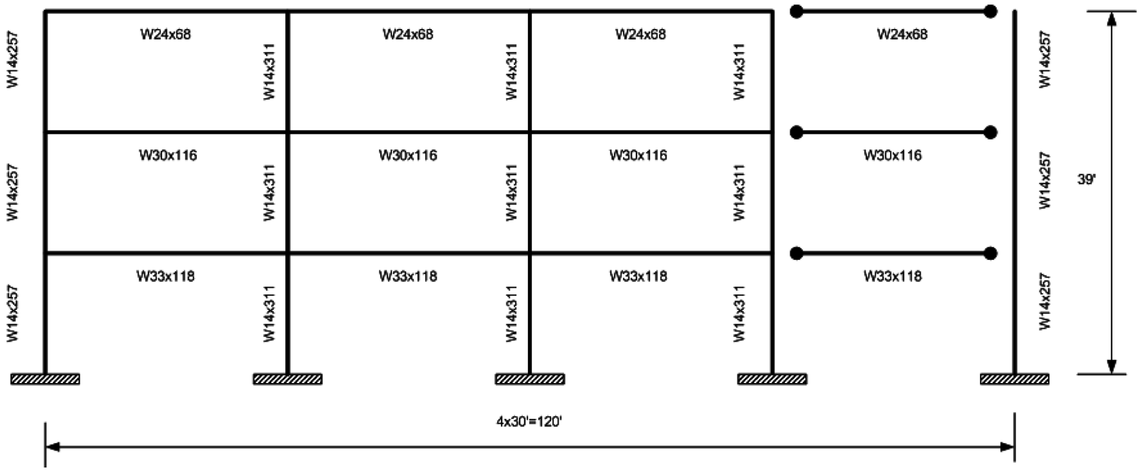

Fig. 2 Four-bay 3-story simply connected frame (Model-2), (Ohtori, *et al*. 2004)

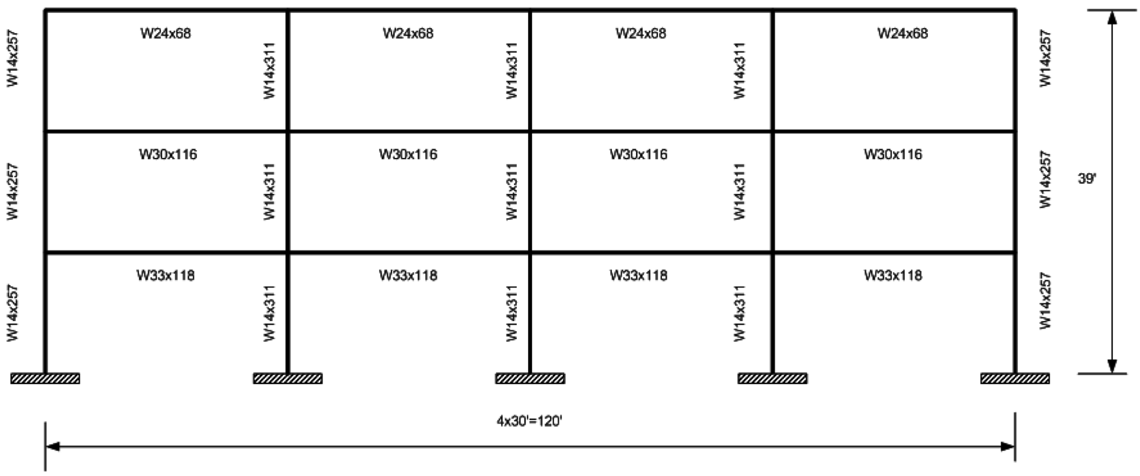

Fig. 3 Four-bay 3-story rigidly connected frame (Model-3)

lateral load resistance. As mentioned above, Model-2 is a moment resisting rigid frame with the last bay simply connected, which coincides with the original benchmark problem presented in (Ohtori, *et al.* 2004). Model-1 is a single bay rigidly connected frame and Model-3 is a four bay rigidly connected frame. The floors are composite steel and concrete construction with enough rigidity to allow for even distribution of inertia forces among the two end frames at the N-S direction (Ohtori, *et al.* 2004).

The seismic mass of levels one and two are 65.5 kips s^2/ft and the third level is 71 kips s^2/ft. Such mass accounts for all components comprising the structural system, namely, decking, floor slabs, rigid frames partitions and supplementary systems (Ohtori, *et al.* 2004). The seismic mass is equally split between both rigid frames at the N-S direction. Beams are designed in 36 ksi steel while columns are designed in 50 ksi steel (Ohtori, *et al.* 2004). This structural information was used in developing models for these frames within a structural analysis package. These models were later used in evaluating the time history of floor lateral displacements for each earthquake record.

3. Pattern identification

The proposed smart pattern recognition technique depends on predefined potential patterns. Such patterns are identified based on the first three un-damped mode shapes. It is well known that the vibration of most structural systems could be reasonably represented in terms of the first three un-damped mode shapes (Clough and Penzein 1975). Usually a predominant mode shape would govern the final deflected shape of the system. In this paper, each story level is assumed to undergo one of three potential positions, namely, negative, zero or positive. By exploring all potential combinations of all story levels, all potential deformed patterns were identified. In case of a three-story system, only twenty-seven potential combinations are possible. However, in case of more complex systems, more potential combinations should be considered. Such pattern classifications represent the required output of any smart pattern recognition scheme.

