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A neural network model to assess the hysteretic energy demand in steel moment resisting frames

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Abstract. Determining the hysteretic energy demand and dissipation capacity and level of damage of the structure to a predefined earthquake ground motion is a highly non-linear problem and is one of the questions involved in predicting the structure's response for low-performance levels (life safe, near collapse, collapse) in performance-based earthquake resistant design. Neural Network (NN) analysis offers an alternative approach for investigation of non-linear relationships in engineering problems. The results of NN yield a more realistic and accurate prediction. A NN model can help the engineer to predict the seismic performance of the structure and to design the structural elements, even when there is not adequate information at the early stages of the design process. The principal aim of this study is to develop and test multi-layered feedforward NNs trained with the back-propagation algorithm to model the non-linear relationship between the structural and ground motion parameters and the hysteretic energy demand in steel moment resisting frames. The approach adapted in this study was shown to be capable of providing accurate estimates of hysteretic energy demand by using the six design parameters.

Keywords: neural network; hysteretic energy demand; steel moment resisting frames; back-propagation.

1. Introduction

Energy-based parameters have gained great attention to be used as seismic design parameters since they were first introduced into the seismic design of structures by Housner (1956). The most rational way to estimate damage of a structure, which involves inelastic behavior, is considered to be the amount of energy imparted to the structure when subjected to an earthquake ground shaking. This energy is called the total energy input, E_I. Part of this energy is dissipated through the hysteretic behavior, which is called the hysteretic energy or hysteretic energy demand, E_H. It should also be noted that the damage to the structural component is due to the hysteretic energy, E_H, not total energy, E_I. Thus, structural failure will occur when the earthquake induced hysteretic energy demand for a structure is larger than the hysteretic energy dissipation capacity of the structure. The hysteretic energy, E_H, and its distribution throughout the structure depend on both the structural systems and the ground motion. Hence, it can be used as a design parameter, especially, when the damage is expected not to exceed some specified limits (Bertero and Teran-Gilmore 1994). Determining the hysteretic energy demand and dissipation capacity and level of damage of the

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structure to a predefined earthquake ground motion (EQGM) is one of the questions involved in predicting the structure's response for low-performance levels (life safe, near collapse, collapse) in performance-based earthquake resistant design (PB-EQRD) (Vision 2000, Chou and Uang 2000, Riddell and Garcia 2001, Bertero and Bertero 1999, Hamburger 1997).

Shen and Akbas (1999) carried out a study on the hysteretic energy demand and its distribution in regular steel moment resisting frames (SMRFs) by nonlinear dynamic time history (NDTH) analysis. A recent study by Manfredi (2001) proposed a method for evaluating hysteretic and total energy based on equivalent number of cycles correlated to the earthquake ground motion characteristics. Riddell and Garcia (2001) also developed a method for deriving the hysteretic energy spectrum of single-degree-of-freedom (SDOF) systems for elasto-plastic, bilinear, and stiffness degrading systems. Cruz and Lopez (2000) investigated the hysteretic energy as a function of structural properties and ground motion characteristics. Choi (2004) investigated the hysteretic energy input characteristics, plastic rotation distributions, and storey drift ratios on 16-storey high-rise SMRFs with mass and stiffness irregularities.

As a result of the developments in computer and software technology, Neural Network (NN) analysis offers an alternative approach for investigation of non-linear relationships in engineering problems. The results of NN analysis yield a more realistic and accurate predictions. The design of a NN is based on simulating the structure and learning activities of the human brain. According to Garrett *et al.* (1997), a NN is "a computational mechanism able to acquire, represent, and compute mapping from one multivariate space of information to another, given a set of data representing that mapping".

NN applications in civil engineering date back to the late eighties (Flood 1989). Structural engineering problems are often too complicated and include incomplete and noisy data. Recent research demonstrated the potential use of this technique in structural engineering (Cladera and Mari 2004, Saasata *et al.* 2004, Tehranizadeh and Safi 2004, Williams and Hoit 2004, Amini and Tavassoli 2005, Papadrakakis *et al.* 2005, Zhao 2005, Kerh and Ting 2005, Yeung and Smith 2005, Lee *et al.* 2005, Ashour and Alqedra 2005, Chen *et al.* 2005). A NN model can help the engineer to predict the seismic performance of the structure and to design the structural elements, even when there is not adequate information available at the early stages of the design process. It also allows the designers to reach an optimal solution during the design process.

The principal aim of this study is to develop and test multi-layered feedforward NNs trained with the back-propagation algorithm to model the non-linear relationship between the structural and ground motion parameters and the hysteretic energy demand in SMRFs.

2. Neural network design

Neural networks (NNs) are simple mathematical structures and suitable tools in establishing a reliable relationship among the various parameters. They are generalization models and can handle highly non-linear problems easily. There are no complex mathematical formulations needed to design a NN. They gather knowledge by learning from examples. A NN can be defined using three fundamental components: transfer function, network architecture and learning law. Rafiq *et al.* (2001) listed some of the major advantages of NN as: (1) NNs learn and generalize from examples and experience to produce meaningful solutions to the problems even in cases where the input data contains error or is incomplete; (2) NNs are able to adapt solutions over time and to compensate for

