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Displacement Based Intelligent Seismic Assessment of Existing Steel Buildings

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Abstract. *Performance based seismic design usually requires nonlinear dynamic or static analyses to assess the performance level of the structure under seismic action. To trace the exact performance point of a structure, these analyses should sometimes be repeated several times over. Analysis iterations mainly depend on the initial design and performance of the structure. So, a method that can present an appropriate initial selection with minimum time and effort would be precious. Such a method would also be very effective for seismic structural assessment. In this paper, an intelligent system has been created for the estimation of plastic hinge distribution and lateral ductility distribution and, also, for the assessment of existing steel structures, based on a direct displacement based design procedure. The method has been applied to the steel braced frames with concentric bracing systems in low, medium and high rise buildings. The designer can use this knowledge based system to obtain the performance level of existing steel structures, according to proposed seismic code levels. Finally, the intelligent system has been verified using nonlinear dynamic analysis.*

Keywords: *Performance assessment; Artificial intelligence; Back propagation neural network; Nonlinear analysis.*

INTRODUCTION

Earthquake induced forces are direct functions of the energy absorption, damping and ultimate damage capacity of structural members, which all depend on deformation. The purpose of Performance Based Design is to design the structure with sufficient and proportioned stiffness and strength in the structural members so as to develop inelastic action in the ductile designed members and to have appropriate overstrength in the brittle members. Then, the structure must be checked so that demands do not exceed existing capacities. This is best performed using a set of nonlinear dynamic analyses under earthquake with appropriate characters. In the last four decades, the idea of DBD, introduced and developed by different researchers, started by introduction of the concept of a substitute structure [1]. This idea has been adopted for the direct displacement design of SDOF and MDOF reinforced concrete bridges [2]. In all this research, seismic demand is specified as either a displacement spectrum or an acceleration-displacement response spectrum.

In this paper, the direct DBD method is briefly reviewed for multi-story steel buildings. Displacement based seismic design usually requires nonlinear dynamic or static analyses to assess the performance level of the structure under seismic action. To trace the exact performance point of a structure, these analyses should sometimes be repeated several times over. Analysis iterations mainly depend on the initial design and performance of the structure. So, a method that can present an appropriate initial selection with minimum time and effort would be precious. Such a method would also be very effective for seismic structural assessment. In this paper, artificial neural networks (ANN) have been employed for estimation of plastic hinge distribution and lateral ductility distribution and, also, for the assessment of existing steel structures, based on a direct displacement based design procedure. The method has been applied to steel braced frames with concentric and eccentric bracing systems in low, medium and high rise buildings. The designer can use this knowledge based system to obtain the performance

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level of existing steel structures, according to proposed seismic code levels. Finally, the intelligent system has been verified using nonlinear dynamic analysis.

SEISMIC DESIGN METHODOLOGY

Displacement Based Design of Steel Frames

The conventional DBD of multi story buildings is based on generation of the equivalent SDOF system or the substitute structure concept (Figure 1). For this purpose, it is assumed that the structure vibrates in a pre-defined harmonic displaced shape. The base shears and the works developed by lateral external forces are also assumed the same for both equivalent and main structures [3,4]. Consider the relative displacement vector, $\{\delta(h,t)\}$, for the multistory building with total height of H, expressed in a decomposed form of displacement and time and assume a harmonic response with amplitude Δ for the system. One can write [5]:

$$\{\delta(h,t)\} = \Delta.\sin(\omega.t).\{\Phi(h)\}, \quad 0 \le h \le H, \tag{1}$$

which results in an acceleration vector, $\{a(h,t)\}$, proportional to the assumed normalized displacement vector, $\Phi(h)$, as follows:

$$\{a(h,t)\} = -\Delta.\omega^2.\sin(\omega.t).\{\Phi(h)\} = -\omega^2.\{\delta(h,t)\}. \tag{2}$$

In order to obtain the equivalent system parameters, the normalized displacement vector, $\{c(h,t)\}$, is defined as:

$$\{c(h,t)\} = \frac{1}{\delta_{\text{eff}}}\{\delta(h,t)\}, \tag{3}$$

where δ_{eff} is called the effective displacement. From Equations 2 and 3, one may have:

$$c_i(h,t) = \frac{\delta_i(h,t)}{\delta_{\text{eff}}} = \frac{a_i(h,t)}{a_{\text{eff}}}, \quad i = 1, 2, \cdots, n, \tag{4}$$

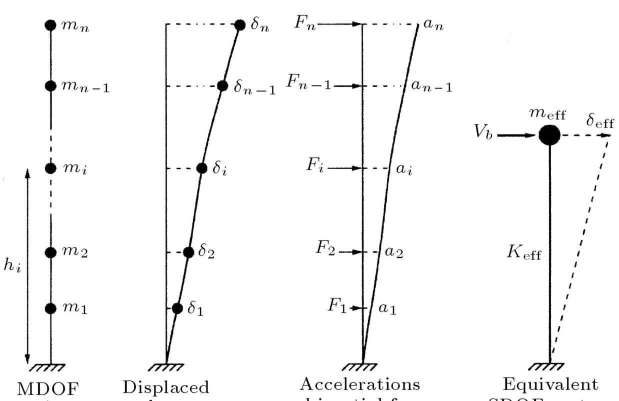

Figure 1. Idealized model of equivalent single degree of freedom system.