For the purposes of this study, all twenty-seven potential pattern classifications were identified. Each pattern classification was assigned a representative code that reflects how the deformed shape would look like. These classification codes were then employed in training the smart pattern recognition scheme. For a Neural Network Model, these codes were used as the required output of the network. The network was trained to identify the deflected pattern of a similar structure and assign the proper classification code. Such codes should be employed later on, by a smart control system, in selecting the proper control strategy and the appropriate location and firing sequence of actuators. Figs. 4(a)-(c) show all potential deformed patterns, for a single bay three-story system. Table 1 defines the classification codes for each potential combination, i.e., deformed pattern.

4. Neural network model

Artificial Neural Networks have always been associated with pattern recognition problems. Their parallel processing nature and learning capabilities, allow them to be trained to identify predefined pattern classifications (Caudill and Butler 1990, Hayken 1999, Lippman 1989 and Wasserman 1989). In this paper, Artificial Neural Networks are explored as a potential smart pattern identification scheme for structural systems, under earthquake excitation. Pattern classifications, identified in the previous section, are sought as the network output. When correlated with the underlying structural deformed pattern, such classifications could be employed as a pattern identification code.

The proposed model is a feed-forward back-propagation network, which comprises three layers. In addition to the input layer, the network employs two hidden layers and a third output layer. Networks, having multiple hidden layers with tan-sigmoid transfer functions, have proved successful in modeling highly nonlinear input/output relations (Caudill and Butler 1990, Hayken 1999, Lippman 1989 and Wasserman 1989).

The proposed network employs three neurons, for its first layer, which coincides with the number of degrees of freedom of the modeled system (Hassan and Ayyub 1995, 1997). The neurons are connected, through sensors, to the corresponding degrees of freedom of the modeled system. A neuron, in the first layer, could be mathematically expressed as follows (Hayken 1999);