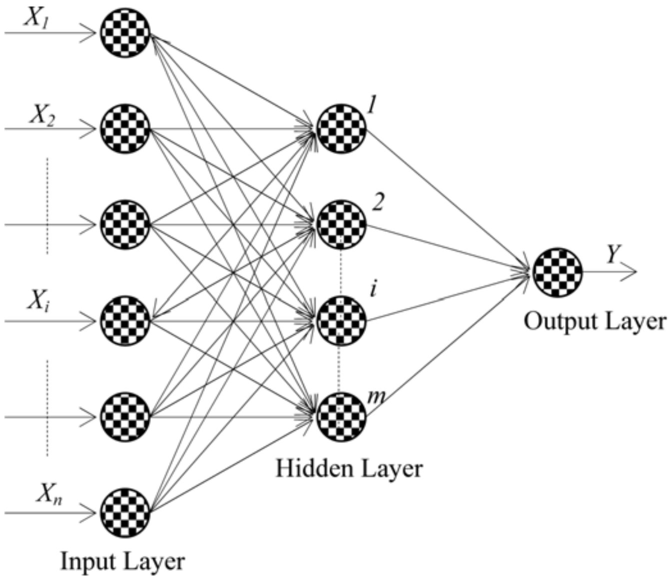


Fig. 1 Typical neural network model

changing circumstances; (3) NNs can evaluate theoretical, experimental, or empirical data based on good and reliable past experience or a combination of these. A typical three-layer feedforward NN with n input nodes, m hidden nodes and one output node is shown in Fig. 1. The input nodes accept the data presented to the NN, whereas the output nodes produce the NN output. The hidden layer (Fig. 1) functions as the interface to extract and to remember the useful features and the sub features from the input patterns to predict the outcome of the network (Rafiq *et al.* 2001, Gunaydin and Dogan 2004).

A typical NN consists of a group of processing elements (PEs) (called neurons) linked together in an attempt to construct a relation in an input/output set of learning patterns. A PE is defined as an information-processing unit with three basic components: (1) a set of synapses; (2) an adder; (3) an activation function (Haykin 1994). In mathematical terms, a PE may be described by computing the sum of their weighted inputs, subtracting its threshold from the sum, and transferring these results by a function as follows (Haykin 1994):

$$u_i = \varphi\left(\sum_{j=1}^{n} w_{ij}x_j - \theta_i\right) \tag{1}$$

where u_i represents the output of a PE, w_{ij} represents the synaptic weights associated with PE i, x_j represents the input signal, θ_i represents the threshold value of the PE, and $\varphi(.)$ presents the transformation (or activation) function. The activation function is used for limiting the amplitude of the output of a PE. Any change in the synaptic weights will, in turn, change the input-output behavior of the NN (Haykin 1994). The PEs are independent of each other through weighted connections that form the power of the influence between the PEs. All PEs are connected to the other PEs in the next layer and operate in parallel. An activation function defines the output of a PE in terms of the activity level at its input. The activation function can be linear or non-linear. A linear activation function's output is simply equal to its input. The most common form of activation function used in the construction of NN is the hyperbolic tangent function that generates output values between −1 and 1 as given below (Neuro Solutions 2003):

$$f(x_i) = \tanh(\beta x_i) \tag{2}$$

where β is used for controlling the slope of the function. There is no guideline to determine the number of PEs required. That is why the effective number of PEs for the hidden layers should be determined by trial-and-error. It depends on the problem and the number and the quality of training pattern. It is recommended that it be more appropriate to carry out a parametric study by changing the number of PE in the hidden layer in order to test the stability of the network (Neuro Solutions 2003). For most of the practical engineering problems, a single hidden layer with an optimum number of PEs is considered to be sufficient (Rafiq *et al.* 2001).

There are basically two classes of NN algorithm: supervised learning and unsupervised learning. Supervised learning NN algorithms, for example back propagation neural networks, require the training data to have been previously specified in different classes so that a subsequent test sample may be assigned to the most appropriate class. Even though, they train slowly and require many training data, the back-propagation neural network (BPNN) is the most commonly used NN for the analysis of structural and civil engineering problems due to its versatile and robust technique and are capable of solving predictive problems (Neuro Solutions 2003). Unsupervised learning, on the other hand, requires no a priori information since its main purpose is to organize the data into clusters that effectively define the various classes or similarities that exist within the data set (Yeung and Smith 2005). Supervised learning algorithms with static back-propagation neural network are selected for the purpose of this study.

The NN model in this study was developed in three phases: the modeling, the training, and the testing phases. The analysis of data, the identification of structural and ground motion parameters, and the internal rules were considered in the modeling phase. The preparation of the data and the adaptation of the learning law for the training were performed during the training phase. And the prediction accuracy of the model were evaluated at the testing phase, i.e., the comparison of the actual hysteretic energy demands and the estimated hysteretic energy demands.

2.1 Modeling the neural network

The selection of the input variables affects the accuracy of the NN model predictions significantly. Different results for different parameters would give different results. Too many input and output parameters cause the learning process to slow down, while too few training sets provide insufficient information. In this study, only the variables that can easily be identified through the non-linear dynamic time history (NDTH) analysis, mode analyses, and pushover analyses were considered. The six design parameters for the input layer were selected to evaluate the hysteretic energy demand (output data) in SMRFs as shown in Table 1. The parameters are 1) earthquake (EQ) intensity, 2) number of stories, 3) soil type, 4) fundamental period (T), 5) strength index (η), 6) E_H/E_I ratio. Earthquake intensity determines the building's seismic behavior and the potential damage. Number of stories considerably impacts the structural properties. Soil type is a key parameter on the seismic design and highly affects the seismic response of the building. Strength index (η) is defined as the ratio of the base shear value at which the structure begins to yield to the seismic weight of the