in which n stands for number of stories, a_{eff} is called the effective acceleration of the equivalent SDOF system and δ_i and a_i are the story displacement and acceleration, respectively. Using Equation 4, the base shear can now be determined in terms of the multi story structure and the equivalent system parameters as:

$$V_b = \sum_{i=1}^{n} f_i = \sum_{i=1}^{n} m_i.a_i = \left\{\sum_{i=1}^{n} m_i.c_i\right\}.a_{\text{eff}}$$

$$= m_{\text{eff}}.a_{\text{eff}}, \tag{5}$$

which leads to the definition for the effective mass as $m_{\text{eff}} = \sum_{i=1}^{n} m_i.c_i$. The lateral force at each level, f_i, may also be determined using Equations 4 and 5 as:

$$f_i = \frac{m_i.\delta_i}{\sum_{j=1}^{n} m_j.\delta_j} V_b. \tag{6}$$

Equating the external works for the two systems, $V_b.\delta_{\text{eff}} = \sum_{i=1}^{n} f_i.\delta_i$, and using Equation 6, one can obtain the definition for effective displacement as:

$$\delta_{\text{eff}} = \frac{\sum_{i=1}^{n} m_i.\delta_i^2}{\sum_{i=1}^{n} m_i.\delta_i}. \tag{7}$$

The effective stiffness of the substitute SDOF system may also be obtained by entering the effective displacement into the displacement response spectrum with the appropriate damping value and then substituting the obtained effective period and effective mass from Equation 5 into the following equation:

$$K_{\text{eff}} = \frac{4\pi^2 m_{\text{eff}}}{T_{\text{eff}}^2}. \tag{8}$$

The effect of story ductility may be considered, substituting δ_i, defined in Equation 4, with the following relationship:

$$\delta_i = \mu_i.\delta_{yi}, \tag{9}$$

where μ_i is the story ductility demand and δ_{yi} is the story yield displacement. The problem is now how to determine these two parameters. The story yield displacement, δ_{yi}, may be obtained by defining the story yield mechanism. Finally, for detailed design of the structure, the base shear is obtained as $V_b = K_{\text{eff}}.\delta_{\text{eff}}$ and, then, the story forces, f_i, are computed using Equation 6. Then, the capacity design of the structure can be started, considering the ductility capacities. This capacity-designed structure may then be verified using time history or static push-over analyses.

Design Displacement Spectrum

In this paper, a displacement response spectrum has been used, which was obtained by the authors through a deterministic procedure, based on acceleration data for Iranian earthquakes [6]. These accelerograms were selected from more than 2000 records for different stations and earthquakes in Iran. The spectrum with 5 percent damping for soil type C (or II, according to the Iranian seismic code) has been presented in Figure 2 [6]. Assuming a single displacement cycle based on ultimate displacement, the following well-known relationship between ξ_{eff} and ductility demand μ for Elastic-Perfectly Plastic (EPP) behavior is obtained [3]:

$$\xi_{\text{eff}} = \frac{2}{\pi}\left(1 - \frac{1}{\mu}\right) + \xi_{\text{elastic}}, \tag{10}$$

where ξ_{elastic} stands for the damping of the elastic structure. The equivalent viscous damping for bilinear systems with strain hardening ratio α and ductility μ may also be determined using the following equation [5]:

$$\xi_{\text{eff}} = \frac{2}{\pi}\left(\frac{(1-\alpha).(\mu-1)}{\mu - \alpha\mu + \alpha\mu^2}\right) + \xi_{\text{elastic}}. \tag{11}$$

Assuming 3.0% elastic damping for steel structures, the effect of hardening on the effective damping values has been presented in Figure 3. The obtained effective damping, which is greater than the elastic viscous damping, due to the hysteretic behavior, is then used to get the effective period from the displacement spectrum.

Ductility Demand Distribution Patterns

In conventional DBD, in which the ductility is assumed uniform over the height, the effective stiffness will not change with the ductility. As shown in Figure 4, such

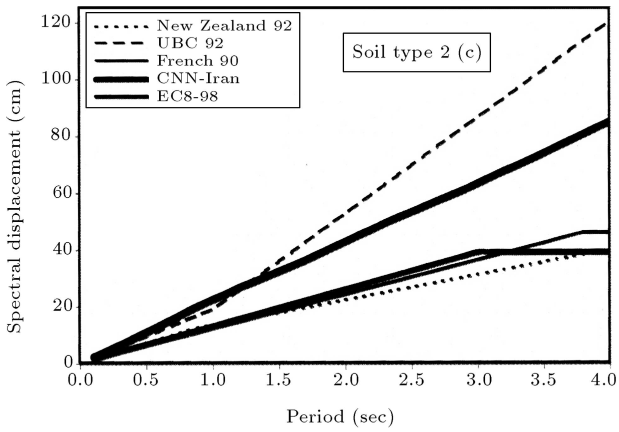

Figure 2. The displacement spectrum based on filtered Iranian earthquakes and the design curve.