$$v_i^I = \sum_{j=1}^{3} w_{ij}^I * X_j \tag{1a}$$

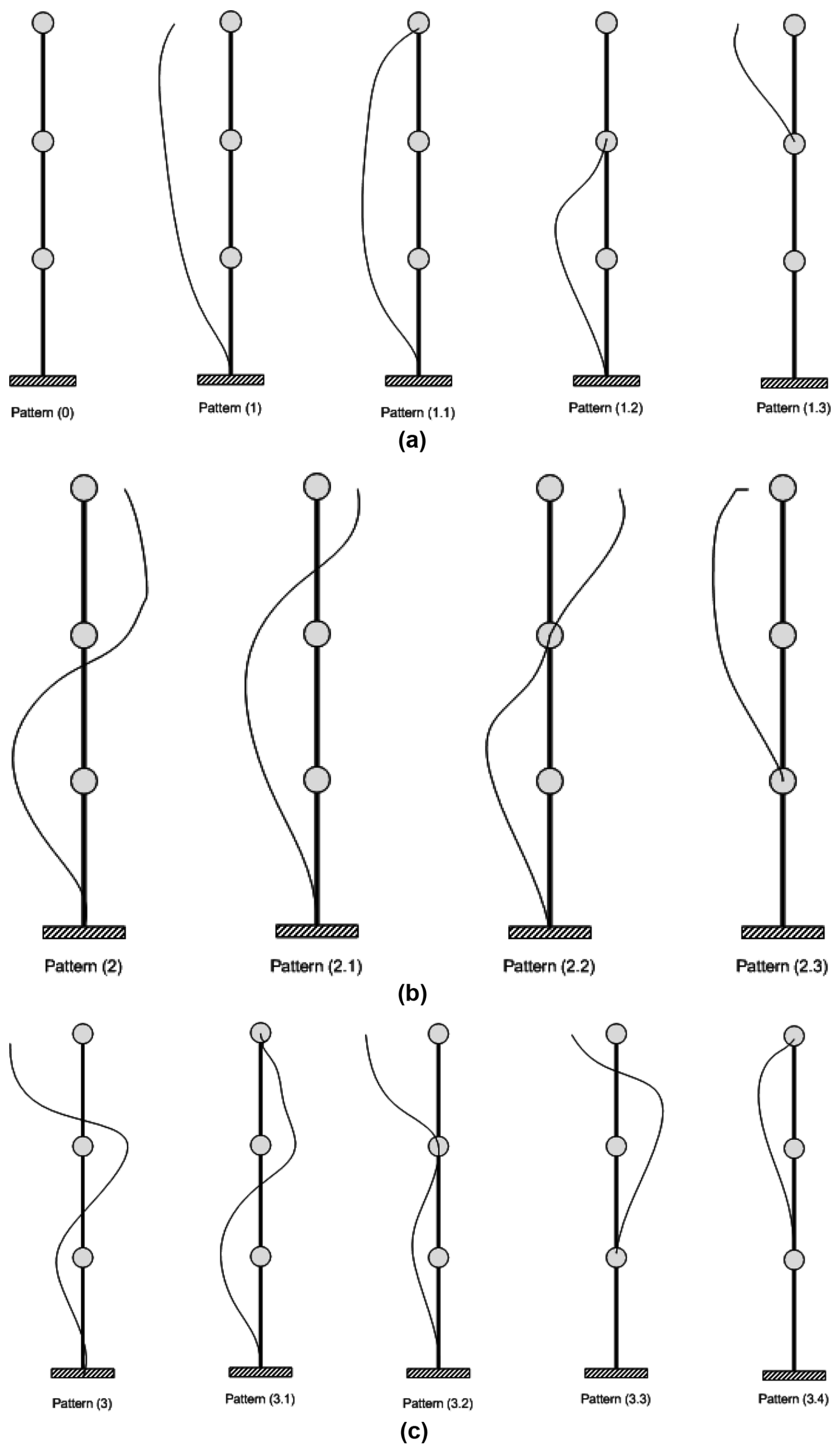

Fig. 4 Potential deflection patterns

Table 1 Pattern classifications

Pattern classification	Mode shape	Level (1)	Level (2)	Level (3)
0		Zero	Zero	Zero
1	First mode	Positive	Positive	Positive
1.1		Positive	Positive	Zero
1.2		Positive	Zero	Zero
1.3		Zero	Zero	Positive
2	Second mode	Positive	Negative	Negative
2.1		Positive	Positive	Negative
2.2		Positive	Zero	Negative
2.3		Zero	Positive	Positive
3	Third mode	Positive	Negative	Positive
3.1		Positive	Negative	Zero
3.2		Positive	Zero	Positive
3.3		Zero	Negative	Positive
3.4		Zero	Positive	Zero
-3.4	Third mode	Zero	Negative	Zero
-3.3		Zero	Positive	Negative
-3.2		Negative	Zero	Negative
-3.1		Negative	Positive	Zero
-3		Negative	Positive	Negative
-2.3	Second mode	Zero	Negative	Negative
-2.2		Negative	Zero	Positive
-2.1		Negative	Negative	Positive
-2		Negative	Positive	Positive
-1.3	First mode	Zero	Zero	Negative
-1.2		Negative	Zero	Zero
-1.1		Negative	Negative	Zero
-1		Negative	Negative	Negative

And

$$y_i^I = \Theta(v_i^I) \tag{1b}$$

Where, v_i^I = is the activation potential of the ith node in layer (I); w^I_{ij} = is the synaptic weight of the connection joining the ith neuron, in layer (I), to the jth input sensor; X_j = is the jth neuron input, which is the deflection value measured by the sensor connected to jth degree of freedom; y^I_i = is the output of the ith neuron in layer (I); and Θ(.) = is the activation function associated with the defined neuron. The activation function for this layer was chosen to be the tan-sigmoid function, which is mathematically defined as:

$$\Theta(\nu) = \frac{2}{1 + \exp(-2\nu)} - 1 \tag{2}$$

Where, ν = is the activation potential of a given neuron; exp(.)= is the exponential function; and Θ(.) =

is as defined above. The reason such function was adopted, is the need for a normalized value that represents the deflection, associated with any given neuron. Such normalized value only needs to reflect the sign of the deflection with a value that is, relatively, consistent with the original deflection.

The second layer was modeled after an earlier neural network model that was proposed for the same application (Hassan and Ayyub 1995, 1997). This layer has a number of neurons, which is equal to N x N, where, N is the degree of freedom of the modeled system. The layer models the linear superposition approach, employed in mode-shape analysis techniques (Connor 2003, Clough and Penzein 1975 and Hassan and Ayyub 1995, 1997). Such approach is based on the notion that any deflected pattern could be expressed in terms of linear combinations of the free un-damped mode-shapes of the modeled system. The layer is fully connected with the previous layer. For all modeled systems, such a layer comprises nine neurons. A neuron in the second layer could be mathematically expressed as follows;

$$\nu_i^{II} = \sum_{j=1}^{3} w_{ij}^{II} * y_j^{I} \tag{3a}$$

And

$$y_i^{II} = \Theta(\nu_i^{II}) \tag{3b}$$

Where, ν_i^{II} = is the activation potential of the i^th^ node in layer (II); w_{ij}^{II} = is the synaptic weight of the connection joining the i^th^ neuron, in layer (II), to the j^th^ neuron in layer (I); y_j^{I} = is the j^th^ neuron output in layer (I); y_i^{II} = is the output of the i^th^ neuron in layer (II); and $\Theta(.)$ = is the activation function associated with the defined neuron. This layer still employs the tan-sigmoid function, as defined in Eq. (2), as its activation function. It is common practice for networks of that structure to include several tan-sigmoid hidden layers (Hassan and Ayyub 1995, 1997). Such architecture allows the network to identify and model the nonlinear relationship among the inputs and outputs (Caudill and Butler 1990, Hayken 1999, Lippman 1989 and Wasserman 1989).

The third and final layer is the superposition layer. It employs only one neuron since the output should be a single deflected shape vector. This layer incorporates a linear activation function in order to perform a linear superposition of the outputs of all neurons of the previous layer. Keeping in mind that the developed vector should be the original deflected shape, the linear function is the best choice for that layer. This procedure reconstructs the deflected shape vector, after being decomposed through the previous layers. A neuron in this final layer is mathematically expressed as follows;

$$\nu^{O} = \sum_{j=1}^{9} w_j^{O} * y_j^{II} \tag{4a}$$

And

$$Y = \Gamma(\nu^{O}) \tag{4b}$$

Where, ν^{O} = is the activation potential of the node in output layer (O); w_j^{O} = is the synaptic weight of the connection joining the single neuron, in layer (O), to the j^th^ neuron in layer (II); y_j^{II} = is the j^th^ neuron output in layer (II); Y = is the network output; and $\Gamma(.)$ = is the activation function associated with the defined neuron. The linear activation function of this neurons is defined as follows;

$$\Gamma(\nu) = a * \nu + b \tag{5}$$

Where, ν = is the activation potential of the single neuron in the output layer; and a, b = are parameters of the linear function. The linear parameters, a & b, were taken as 1 and 0 respectively which reduces to