Table 1 Design parameters

Design parameter	Definition	Range
X_1	Earthquake (EQ) Intensity	1, 2, 3
X_2	No. of Stories	3, 9, 20
X_3	Soil Type	1, 2, 3
X_4	Period (sec)	1.0109, 2.2862, 3.7863
X_5	Strength Index (η)	0.22, 0.11, 0.058
X_6	E_H/E_I	0.68-0.91
Y	E_H/m (cm/sec)^2	415-24614

building (W). Fundamental period (T) is a dynamic property of the building and highly effective on the seismic response of the building depending on the soil type. E_H/E_I ratio gives an idea of how much hysteretic energy is imparted to the structure to be dissipated by yielding and hysteretic behavior as a percentage of the energy input. It should be pointed out that E_H is selected as the output parameter. Hence, selecting E_H/E_I ratio as an input parameter might not look reasonable. However, E_H/E_I ratio can be predicted with adequate accuracy for inelastic systems during the design process (Akiyama 1985, Kuvamura and Galambos 1989, Fajfar *et al.* 1992, Fajfar and Vidic 1994). These six parameters are assumed to be the predominant hysteretic energy demand drivers of this study. Hysteretic energy demand per unit mass (E_H/m) was taken as the output. The energy input into an inelastic system due to an EQGM is dissipated by both viscous damping and yielding. For an inelastic system subject to an EQGM, the following energy terms can be defined by integrating the equation of motion as follows (Chopra 2000):

$$\int_0^u m\ddot{u}(t)du + \int_0^u c\dot{u}(t)du + \int_0^u f_s(u, \dot{u})du = -\int_0^u m\ddot{u}_g(t)du \tag{3}$$

where m is the mass; c is the viscous damping coefficient, f_s is the restoring force (for a linear elastic system $f_s = ku$, k = rigidity), u is the relative displacement of the mass relative to the ground, u_g is the earthquake ground motion displacement. The right side of Eq. (3) represents the seismic energy input, E_I, to the structure. $E_I(t)$ is defined as the work done by the effective seismic force (the mass times ground acceleration) over the structural deformation.

$$E_I(t) = -\int_0^u m\ddot{u}_g(t)du \tag{4}$$

The first term on the left side of Eq. (3) is the kinetic energy, E_k. $E_k(t)$ is proportional to relative velocities of masses at time t, which is only related to the instant response of the structure at time t and can be found by multiplying half of the mass with its motion relative to the ground as follows:

$$E_k(t) = \int_0^u m\ddot{u}(t)du = \int_0^u m\dot{u}(t)d\dot{u} = \frac{m\dot{u}^2}{2} \tag{5}$$

The second term on the left side of Eq. (3) is the damping energy, E_D, which is physically interpreted as the energy dissipated by the viscous damping of the system and a cumulative quantity, ever increasing with the time during the EQGM.

$$E_D(t) = \int_0^u f_D(t)du = \int_0^u c\dot{u}(t)du \tag{6}$$

The third term on the left side of Eq. (3) is the sum of the hysteretic energy, E_H, and the elastic strain energy, E_e. $E_e(t)$ is an instant quantity depending on the current elastic deformation level at time t.

$$E_e(t) = \frac{[f_S(t)]^2}{2k} \tag{7}$$

where k is the initial stiffness of the system. $E_H(t)$ is a cumulative quantity over the plastic deformation throughout the entire duration of the EQGM, and will be zero if the structure remains elastic.

$$E_H(t) = \int_0^u f_S(u, \dot{u})du - E_e(t) \tag{8}$$

E_H includes the inelastic deformation of structural members and is directly related to the cyclic deformation capacity of structural components. In an elastic response, E_H is equal to zero, whereas E_e is negligible compared to E_H in an inelastic response. At any instant time t, E_k and E_e can be computed from Eqs. (5) and (7), respectively. Thus, the energy response terms of a non-linear system can be written as

$$E_k(t) + E_D(t) + E_e(t) + E_H(t) = E_I(t) \tag{9}$$

The instant kinetic energy and elastic strain energy consist of relatively small portion of the E_I at any time during the EQGM and diminish near the end of the EQGM. The E_D and E_H, therefore, are major contributors for dissipating the E_I. Thus, E_k and E_e are negligible in an inelastic response and Eq. (9) can be practically written as

$$E_D + E_H = E_I \tag{10}$$

For a given structure and EQGM, the quantities in Eq. (10) at the end of the EQGM can be determined and the hysteretic energy demand of the structure can be evaluated.

To determine the above-mentioned input parameters; mode, NDTH, and pushover analyses were carried out on three steel buildings with 3-, 9-, and 20-stories. These buildings were designed for gravity, wind, and seismic loads as part of the SAC (Joint venture of SEA, ATC, and CUREE) Steel Project and represent typical low-, medium-, and high-rise steel buildings (Ohtori *et al.* 2000). The structural system for all buildings consists of perimeter SMRFs for lateral loads and interior simply connected frames for gravity. The planes of the buildings are symmetrical. The 3-story building has plan dimensions of 36.60 m × 54.90 m and consists of four-bay and six-bay frames in N-S and E-W directions, respectively, spaced at 9.15 m. The story height is 3.96 m. The 9-story building has plan dimensions of 45.75 m × 45.75 m and consists of five-bay frames in both N-S and E-W directions spaced at 9.15 m. The story height is 3.96 m except at the ground level where it is 5.49 m. The 20-story building has plan dimensions of 45.75 m × 54.90 m and consists of five-bay and six-bay

