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Seismic design of steel frames using multi-objective optimization

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Abstract. In this study a multi-objective optimization problem is solved. The objectives used here include simultaneous minimum construction cost in term of sections weight, minimum structural damage using a damage index, and minimum non-structural damage in term of inter-story drift under the applied ground motions. A high-speed and low-error neural network is trained and employed in the process of optimization to estimate the results of non-linear time history analysis. This approach can be utilized for all steel or concrete frame structures. In this study, the optimal design of a planar eccentric braced steel frame is performed with great detail, using the presented multi-objective algorithm with a discrete population and then a moment resisting frame is solved as a supplementary example.

Keywords: seismic design; multi-objective optimization; eccentric braced frame (EBF); moment resisting frame; neural networks; damage index; construction cost

1. Introduction

Optimal design of multistory structures is usually performed with two conflicting objectives that are the minimum present construction cost and the maximum performance in future under the probable ground motions. The first objective is related to the structural weight and the second one is related to the minimum damage of the structure. Common single-optimization approaches cannot achieve these goals, and making a new model that can optimize a variety of objectives has been a challenging topic among researchers throughout the world proposing different kinds of methods. In this paper, weight, minimum damage to structure, and minimum non-structural damage in the term of inter-story drift are considered as three main objectives. Different techniques of finding multiple answers employing evolutionary algorithms (EA) have been previously developed. Although the importance of finding multiple answers are quite obvious, however, the recent usages of these methods in multi-objective optimization problems are often based on preference. The first real application of EA in finding multiple answers was presented by David Scaffer in his doctoral thesis (1984). David Goldberg (1989b) presented a 10 line multi-objective evolutionary algorithm (MOEA) by the use of domination concept. Following his

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work, other researchers developed different applications of multi-objective evolutionary algorithms. Among these, one can refer to the multi-objective genetic algorithm of Fonseca and Feliming (1995), non-dominated sorting genetic algorithm (NSGA) of Srinivas and Deb (1994), modified form of NSGA called NSGA-II (Deb *et al.* 2002), and pareto genetic algorithm of Horn, Nafploitis and Goldberg (Horn *et al.* 1994). These were employed in real problems in order to show that the multi-objective evolutionary algorithms (MOEA) based on domination can be used for finding multiple answers. Nowadays EAs are vastly applied to engineering problems. In 2007 a procedure was proposed for optimization of wind-excited structures utilizing the simulated annealing algorithm. This method was combined with dynamic analysis of response in both frequency and time domain (Venanzi and Materazzi 2007). Multi-objective design optimization of laminated composite components with objectives of minimizing weight and total cost of composite component was another example of using multiple objectives (Omkar *et al.* 2009). Ohsaki *et al.* (2007) formulated seismic design problem of a steel moment-resisting frame as a multi-objective programming problem with objectives of total structural volume and plastic dissipated energy. Afshar *et al*. (2009) developed a new multi-colony ant algorithm to solve a time-cost multi-objective optimization problem. Kaveh and Talatahari (2010) presented a novel optimization method called imperialist competitive algorithm (ICA) to optimize skeletal structures. Assessment of seismic design codes has been the subject matter of some researches to disclose weak points that have come from some limitations in predicting with satisfactory accuracy of the structures response under ground motions. Lagaros and Papadrakakis (2007) evaluated the European seismic design code used for the design of reinforced concrete buildings by utilizing a performance-based design procedure in a framework of a multi-objective optimization concept. The initial construction cost and maximum inter-storey drift for the 10/50 hazard level were considered as two objectives in formulating the multi-objective optimization problem. Beck *et al*. (1999) presented a framework for multi-criteria optimal design for performance-based design of structural systems by use of a decision theoretic approach based on aggregation of preference functions for the multiple design criteria. Li *et al*. (1999) presented a new application of multi-objective and multi-level optimization procedures for optimizing steel frames in which total structural strain energy and total structural weight were considered as objectives at system level and member weight was considered as an objective at element level. Liu (2003) developed multi-objective optimization procedures for seismic design of SMRF structures. In 2004 Alimoradi *et al*. (2004) studied the problem of optimizing construction cost with constraints of confidence levels in different hazard levels. Liu formulated the performance-based design of SMRF structures as a multi-objective optimization problem in which initial construction cost and seismic risk were considered as conflicting objectives. Construction cost and seismic risk were considered in steel material weight and maximum inter-story drift demands terms, respectively (Liu *et al.* 2005). A variety of other researches have been presented using evolutionary algorithms in multi-objective problems. Also other hybrid meta-heuristic algorithms are employed in multi-objective optimization of structures (Kaveh and Laknejadi 2011a, b, 2012).