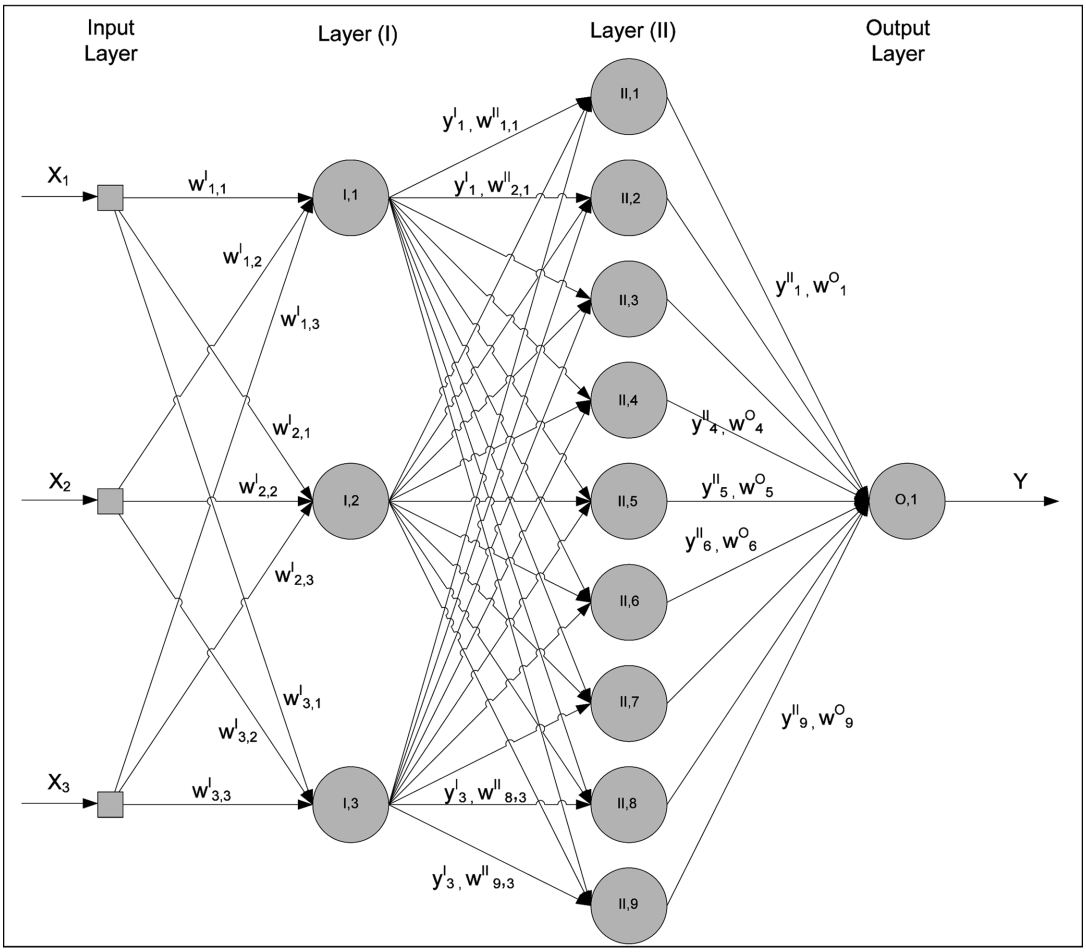

Fig. 5 Neural network model

a 45° straight line. The network, practically, decomposes the deformed pattern, using the linear superposition procedure, and then reconstructs the deformed pattern again. In doing such decomposition and reconstruction, the network is capable of identifying the deformed pattern of the system, real-time and the contribution of each individual mode shape to the final deformed pattern. This information is of great importance when it is communicated to a smart controller for actuator firing sequence. Fig. 5 shows a schematic diagram for the proposed network.

4.1. Neural network learning

The learning process proceeds by evaluating the performance function of the proposed network. The proposed network employs the mean square error as the network performance function (Demuth and Beale 2002). Such an error is evaluated for the network target vector and the network output vector as follows;