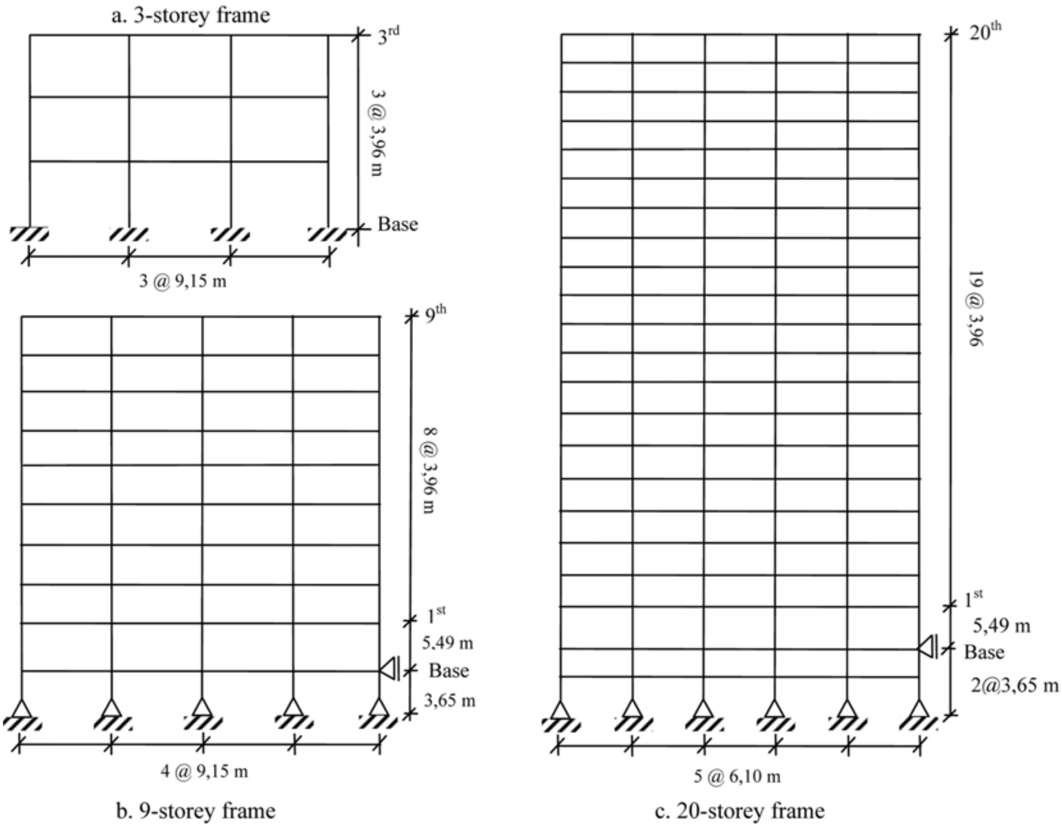


Fig. 2 Elevation of the frames

frames in N-S and E-W directions, respectively, spaced at 9.15 m. The story height is 3.96 m except at the ground level where it is 5.49 m.

The seismic masses of the buildings are 2950 t, 9000 t, and 11100 t for 3-, 9-, and 20-storey buildings, respectively. The perimeter frames were modeled by DRAIN-2DX (Prakash *et al.* 1993). DRAIN-2DX is a general purpose computer program for non-linear dynamic and static time history analysis of plane structures. Step-by-step solution algorithm with a tangent stiffness update at each step and constant-acceleration assumption for the time history analysis are used in DRAIN-2DX. An inelastic truss bar element, a plastic hinge beam-column element, a simple connection element, an elastic panel element, a compression/tension link element, and a fiber beam-column element are included in the element library of the program. The two-dimensional models of the perimeter frames were built for the analyses. The elevation of the frames is given in Fig. 2. Beam-column elements were used in the analyses and inelastic effects were assigned to plastic hinges at member ends. The bilinear inelastic behavior was assumed with a strain hardening of 5% of the initial stiffness in all elements. Mass was assumed to be lumped at the joints. Damping ratio was assumed to be 5% as specified in seismic design codes and Rayleigh damping with the first, second and fourth, and third and sixth natural frequencies for the 3-, 9-, and 20-storey frames, respectively, was used in the analyses. *P-M* (axial load-moment) interaction relation, suggested by AISC-LRFD

(1999), was used as yielding surface of column elements. Beams were modeled as flexural elements. The panel zone effect was neglected in the analyses, but large deformation (P-Δ) effect was considered on the analyses of 9- and 20-storey frames. Panel zone is defined as the area between the stiffeners in the column web. Panel zone strength can affect the connection performance. In inelastic analysis of moment-resisting frames, it is recommended that panel zones be neglected in the model and center-line-to-center-line framing dimensions be used for simplicity (FEMA-350 2000). From the mode analyses, the first natural periods of the 3-, 9-, and 20-storey frames were found to be 1.01 sec, 2.29 sec, and 3.79 sec, respectively. For NDTH analyses, an ensemble of 90 earthquake ground motions (EQGMs) recorded on four different soil types (Type A, B, C and D) were used in the study (Sari 2003). For *Type A, B, C* and *D* soil types, shear velocities (V_s) are bigger than 750 m/sec, between 360-750 m/sec, 180-360 m/sec and less than 180 m/sec, respectively (Sari 2003). The EQGMs were grouped as *Type A&B, Type C* and *Type D* each having 30 EQGMs making a total of 90. Detailed information about the EQGMs can be found at Sari (2003). The peak ground accelerations ($\ddot{u}_{g0}$) of the EQGMs were scaled to 0.4 g, 0.6 g, and 0.8 g, where g is the acceleration due to gravity. Each frame was subject to the EQGMs in each group. A total of 810 NDTH analyses were carried out. Pushover analyses were also carried out on the frames to obtain the strength indices (η) which were found to be 0.22, 0.11, and 0.058 for the 3-, 9-, and 20-story frames, respectively. The three-frames cover the fundamental period from 1.01 to 3.793 sec, and the strength index from 0.058 to 0.22.