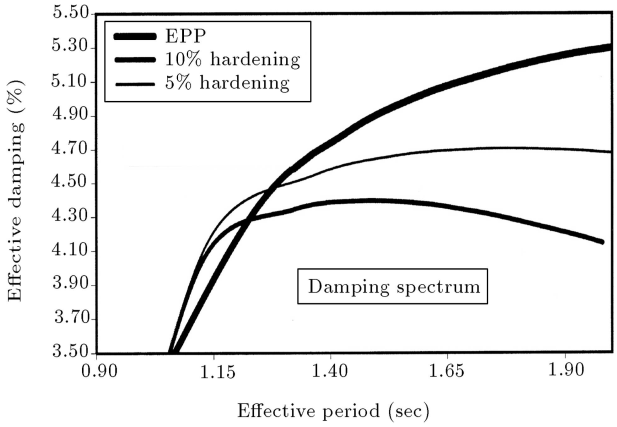

Figure 3. Damping spectrum for EPP; 5 and 10 percent hardened systems.

assumptions may result in vagueness of story ductility values. For example, one target ductility value for the roof or the whole structure may have been obtained from different ductility distributions and, thus, lead to inappropriate design. If the ductility is distributed according to the ductile design of braces over the height, for example, based on the elastic modal vibration of the structure, the brace characteristics will interfere with the lateral displacement. The increase in resulted ductility, in comparison with uniform distribution, will cause reduction in the effective mass. Due to the rise in effective displacement, this will result in an increase in the effective period and, thus, reduce the resulted effective stiffness of the substitute SDOF structure. In the presented DBD method, the lateral displaced shape of the structure is modified using multi-modal, polynomial and exponential distributions of ductility over the height of the structure, in order to take into account higher mode effects and combined shear and flexural lateral deformations. Higher mode effects cause considerable changes in the dynamic response of large period or flexible structures, such as tall buildings. The selected pattern is an exponential function, with parameter a, as follows [2]:

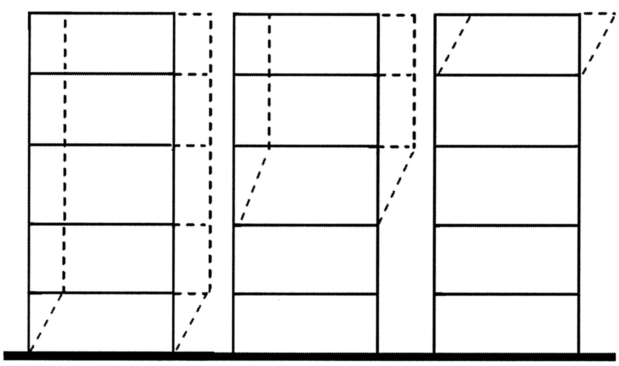

Figure 4. Examples showing the importance of story ductility distribution pattern.

$$\phi_{\mu[\mathrm{EXP}]} = \mu_{\max}.\frac{1-\mathrm{EXP}(-ah/H)}{1-\mathrm{EXP}(-a)}, \tag{12}$$

where h is the location to calculate the pattern value, $\phi_{\mu[\mathrm{EXP}]}$, and H is the total height of the building.

NEURAL NETWORK MODEL

Back Propagation Neural Networks

In this study, the back error propagating neural network is employed as the nonlinear identification approach. These networks are introduced with three basic elements, which are nodes or units, layers or architecture and the activation function. The general procedure of these networks has been briefly presented in Table 1.

In a back error propagating algorithm with a gradient descent rule, the learning rate is reduced as the error is propagating backward to the input channel. In other words, the gradient gets attenuated by each layer in this reverse. So, it was preferred to use a small learning rate for layers near the output channel and an increasing learning rate as layers moving back toward the input channel. With the standard steepest descent, when the learning rate is held constant through training, for a high learning rate, the algorithm may oscillate and become unstable and, for small learning rates, the algorithm will take too long to converge. The adaptive learning rate used in this study kept the learning step sizes as large as possible and made them responsive to the complexity of the local error surfaces. In the adaptive learning rate, the weights and biases are corrected at each epoch using the correct learning rate. If the error in the current epoch is less than the previous one, the learning rate is increased by about 5 to 10 percent and, otherwise, decreased. Also, a momentum term was added in the modification of weights, but the momentum factor, "ε", remained unchanged during training:

$$\Delta w_{ij}^{n+1} = \varepsilon(\delta_{pi}.a_{pj}) + \alpha \Delta w_{ij}^{n}. \tag{13}$$

Networks with biases can represent relationships between inputs and outputs more easily than networks without biases. For example, a neuron without a bias will always have a net input to the transfer function of zero when all of its inputs are zero. While a network with bias can learn to have any net transfer function input under the same conditions by learning an appropriate value for the bias. On the other hand, some studies have shown no noticeable effects for the bias terms in network performance. However, in this study, bias terms were provided for all hidden layers and initiated with random values. Also, in each phase where a node or layer was added, full connections between the neurons were provided and the training process was initiated.

ARTIFICIAL INTELLIGENCE FOR PERFORMANCE BASED DESIGN

In this session, application of a back propagation neural network in the performance based seismic design of steel structures has been reviewed. The following main objectives are considered for obtaining the algorithm:

- Reducing time and effort for iterative design;
- Pertaining acceptable accuracy of calculations and results;

Table 1. The back error propagation network algorithm.