$$\mathrm{MSE} = \frac{1}{N}\sum(T-Y)^2 \tag{6}$$

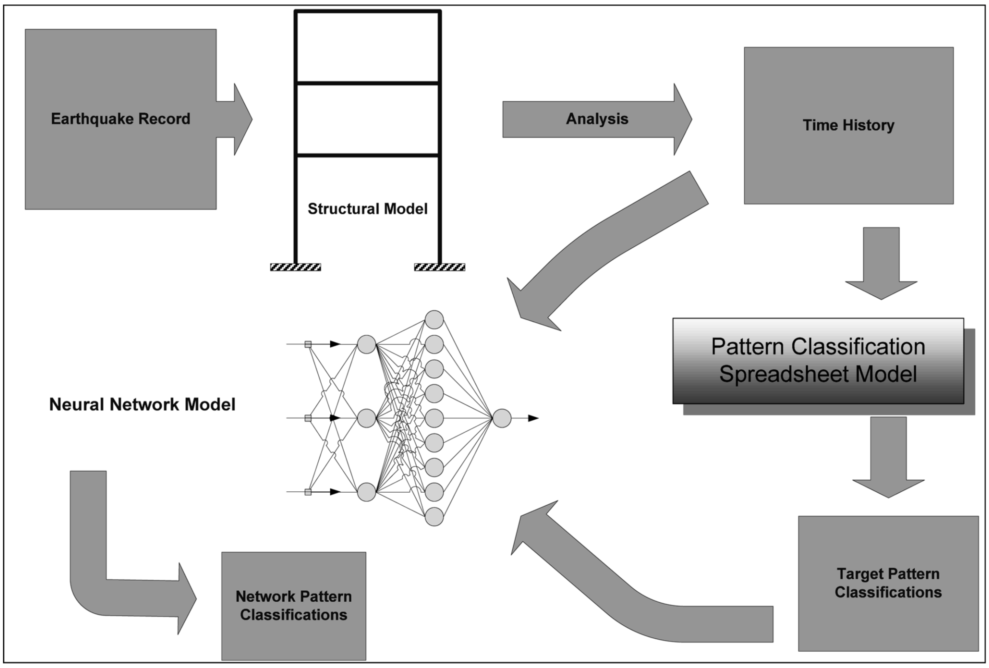

Fig. 6 Neural network learning mode operation

Where, MSE = is the mean square error; N = number of earthquake time history records; T = is the network target evaluated by a spreadsheet model, as defined in Table 1; and Y = is the network output. In order to perform network training successfully, adequate input/target data sets should be fed to the network. In this paper, data sets were generated for several earthquake input records. Three earthquake records were employed, namely, Kobe, North-Ridge and Hachinohe. The earthquake time history was applied to the three modeled systems, using a structural analysis package, in order to evaluate the displacement time history for the three story levels. A spreadsheet model was then developed in order to calculate the pattern classification for each time instant, as defined in Table 1. The developed data sets constituted enough input/output ensembles for training and testing the performance of the developed network model. Fig. 6 outlines the basic steps involved in the neural network learning operation.

The proposed model was trained, for all three modeled systems, by employing the data sets generated by the Hachinohe earthquake records. The Hachinohe earthquake record was selected because of its large time history ensembles. Although several studies have estimated the required minimum number of data sets for training and testing the performance of artificial neural networks, such estimates did not prove adequate in the current application (Caudill and Butler 1990, Hayken 1999, Lippman 1989 and Wasserman 1989). Because of the fact that the same displaced pattern could result from so many combinations of actual displacements, at the corresponding floor levels, a large data set is required in order to capture this highly uncertain relationship. Therefore, it was decided to select the earthquake record with the highest number of data sets for the training process. Network testing was then performed by employing other earthquake records, namely, Kobe and Northridge time histories.

The adopted training algorithm is a back-propagation scheme, based on the quasi-Newton learning procedure (Demuth and Beale 2002). The details of the training algorithm are beyond the scope of this paper. Several, other, algorithms were tested for training the proposed network; however the back-

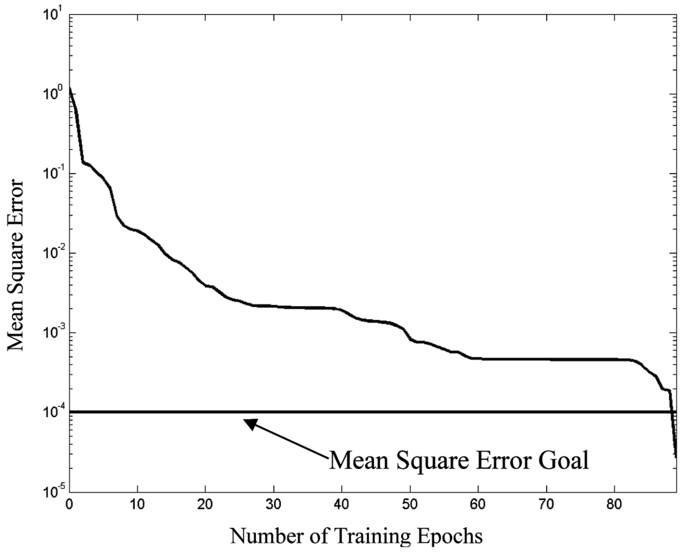

Fig. 7 Training performance for hachinohe earthquake Model-1

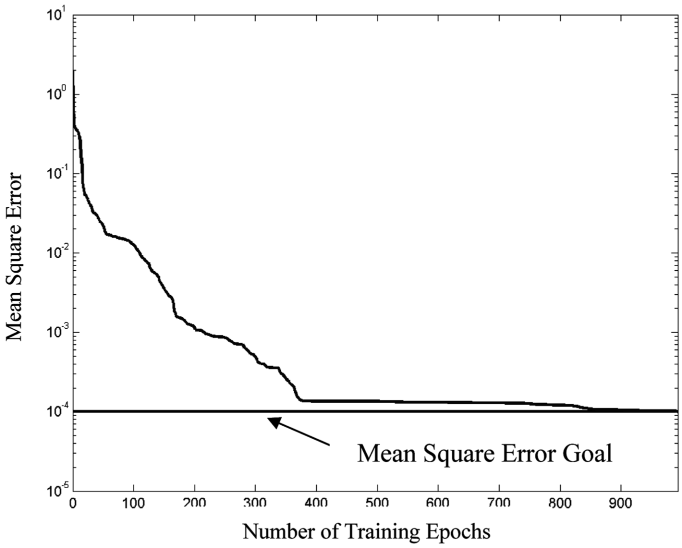

Fig. 8 Training performance for hachinohe earthquake Model-2

propagation scheme proved to be the most efficient. The training/network performance was measured by the mean square error as defined in Eq. (6). The training was performed in a batch mode, where, the weights were adjusted after the application of all input/output pairs (Demuth and Beale 2002).