The ranges of data for the selected design variables are given in Table 1. The earthquake intensity were designated the values of 1, 2, and 3 corresponding to $\ddot{u}_{g0}$ = 0.4 g, 0.6 g, and 0.8 g, respectively. An EQGM is considered to be severe and very severe for $\ddot{u}_{g0}$ = 0.4 g and 0.6 g or 0.8 g, respectively. The number of stories could be either 3, 9, or 20. The three soil types were numbered as 1, 2, and 3 corresponding to *Type A&B*, *C*, and *D*, respectively. E_H/E_I ratio were in the range of 0.68 and 0.91. This range is in the range of the E_H/E_I ratios obtained by empirical formulas offered by other researchers for single-degree-of-freedom systems (Akiyama 1985, Fajfar *et al.* 1992, Fajfar and Vidic 1994). The E_H/E_I ratios for the frames is found to be constant as 0.50, 0.80, and 0.85 according to Akiyama (1985), Fajfar *et al.* (1992), and Fajfar and Vidic (1994), respectively. The hysteretic energy demand per unit mass (E_H/m) varied between 415 and 24614 (cm/sec)^2 (Table 1). This variation is compatible with the results obtained by Choi and Shen (2001) on the hysteretic energy performance of twelve SMRFs with 2- and 6-stories and 3- and 6-spans. All the design variables were input to the NN as given above.

A total of 27 cases were used for the NN model. Table 2 shows the value of the design parameters for each case. E_H/E_I ratio and E_H/m in each case represent the mean of the thirty runs of the NDTH analyses for a specific soil type and EQGM intensity. The hysteretic energy demand (output) and the input variables from the 27 cases were divided into two sets. One set was put aside for the training of the NN (first 22 cases in Table 2), and the other was for validating the performance of the trained network (testing). For testing purposes, 20% of the data (5 cases) were selected at random order for the testing set for each training cycle (cases below the dotted line in Table 2). The data between the maximums and minimums were selected for testing purposes.

For the modeling of the NN, the data set including training and testing was first normalized. For normalization, the data set were multiplied by normalization coefficients: amplitude and offset. The normalization coefficients were computed based on the minimum and maximum values found among all of the data set. The normalization coefficients for each input PE i (six in this study) were calculated using the following formula (Neuro Solutions 2003):

Table 2 Cases used in constructing the NN model

Case No.	(X_1) EQ intensity	(X_2) No. of stories	(X_3) Soil type	(X_4) Period (sec)	(X_5) Strength index (η)	(X_6) E_H/E_I	(Y_1) E_H/m (cm/sec)^2
1	1	3	1	1.0109	0.22	0.84	4160
2	1	3	2	1.0109	0.22	0.80	4011
3	1	3	3	1.0109	0.22	0.87	5751
4	1	9	2	2.2862	0.11	0.70	415
5	1	9	3	2.2862	0.11	0.81	835
6	1	20	1	3.7863	0.058	0.78	1503
7	1	20	2	3.7863	0.058	0.68	1081
8	1	20	3	3.7863	0.058	0.80	1849
9	2	3	1	1.0109	0.22	0.88	10948
10	2	3	2	1.0109	0.22	0.86	11219
11	2	3	3	1.0109	0.22	0.90	13953
12	2	20	1	3.7863	0.058	0.83	4075
13	2	20	2	3.7863	0.058	0.75	3131
14	2	20	3	3.7863	0.058	0.83	4496
15	3	3	1	1.0109	0.22	0.90	20140
16	3	3	2	1.0109	0.22	0.88	21383
17	3	3	3	1.0109	0.22	0.91	24613
18	3	9	2	2.2862	0.11	0.82	2484
19	3	9	3	2.2862	0.11	0.88	4387
20	3	20	1	3.7863	0.058	0.85	7656
21	3	20	2	3.7863	0.058	0.79	6202
22	3	20	3	3.7863	0.058	0.85	8173
1	1	9	1	2.2862	0.11	0.85	1760
2	2	9	1	2.2862	0.11	0.89	4809
3	2	9	2	2.2862	0.11	0.78	1241
4	3	9	1	2.2862	0.11	0.90	9042
5	2	9	3	2.2862	0.11	0.86	2361

$$Amplitude(i) = [upperlimit - lowerlimit] / [max(i) - min(i)] \tag{11a}$$

$$Offset(i) = upperlimit - Amplitude(i) * max(i) \tag{11b}$$

where $max(i)$ and $min(i)$ represent the maximum and minimum values found within the input $PE\ i$, and *upperlimit* and *lowerlimit* were taken as (1) and (–1), respectively. Then, the data set was normalized as follows (Neuro Solutions 2003):

$$NormalizedData(i) = Amplitude(i) * Data(i) + Offset(i) \tag{12}$$

At the end of the training, the NN data were denormalized using Eq. (12) as follows:

$$Data(i) = [NormalizedData(i) - Offset(i)] / Amplitude(i) \tag{13}$$

Table 3 Combinations of design parameters used in estimating E_H/m

Combo No.	(X_1) EQ intensity	(X_2) No. of stories	(X_3) Soil type	(X_4) Period (sec)	(X_5) Strength index (η)	(X_6) E_H/E_I
1	√	√	√			
2	√		√	√		
3	√		√		√	
4	√		√			√
5	√	√	√	√		
6	√	√	√		√	
7	√	√	√			√
8	√		√	√	√	
9	√		√	√		√
10	√		√		√	√
11	√	√	√	√	√	
12	√	√	√		√	√
13	√		√	√	√	√
14	√	√	√	√	√	√

2.2 The training phase

Standard back-propagation algorithm for the training of the network was employed in this study. A commercial NN software (Neuro Solutions 2003) was used to implement this training method in this study. To investigate which combination of the six design parameters estimates the hysteretic energy demand the best, a total of 14 combinations were used. Table 3 summarizes the design parameters used in each combination. Each combination had EQ intensity and Soil Type as default. Combo no. 1, 2, 3, and 4 were 3-parameter combos, while Combo no. 5, 6, 7, 8, 9, 10 and Combo no. 11, 12, 13 were 4- and 5-parameter combos. Combo no. 14 had all the six design parameters. Thus, the NN models in this study were created using an input layer of 3-, 4-, 5-, and 6-six interconnected PEs corresponding to the 3-, 4-, 5-, and 6-six input parameters, respectively, and one PE corresponding to an output layer selected as the target. Several trials during the testing phase led to the selection of one hidden layer. The hyperbolic tangent function was used as the activation function in this study.