• Set all weights, biases, weight modifiers and bias modifiers to random values in the desired ranges;
• Scale and present input vector to the input layer;
• Calculate input vector of the hidden layers: $Y_u^{\mathrm{in}} = \nu_u + \sum_{h=1}^{H} x_h.w_{hu}$;
• Determine output vector using the transfer function:
$Y_u^{\mathrm{out}} = f(Y_u^{\mathrm{in}})$
Continue the procedure for all layers to obtain output vector;
• Calculate the error vector and total error to check for convergence:
• $\delta_u = (t_u - y_u).f'(Y_n^{\mathrm{in}}), \qquad E = \frac{1}{2}\sum_{u=1}^{U}(t_u - y_u)^2,$
• Calculate weight and bias modifiers:
• $\Delta\nu_{hu} = \alpha.\delta_u, \qquad \Delta w_{hu} = \alpha.\delta_u.y_h,$
• Modify weights and biases in the output layer:
• $w_{hu}^{\mathrm{new}} = w_{hu}^{\mathrm{old}} + \Delta w_{hu}, \qquad \nu_{hu}^{\mathrm{new}} = \nu_{hu}^{\mathrm{old}} + \Delta\nu_{hu},$
• Back propagate error in the hidden layers of the network, modify weights,
biases, weight modifiers and bias modifiers and try again;
• The procedure is continued until the convergence criteria are met.

- Reduction of input and output parameters for network convergence by minimum effort and time;
- Usage of appropriate parameters and training algorithms for better convergence.

Figure 5 shows the final design algorithm, based on the procedure described in the previous sections of the paper, where the use of a neural network is highlighted. As shown in Figure 5, the main usage of a back propagation neural network has been introduced here. The first one is the estimation of plastic hinge locations for the structure under nonlinear behavior. The second one is the estimation of the lateral distribution of ductility demand for different performance levels. Allocation of plastic hinges in a structure is a rigorous task in the seismic analysis of structures. On the other hand, in order to perform the capacity design procedure in a structure, the location of plastic hinges in large earthquakes is of high importance. If the plastic hinges are known, the capacity design of the beam-to-column connection will follow Equation 14 [7]:

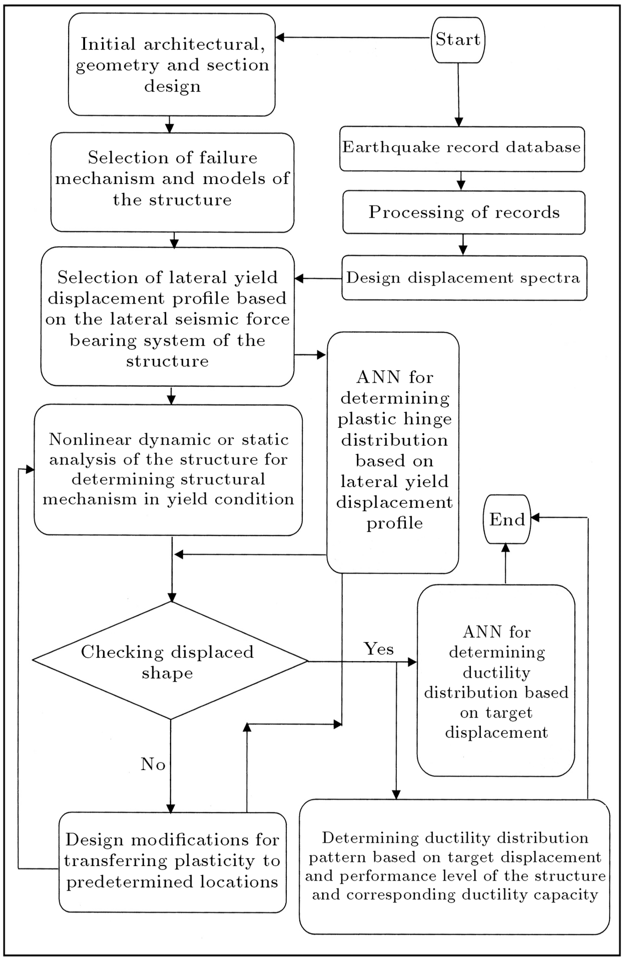

Figure 5. Intelligent systems for performance based seismic design.

$$\frac{\sum M_{pc}^*}{\sum M_{pb}^*} > 1, \tag{14}$$

where the total plastic moment of beams $\sum M_{pb}^*$ and columns $\sum M_{pc}^*$ can be obtained using the following relationship:

$$\sum M_{pc}^* = \sum Z_c \left(F_{yc} - \frac{P_{uc}}{A_g} \right), \tag{15}$$

$$\sum M_{pb}^* = \sum (1.1 R_y . F_{yb} . Z_b + M_y), \tag{16}$$

where A_g is the column gross area, Z is the plastic section modulus, F_y is the characteristic yield strength, M_y is the yield beam moment and P_{uc} is the axial capacity of the column. R_y depends on the type of steel and may be equal to 1.5.