Figs. 7, 8 and 9 summarize the training performance for each modeled system. The figures indicate a smooth training curve where the mean square error is plotted against the training epochs. The figures indicate that the target performance measure, i.e., a mean square error of (1e-4), is attained on the average after (90-1000) training epochs, according to the trained model. Other simulations were performed suggesting that the number of training epochs sometimes vary considerably according to the initial random assumption of network synapse weights. However, it is worth noting that regardless of the

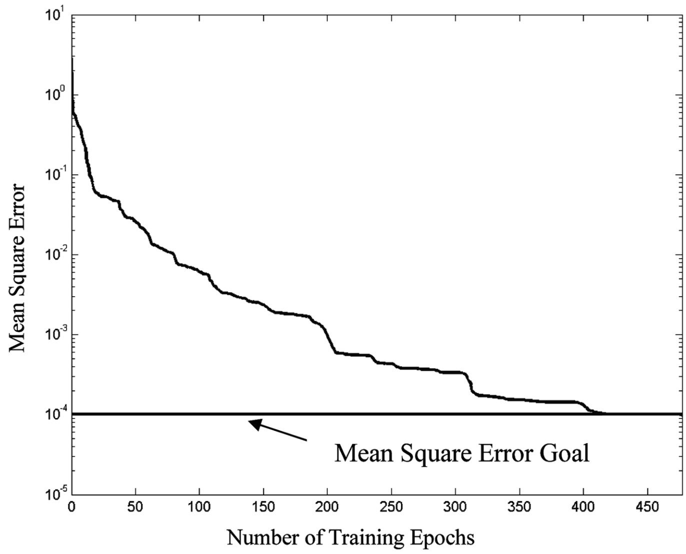

Fig. 9 Training performance for hachinohe earthquake Model-3

number of training epochs necessary to attain the desired mean square error, the network was always successful in fulfilling its training objective. In order to evaluate the network performance, other unseen earthquake records were introduced to the trained network and its performance evaluated and compared to the expected target. The performance of the trained network is discussed in detail in the following sections.

5. Discussion of results

As mentioned above, all three structural models were analyzed using a heuristic state identification technique, namely, a neural network model. Three earthquake records were employed in this analysis,