In BB algorithm, NNs learn from examples and training or learning data are introduced into the network with a series of examples of associated input and target output values. Once the input data is processed through the input layer to hidden layer until it reaches the output in a forward direction, the output is compared to the given output. The error between the NN output and target output is processed back through the network (backward pass) adjusting the individual weights (Ashour and Alqedra 2005). During the learning, a gradual reduction of error between the model output and the target output occurs and the error is minimized so as to minimize the sum of squared errors (Haykin 1994). The mean square error (MSE) is defined as Gunaydin and Dogan (2004):

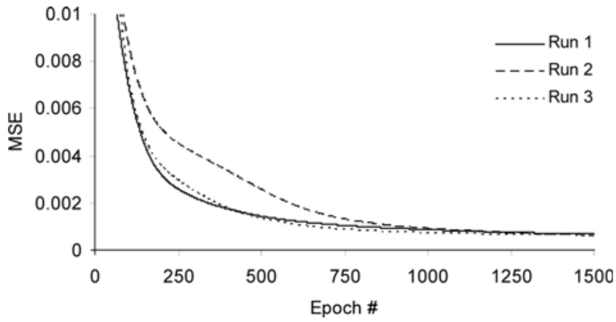


Fig. 3 Learning curve for Combo 14

$$MSE = \frac{\sqrt{\sum_{i=1}^{n}(x_i - X(i))^2}}{n} \tag{14}$$

where n is the number of samples to be evaluated in the training phase, (n = 22 for this study), x_i is the model output related to the sample i (i = 1, 2, ..., n), and $X(i)$ is the target output, i.e., the estimated hysteretic energy demand. *MSE* is a good indicator of how successful the training run was. The error was measured for each run of the epoch number selected and the results for Combo no. 14 are shown in Fig. 3. Epoch number is defined as the training of all cases in a training set. Fig. 3 is a typical learning curve and indicates a reduction in the *MSE* from 0.72 to 0.0007. Training is stopped when the *MSE* remained unchanged for a given number of epochs. If it is not stopped, the NN memorizes the training values and is unable to make predictions when an unknown example is introduced to the NN. For supervised learning control, the maximum number of epochs should be specified showing the number of iterations over the training set. In this study, an epoch number of 5000 for 3-parameter Combos and 1500 for 4-, 5-, and 6-parameter Combos were found to be adequate for the final training process in a series of more than 50 runs for each NN model.

Each layer in NN has a vector of *PE*s, learning rule, and learning parameters. The learning rule is the way by which the correction term is introduced. The learning rate is the amount of correction to be applied to the weights. Momentum as the learning rule is widely used due to its simplicity and efficiency compared to the standard gradient minimum. Selection of a step size is a key parameter in gradient search procedures. If the step size is chosen too small, then it will take too long to get the minimum. If the step size is chosen too large, then it might cause the solution to diverge. The appropriate step size and learning rate (momentum coefficient) should be decided based on the learning of the network. These terms are specified at the start of the training cycle and affect the speed and stability of the NN. The learning rate ranges between 0.0-1.0 and determines the amount of weight modification among the neurons during each cycle of training iteration (Neuro Solutions 2003). In this study, a momentum coefficient of 0.5 for the hidden layer and 0.7 for the output layer performed very well. The step size was selected as 1.0 for the hidden layer and 0.7 for the output layer.

2.3 The testing phase

Testing set gives an idea about the performance of the network. The testing is performed with the best weights obtained during the training. The weighting factors remain unchanged in this phase. The trained weighting factors of the NN are validated with testing data to test the accuracy of the predictions of the trained NN model. The NNs performance in this study was measured by using the hysteretic energy demand percentage error (EPE_{ED}) formula as follows:

$$EPE_{ED} = \frac{x(i) - X(i)}{X(i)} \times 100\% \tag{15}$$

To evaluate the entire NNs overall performance, weighted error (WE) was defined as follows (Hegazy and Ayed 1998):

$$WE(\%) = 0.5 \text{ (Average } EPE_{ED} \text{ for Training Set)} + 0.5 \text{ (Average } EPE_{ED} \text{ for Testing Set)} \tag{16}$$

Table 4 summarizes the performance of the NN models for each Combo. Among all Combos, the highest error rate was obtained for Combo no. 4. The smallest EPE_{ED} for the training set was for Combo no. 6. The smallest EPE_{ED} for the testing set and WE were for Combo no. 14, which included all parameters. Ignoring Combo no. 4, one can say that the WE for any combination of six parameters was less than 7%. EPE_{ED} for Combo 14 varied between 0.41% and 7.31% (Fig. 4).

EPE_{ED} for the testing set in each NN model is given in Fig. 4. The highest error in the testing set was observed for Combo no. 4 and the smallest error was for Combo 14 (Fig. 4). Average EPE_{ED} for the 5 testing cases for Combo 14 was calculated as 2.78%, while it was 4.97% for the training set (22 cases). Thus, the WE was found to be 3.87% (Table 4).