ANN for Determining Ductility Distribution Pattern

Figure 6 shows the network designed for the estimation of the ductility distribution pattern in steel buildings. The input vector of this network contains the vector of stiffness distribution throughout the height of the structure, which has been defined using 10 points. It means that the stiffness distribution function through the height of the building has been replaced with 10

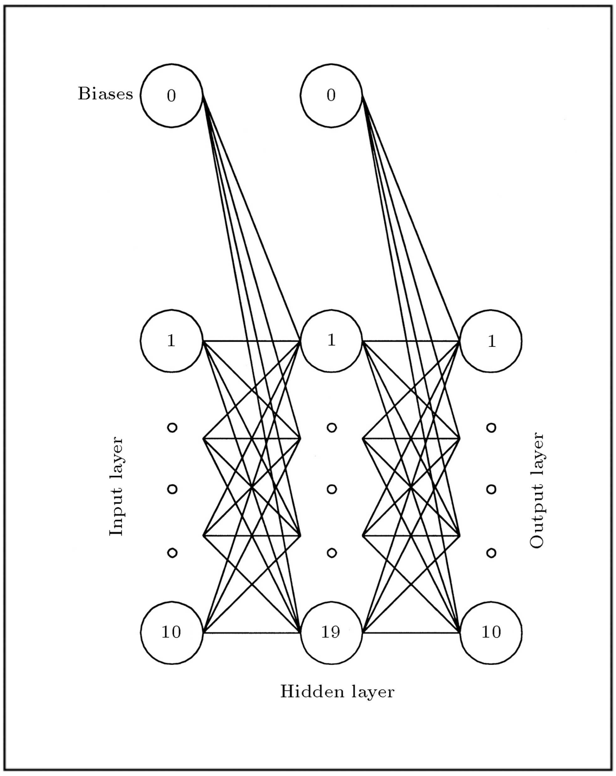

Figure 6. ANN model for determining ductility distribution pattern.

equally spaced points. Thus, the network has 10 input neurons. This parameter has shown the largest correlation with ductility in the numerical studies and may easily be calculated for any structure with any lateral force resisting system. The output also contains 10 units, which present the predicted value of ductility at the points with the same spatial coordinates. The network should be trained for every performance level, as the response of the structure and the ductility for each level is different. The number of units or neurons in the hidden layer may be obtained by a dynamic node creation scheme or a trial and error process until the best network convergence is reached [8,9]. For the collapse prevention level, one hidden layer with 19 units was obtained. The collapse prevention performance level represents a damage state of near complete damage, though the building has experienced neither partial nor total collapse. The damage sustained has substantially degraded both the stiffness and strength of the structure to resist additional lateral loading and the structure is unsafe for occupancy until shored or repaired, which may be impractical to accomplish.

ANN for Determining Plastic Hinge Distribution

This network is specifically designed for allocation of a plastic hinge formation in steel frames with flexural type resisting systems. The columns are assumed to have the same section properties in each story and the beams are also assumed to be the same at each level. The yield stress of all members has also been predefined equal to $F_y = 245$ MPa. The structural system is symmetric and all plastic hinges are restricted to form at the ends of the beam or column.

Figure 7 shows the network designed for estimation of the plastic hinge distribution in steel buildings. Ranges of 9 to 15 story buildings have been used for training. The input vector of this network contains the vector of story stiffness, which has been defined using 30 units. Thus, the network has 30 input neurons. This parameter may easily be calculated. The output also contains 30 units, which present the predicted number of plastic hinges at the top and bottom of each story. The network should be trained for every performance level, as the response of the structure and the ductility for each level are different. For the life safety level, one hidden layer with 44 units was obtained. The life safety level is a performance state in which, although significant damage has been sustained, a margin remains against either partial or total collapse. A building meeting this level of performance will not endanger the safety of occupants during an earthquake.

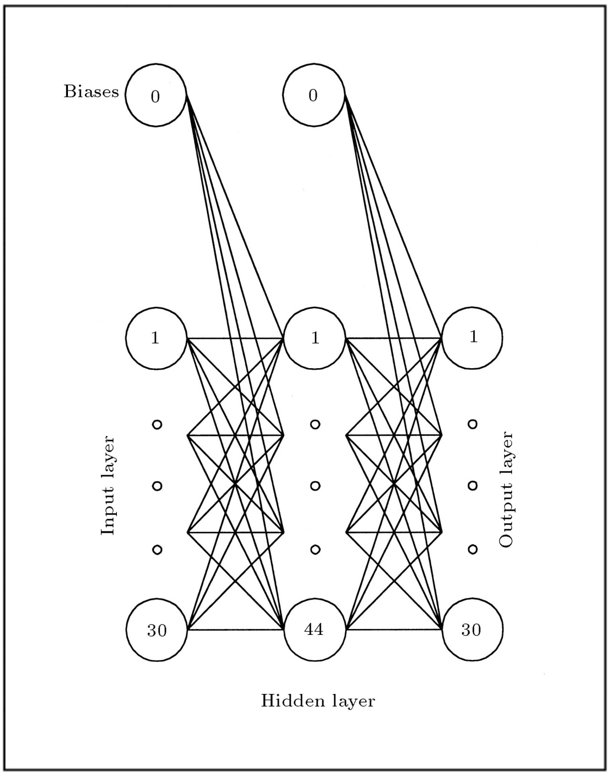

Figure 7. ANN model for determining plastic hinge distribution.