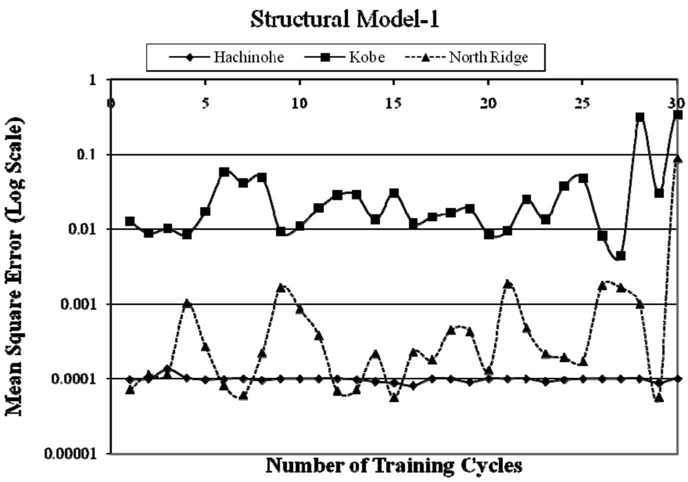

Fig. 10 Mean square error profile for structural Model-1

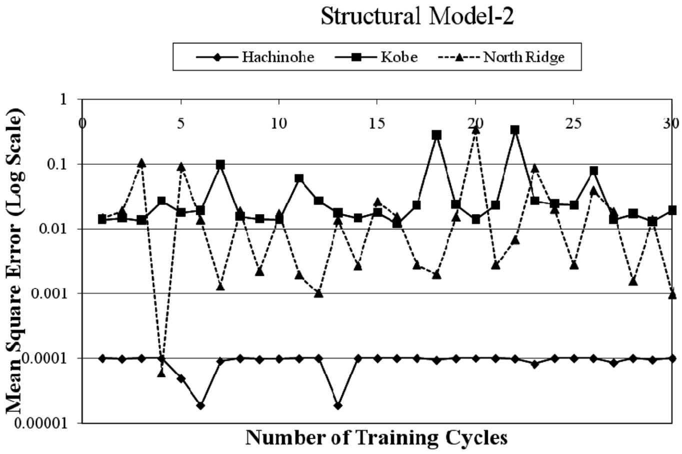

Fig. 11 Mean square error profile for structural Model-2

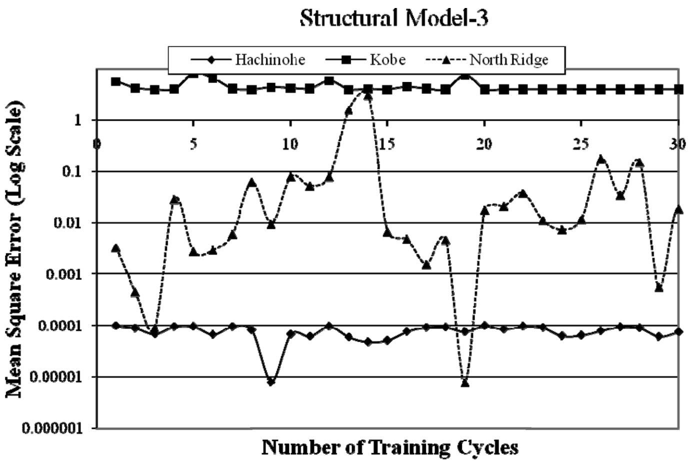

Fig. 12 Mean square error profile for structural Model-3

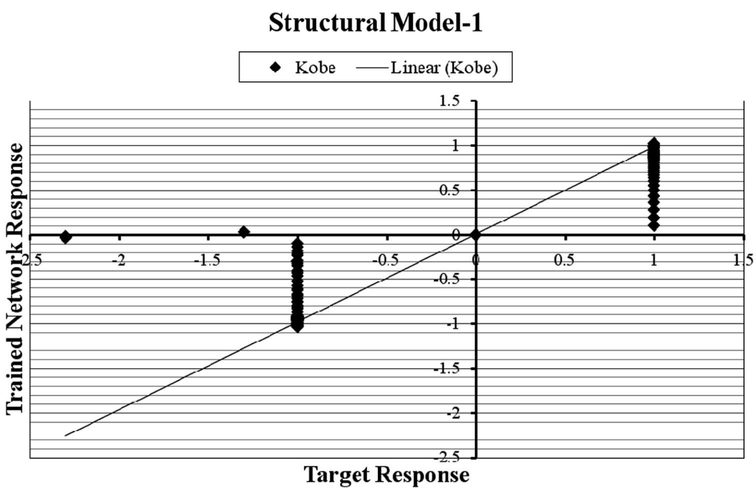

Fig. 13 Testing data performance for Kobe earthquake Model-1

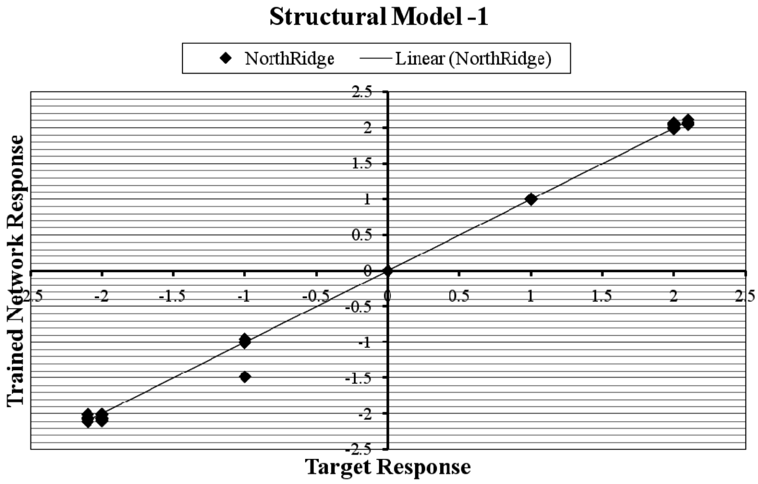

Fig. 14 Testing data performance for NorthRidge earthquake Model-1

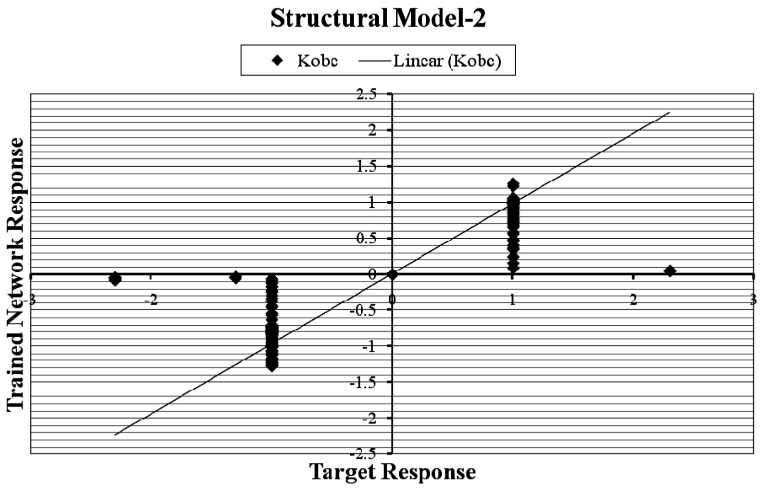

Fig. 15 Testing data performance for Kobe earthquake Model-2

according to the following scheme. Hachinohe earthquake record was employed in training the neural network, then Kobe and North-Ridge earthquake records were employed in testing the performance of the trained network in properly identifying the deformed pattern of all modeled systems. Thirty training cycles were conducted in order to evaluate and gauge the variability and uncertainty associated with the training process.

Figs. 10, 11 and 12 show the mean square error, for each training cycle, for all three structural models. In general, all figures indicate that despite the fact that the training process did reach its set mean square error target, as indicated by the performance of the Hachinohe earthquake, the testing earthquake runs did not achieve that target, i.e, 1×10e-4. In addition, for any given earthquake record the training process shows very high variability and/or uncertainty that is evident in the wide range of mean square error values indicated for individual training cycles. It is also worth noting that for a