Sensitivity analysis provides valuable information about the effect that each network input is having on the network output. This gives the user the option of removing the insignificant channels from the network reducing the size of the network. This would reduce the complexity and the

Table 4 NNs performance

Combo No.	EPE_{ED} (training) (%)	EPE_{ED} (testing) (%)	WE (%)
1	5.12	6.87	5.99
2	5.26	5.07	5.16
3	4.45	7.33	5.89
4	28.46	41.25	34.86
5	3.59	7.34	5.47
6	3.25	10.18	6.72
7	6.96	5.21	6.08
8	5.73	6.72	6.23
9	4.78	6.36	5.57
10	7.00	5.69	6.34
11	4.33	9.21	6.77
12	3.96	6.24	5.10
13	3.59	9.66	6.62
14	4.97	2.78	3.87

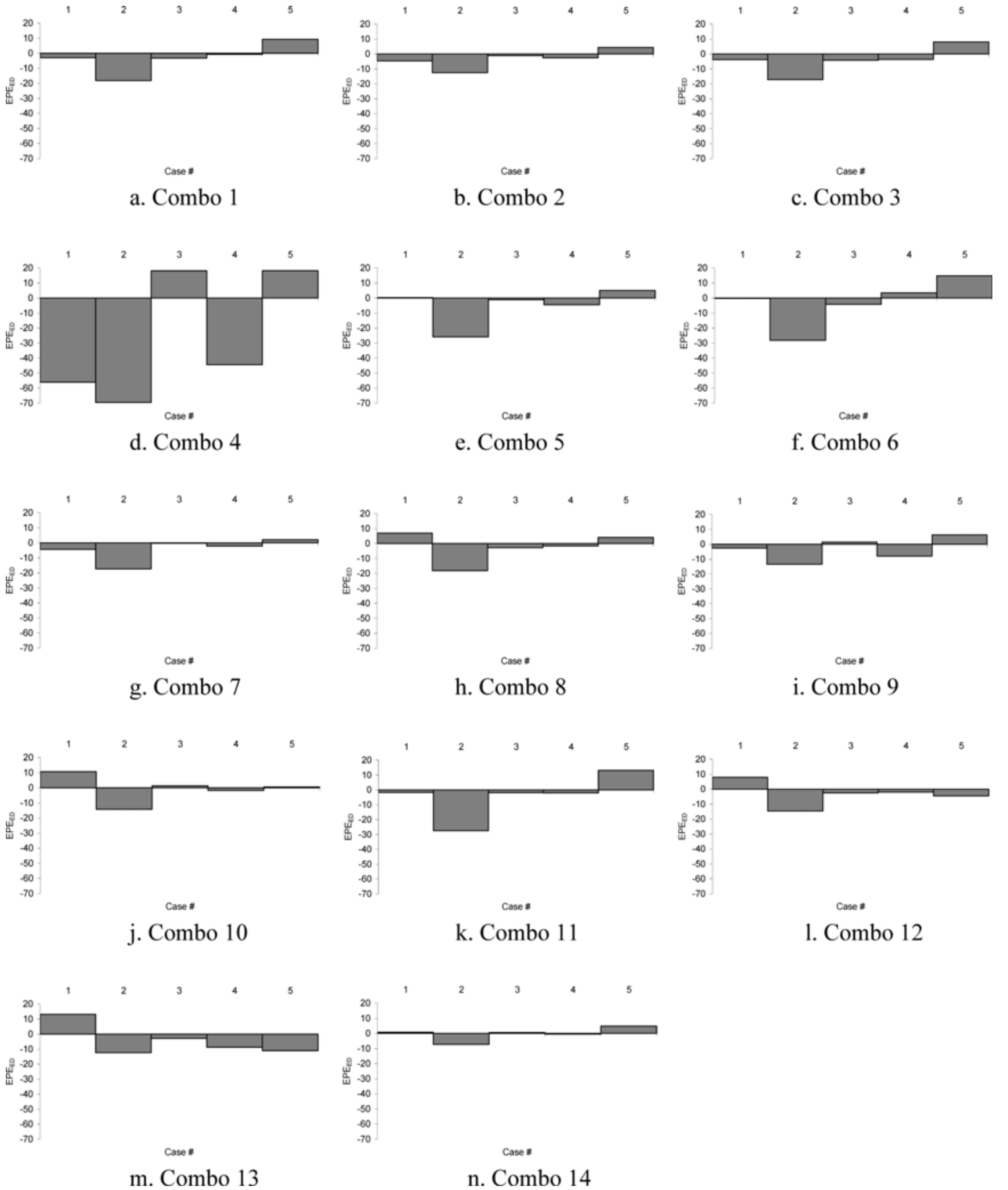
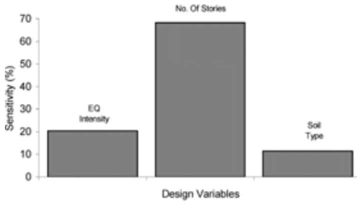
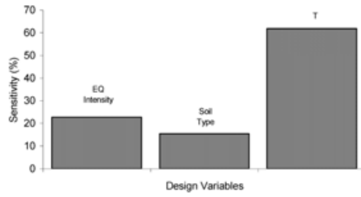


Fig. 4 Error on the estimated hysteretic energy demand vs. actual hysteretic energy demand for the five testing samples

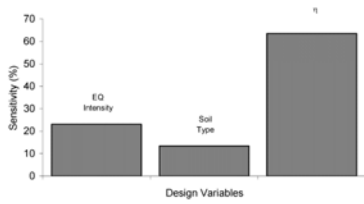
training times. During the analysis, the network weights are not affected, because the network training is disabled. The inputs to the network are shifted slightly and the corresponding change in the output is reported as a percentage summing to 100% in total (Neuro Solutions 2003). In this