Intelligent Seismic Assessment of Existing Steel Structures

The design and assessment for seismic loads are different, not only for the nature of the load, but for the possibility of the extreme non-linear behavior of the structure. An evident confirmation of this can be found in the approximate correspondence of the strain state, defining an ultimate limit state under gravity loads, with a light damage state, with allowed immediate occupancy under seismic loads. The implication was the introduction of behavior factors that are somehow related to ductility and, therefore, to displacement and damage. Only recently has it become clear that it is more rational and potentially more reliable to develop some direct displacement-based design procedures, defining displacement-based limit states and, therefore, directly addressing damage control. This approach is even more appropriate when assessing the seismic response of existing structures, for which this kind of nonlinear response and post-elastic mechanism cannot be assumed, on the basis of the application of capacity design principles. The definition of the limit states of interest is obviously, in principle, different when dealing with existing structures [10].

In structural assessment, the objective is calculation of the strength and ductility capacity of the structure. The displacement-based assessment of an existing structure, which has been employed in this research, includes the following steps:

- Estimation of flexural and shear strength of all members;
- Calculation of plastic rotation capacity of the connections of the structure;
- Estimation of lateral story displacement capacity;
- Prediction of plastic mechanism at each performance level;
- Calculation of effective stiffness of structure;
- Calculation of effective damping based on the mechanism;
- Calculation of displacement demand of structure;
- Comparison of displacement demand and capacity.

The network designed for the assessment of existing steel structures has been shown in Figure 8. This network has been constructed, based on the assumptions used for estimation of the lateral ductility distribution and contains 10 input and output units. In the next section, these networks have been verified using numerical examples.

NUMERICAL ANALYSES

In this section, the presented modifications have been verified through some numerical examples, including three, nine and twenty story braced frames. The geometric data of the models are presented in Table 2 and Figure 9. The steel properties are; yield stress, $F_y = 245$ MPa, initial elastic modulus, $E = 2.10e5$ MPa, with an elasto-plastic behavior with five percent strain hardening, or second modulus, $E_s = \alpha.E$, $\alpha = 0.05$. The dead load is assumed to be 3.9 kPa and the reduced live load 1.4 kPa at floor levels. At roof level, these values are assumed to be 3.2 kPa and 1.0 kPa, respectively. The assumed data may be sufficient for DBD, but for the nonlinear push-over and time history analyses, the detail design of the members must also be available. This has been performed using capacity design procedures and was performed using a SAP2000 commercial program. Nonlinear dynamic analyses have been performed using the DRAIN2DX [11] program, using three selected earthquake records that were compatible with the obtained response spectrum shown in Figure 2. The final design sections for a nine story example have been presented in Table 3.

Results Verification

The parametric studies used for the determination of the network architecture for estimation of the lateral ductility distribution have been shown in Figure 10. In

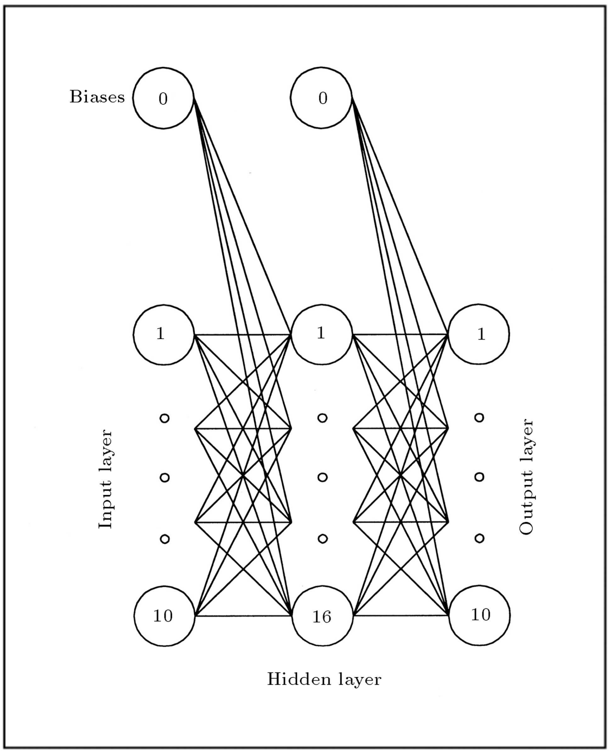

Figure 8. ANN model for seismic assessment of existing steel structures.

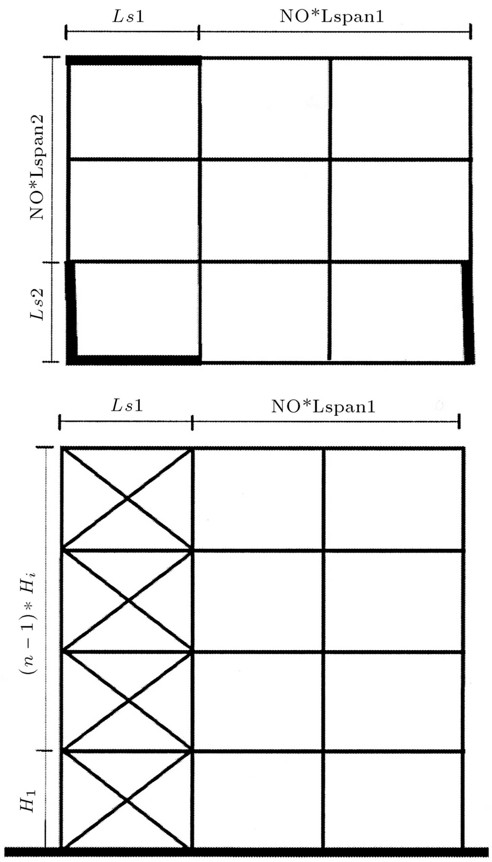

Figure 9. Geometric data for numerical examples.