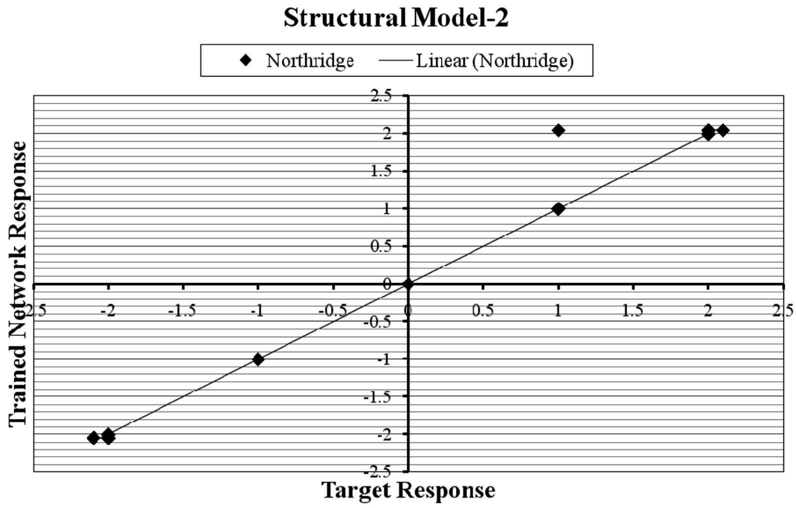

Fig. 16 Testing data performance for NorthRidge earthquake Model-2

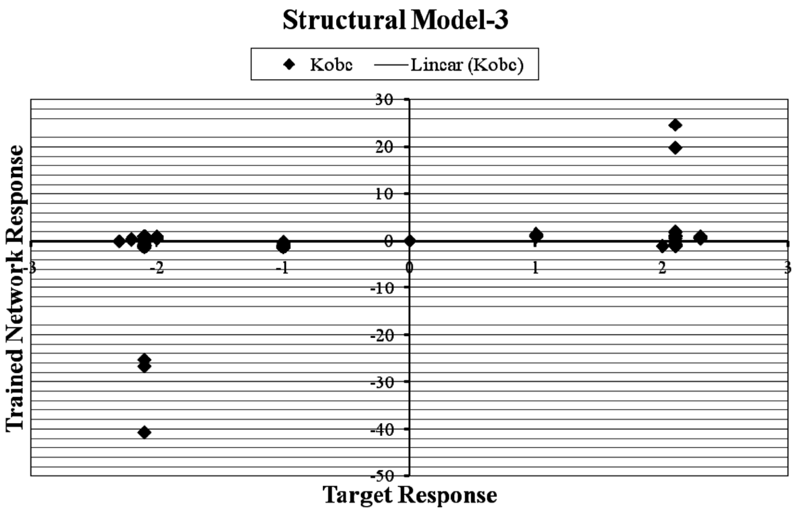

Fig. 17 Testing data performance for Kobe earthquake Model-3

given earthquake record, ex., Kobe, there is a varying performance level which is dependent on the type of structural model.

Figs. 13 and 14 show the performance of the trained network for model-1 under Kobe and North-Ridge earthquakes respectively. Figs. 15 and 16 show the performance of the trained network for model-2 under Kobe and North-Ridge earthquakes respectively. Figs. 17 and 18 show the performance of the trained network for model-3 under Kobe and North-Ridge earthquakes respectively. All figures sketch the target response versus trained network response with an added trend line that reflects the trend of plotted data. By analyzing the referenced figures, it is evident that the trained network performed reasonably well in identifying the deformed pattern classifications of the modeled systems, under the

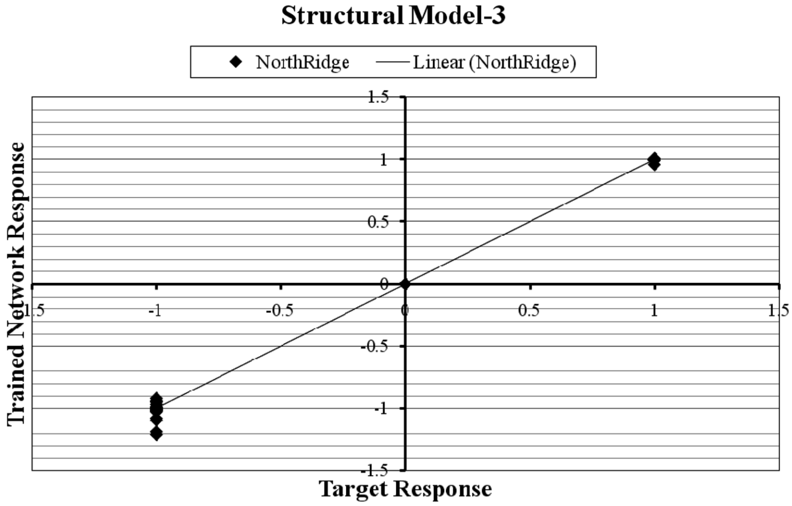

Fig. 18 Testing data performance for NorthRidge earthquake Model-3

effect of North-Ridge earthquake as compared to Kobe earthquake, both being unseen earthquake records. The figures indicate some discrepancies and/or diversion among the target output and the network output, which is largely evident in the Kobe earthquake. However, the significance of such discrepancies can only be evaluated within a reliability assessment backdrop, due to the uncertainties identified above. Fig. 17 indicates that the performance of the network for model-3 under Kobe earthquake is unacceptable which was also reflected by the extremely high mean square error indicated in Fig. 12.

6. Conclusions

In this paper, a smart pattern recognition scheme was explored as a main state identification component to be integrated with a smart structural system. The proposed scheme employed a neural network model for pattern classification. Three structural models were used in testing the performance of the proposed scheme. A pattern classification code was developed in order to identify, in abstract form, the deformed pattern of structural systems under the effect of earthquake excitation. Such pattern classification codes were generated based on the deformed shape of the modeled structural systems. Three earthquake records were employed in training and testing the performance of the neural network pattern identifier. The Hachinohe earthquake record was utilized in training the neural network while both the Kobe and North-Ridge earthquake records were utilized in testing its performance.

Based on the analysis results outlined above, it could be concluded that the employment of a trained neural network in identifying an abstract deformed pattern of structural systems, under the effect of earthquake excitation, has potential applications. However, it is recommended that a reliability assessment measure should be developed in order to accurately evaluate the applicability of such technology under real life conditions. In addition, further fine-tuning of the network design shall be studied such that a more accurate performance could result.

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