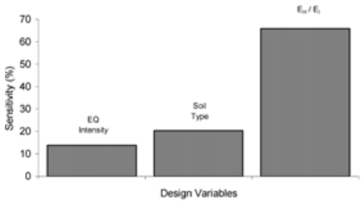
a. Combo 1



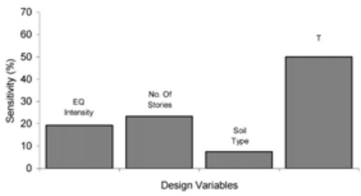
b. Combo 2



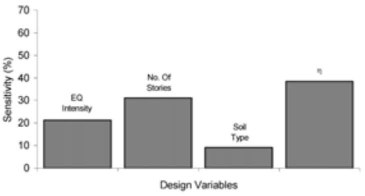
c. Combo 3



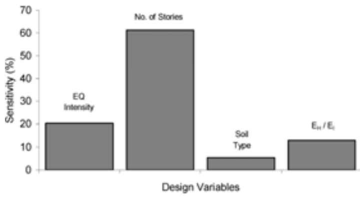
d. Combo 4



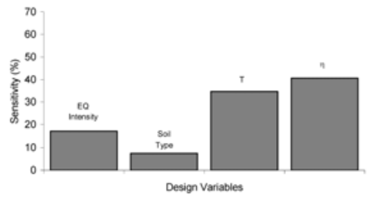
e. Combo 5



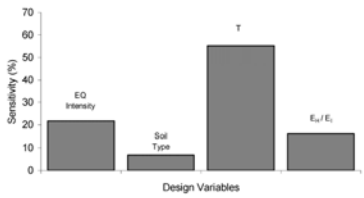
f. Combo 6



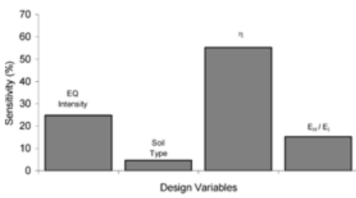
g. Combo 7



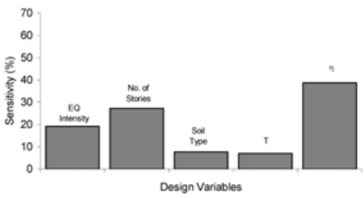
h. Combo 8



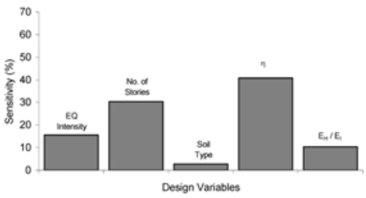
i. Combo 9



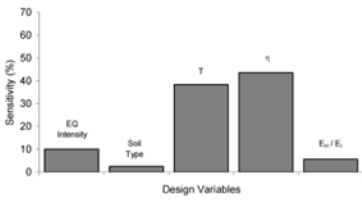
j. Combo 10



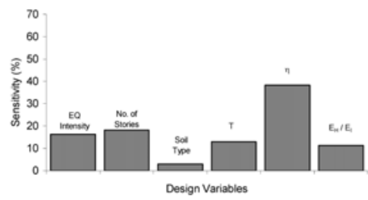
k. Combo 11



l. Combo 12



m. Combo 13



n. Combo 14

Fig. 5 Sensitivity analyses results

study, for the 3-parameter Combos (Fig. 5a, 5b, 5c, and 5d), the most effective parameter was found to be Number of Stories, Period, Strength, and E_H/E_I. Soil Type was observed to be the least significant design parameter for any Combo except Combo 4. For the highest performance Combo (Combo 14), the input parameter strength was found to be the most effective parameter on hysteretic energy demand prediction (38.29%) (Fig. 5). It was also the most effective parameter in any Combo when included. The input parameters EQ intensity and number of stories have the effect of 16.29% and 18.13%, respectively, on the hysteretic energy demand prediction for Combo 14 (Fig. 5n). The effect of the input parameter period and E_H/E_I ratio have only the effect of 12.99% and 11.36% for Combo 14, respectively. The smallest effect is due to the input parameter soil type (2.94%) (Fig. 5n).

2.4 Comments on results

Data from 5 cases were used for testing purposes in this study out of a total 27 cases. The results for the 6-parameter Combo (Combo 14) showed 96.1% of average accuracy with a MSE of 0.0007. For the worst Combo (ignoring Combo no. 4), the average accuracy was 93.3%. Considering that the problem was highly non-linear, these figures were considered to be quite good. For Combo 4, the NN apparently could not learn very much from the data presented to the network, especially E_H/E_I, which is varied only in a small range (0.68-0.91). However, the highest performance observed in 6-parameter Combo (Combo 14) shows that even the small attributes provided by the other parameters such as E_H/E_I may enhance the NNs prediction capability, i.e., the more the number of design parameters, the higher the accuracy. The results from the sensitivity analyses proved the intuitive feeling that in a regular building, strength has the highest effect on the hysteretic energy demand on the structure. However, it was interesting to see that soil type had no significant effect on estimating the hysteretic energy demand on SMRFs. The results were also tested through another NN application and similar results were obtained (Hegazy and Ayed 1998). The WE was found to be 3.68% with an average EPEED of 4.97% and 2.38% for training and testing cases, respectively, using Hegazy and Ayed's method (1998).

3. Conclusions

In this study, the NN model was employed to develop and test hysteretic energy demand prediction in SMRFs. The data of 22 cases were used to train the NN. The testing of the NN was done by the data of 5 testing cases. The approach adapted in this study was shown to be capable of providing the best accurate estimates of hysteretic energy demand by using the six design parameters. The results are considered to be encouraging for further research of expanded data sets. By setting up some random variations in the design parameters, it is possible to estimate the hysteretic energy demand for new or existing regular SMRFs.

It should be noted that neural networks learn from examples of which performance strongly depends on the quality and the quantity of examples. The more examples there are, the less the prediction error is. Thus, to study modeling and prediction methods, and construct an accurate prediction model of hysteretic energy demand, there is a need for reliable, high-quality, full-scale data of buildings of various configurations. The distribution of the hysteretic energy demand throughout the height of the building by NN modeling can also be studied using the same approach.

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