Table 2. Geometric data for numerical examples (Dimensions in meter).

n story	$H1$	$(n-1)*Hi$	$Ls1$	No*Lspan1	$Ls2$	No*Lspan2	l_l
3 story	3.5	2*3.5	2(4.0)	2*4	2(3.5)	2*4	1.5
9 story	4	8*3.5	2(4.2)	2*4.2	2(3.5)	2*4	1.5
20 story	4	19*3.5	2(4.2)	3*4.2	2(3.5)	3*4	1.5

Table 3. Sample design sections for nine story building designed with DBD approach.

Story	Exterior Columns	Interior Columns	Braces	Beams
1	IPB400	IPB340	2UNP160	IPE240
2	IPB400	IPB340	2UNP160	IPE240
3	IPB340	IPB300	2UNP140	IPE200
4	IPB340	IPB300	2UNP140	IPE200
5	IPB300	IPB240	2UNP140	IPE200
6	IPB300	IPB240	2UNP140	IPE160
7	IPB240	IPB200	2UNP120	IPE160
8	IPB240	IPB200	2UNP120	IPE160
9(Roof)	IPB200	IPB160	2UNP120	IPE160

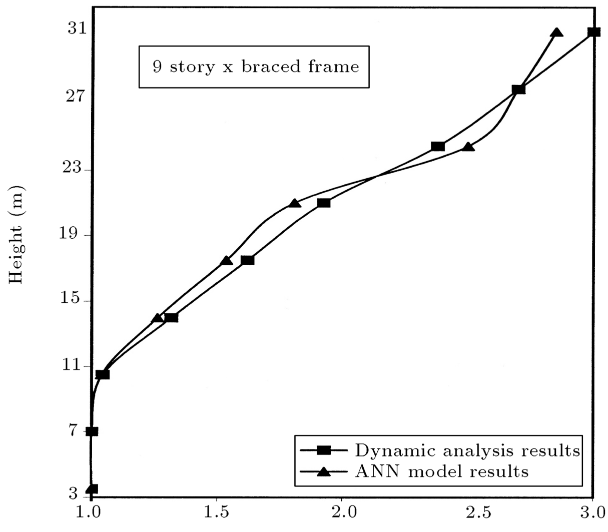

Figure 11. Comparison of ANN results with nonlinear dynamic analysis results for estimation of ductility distribution of nine story braced steel.

assessing the dynamic response of braced steel buildings, brace ductility demand is very important, because the damage to structural and non-structural elements is directly related to it. Thus, the estimation of ductility is very important for the design and assessment of structures. Figure 11 also shows a sample comparison of the network results, with the dynamic analysis result for a nine story steel building. This figure shows the ductility distribution pattern through the height of the structure.

Results show that the presented method overestimates ductility values in upper stories but the total correlation of the results is reasonable. The maximum ductility for the selected design level has been assumed equal to 4. It can be seen that the network had been able to estimate the response with acceptable accuracy, compared to the nonlinear dynamic analysis results. The same results have been presented for the network used for estimation of the plastic hinge distribution in Figures 12 and 13. The verification of the results, in this case, has been done by comparing the results with those obtained from the static pushover analysis. The nonlinear static analysis for this example has been performed under the seismic code load distribution pattern. It is clear that the distribution of plastic hinges

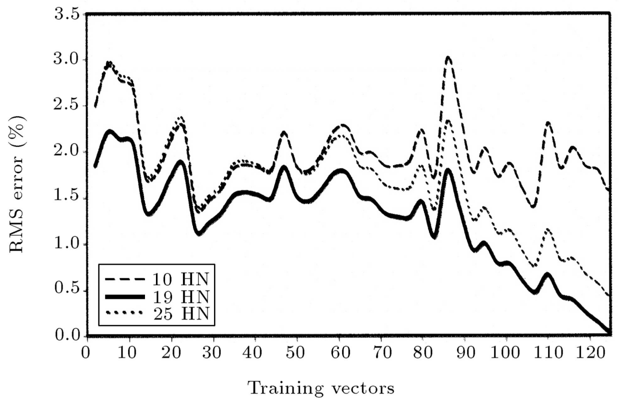

Figure 10. Results of network design for determining ductility distribution pattern.

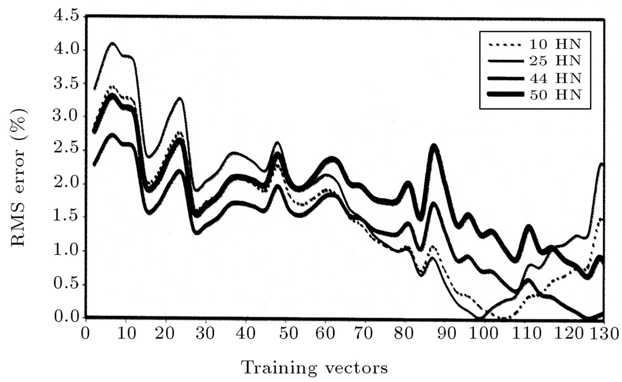

Figure 12. Results of network design for determining plastic hinge distribution.

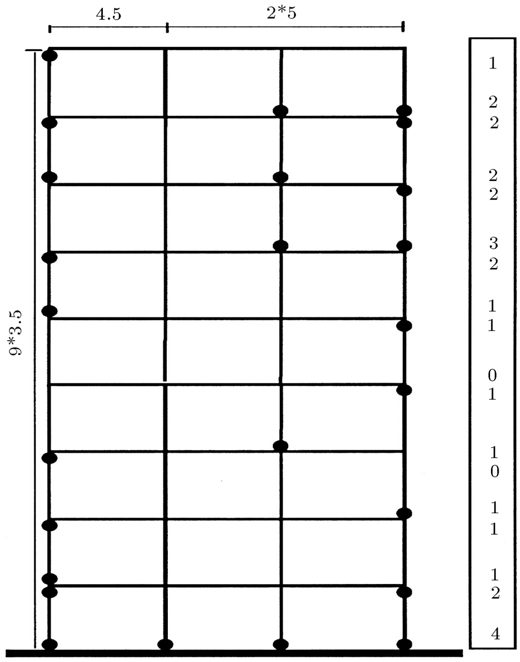

Figure 13. Comparison of ANN results with nonlinear static analysis results for a nine story building at life safety performance level.

highly depends on the initial design of the structure. As mentioned in previous sections, in order to obtain an appropriate seismic performance, the number of plastic hinges should be larger and, preferably, concentrated at beam ends.

This requirement is mainly met by applying the strong column/weak beam philosophy. Figure 14 also shows the verification example for the assessment of

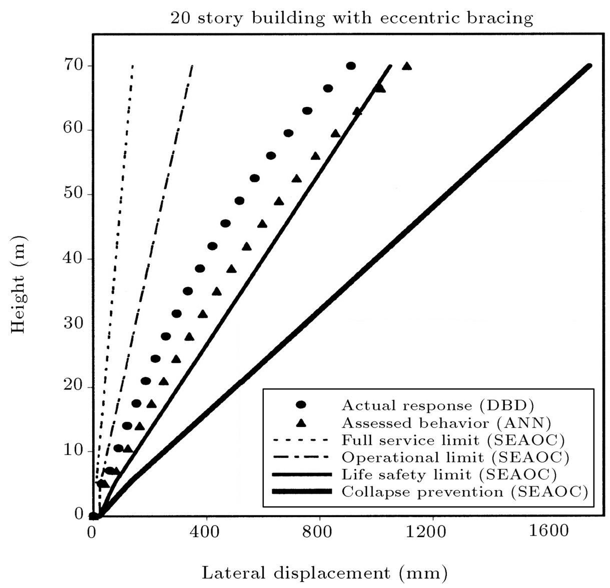

Figure 14. Comparison of ANN results with nonlinear static analysis results for seismic assessment of 20 story braced steel.

existing structures. The responses are presented for all performance levels, based on the SEAOC standard. For this application, it can be seen that the result that has been showcased for the life safety level has good correlation with the actual behavior obtained from nonlinear static analysis.

CONCLUDING REMARKS

Displacement based procedures can directly lead the designer to key design parameters, such as ductility and displacement. The presented method has the ability to account for multiple performance levels, simultaneously, in terms of ductility and displacement and, therefore, can lead to the reduction of damage in buildings subject to earthquake load. The method also considers the capacity design philosophy as strong column/ weak beam criteria. As discussed in this paper, strong-column/weak-beam constraints have considerable influence on design results and serve to eliminate weak-story collapse mechanisms. Artificial intelligence can be used as a very effective tool for assessing the total response of the structure and can be used effectively for a preliminary design with minimum computing time and cost. Finally, a neural network can play an important role in preliminary assessment of the current status of the existing structure. As shown in the previous sections, rapid assessment of an existing building, in terms of displacement and ductility, can be used as an important parameter for seismic vulnerability and retrofit studies of existing buildings. However, numerical studies showed that the selection of appropriate parameters for network input and output is very essential and can significantly improve network behavior.

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NOMENCLATURE

a_{eff}	effective acceleration
f_i	story force
H	total height of building
K_{eff}	effective stiffness
L	total building width
m_{eff}	effective mass
T_{eff}	effective period
V_b	base shear
δ_{eff}	effective displacement

δ_i	story displacement
ξ_{eff}	effective damping ratio
$X{=}(x_1, x_2, \cdots, x_I)$	input vector with I members
$T{=}(t_1, t_2, \cdots, t_U)$	target vector with U members
α	learning rate
ν	biases
Y	input/output of hidden/output layers
W	network weights
δ	error in the layers

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