In this study, a multi-objective optimization technique is utilized for optimal design of EBF structures and then a moment resisting frame is solved as a supplementary example. Construction cost, in terms of standard sections weight, structural damage index and inter-story drift as the non-structural damage index, are considered as the three objectives. A neural network is trained and employed for estimating the relation between the input and output variables. Input variables include the standard sections and outputs include drift, dissipated energy and plastic deformation under ground motions. Output variables are used to calculate the structural and non-structural damages. A multi-objective genetic algorithm is used as an explorer engine for finding the multiple optimal answers.

2. Modeling and analysis of structures

In this study, 120 planar EBF bare-frame structures are modeled in PERFORM3D software. These models are utilized to train a neural network. Design base acceleration and ground type are taken as 0.35 and 2.00, respectively. Structural system type is EBF. Non-linear modeling is performed based on FEMA356 pre-standard by applying concentrated plastic hinge rules. Strain hardening is considered as 3 percent for all the hinges. P-Delta effect due to the interior gravity loads is considered in modeling. Tabas, Parkfield, Kobe, Imperial Valley and Northridge are five strong motions that their records are chosen from the peer website and are scaled. These records with their acceleration response spectrums are provided in Figs. 1 and 2. Near-field earthquakes are the ones for which their distance from the earthquake surface center is less than a specific amount. Some researches have shown that the near-field records can be divided into 2 parts, having pulse and without pulse. Sometimes pulse presence in acceleration, velocity and displacement histories is one of the features that separate near-field earthquakes from far-field ones (Malhotra 1999). In this study earthquakes distances from the surface center are chosen to be less than 10 km, also the first 25 seconds of each earthquake time is considered as the effective time in modeling. Non-linear time history analyses are applied to the designed structures by PERFORM3D software. Average inter-story drifts, dissipated energy and plastic deformations are calculated under each record for each structure and then the amounts are averaged for all the mentioned records. The non-linear dynamic method is utilized because of the possibility of calculating dissipated energy and plastic deformations as terms of the damage index under different records, while in linear and non-linear statics methods this is not possible. Since the calculation of inter-story drifts and damage index are based on averaging different records, the earthquakes are chosen in a way to include a great frequency domain all together to make sure all structures with various periods (0.47-0.65) are excited. Designed structures involve 4 spans and 5 stories. First story height is 280 cm and other stories heights are 320 cm. Side spans involve eccentric braces. The first 3 stories have the same types (similar sections and link beams lengths) and stories 4 and 5 are similar in type as shown in Fig. 3. Design variables in 120 mentioned structures involve braced spans beams, columns and braces dimensions and link beams lengths in each type. Beams in 2 central spans are similar in all stories in all the structures, and they are not considered as design variables. Used sections are presented in Table 1.

In order to avoid uneconomical sections, the optimal sections are chosen based on their stresses, and four sections are utilized for each member. All models used in the neural network are designed based on the utilized code. All the results obtained from multi-objective optimization are checked for satisfying the code limitations, since it is possible that minor errors of the neural network cause optimal answers to fall out of the feasible domain.

The material properties of the frame are as follows:

$$E = 2e8(kN/m^2)\,,\ \rho = 76.82(kN/m^3),\ \text{and}\ \nu = 0.3$$

The constraints utilized in different generations of the genetic algorithm, consists of the following:

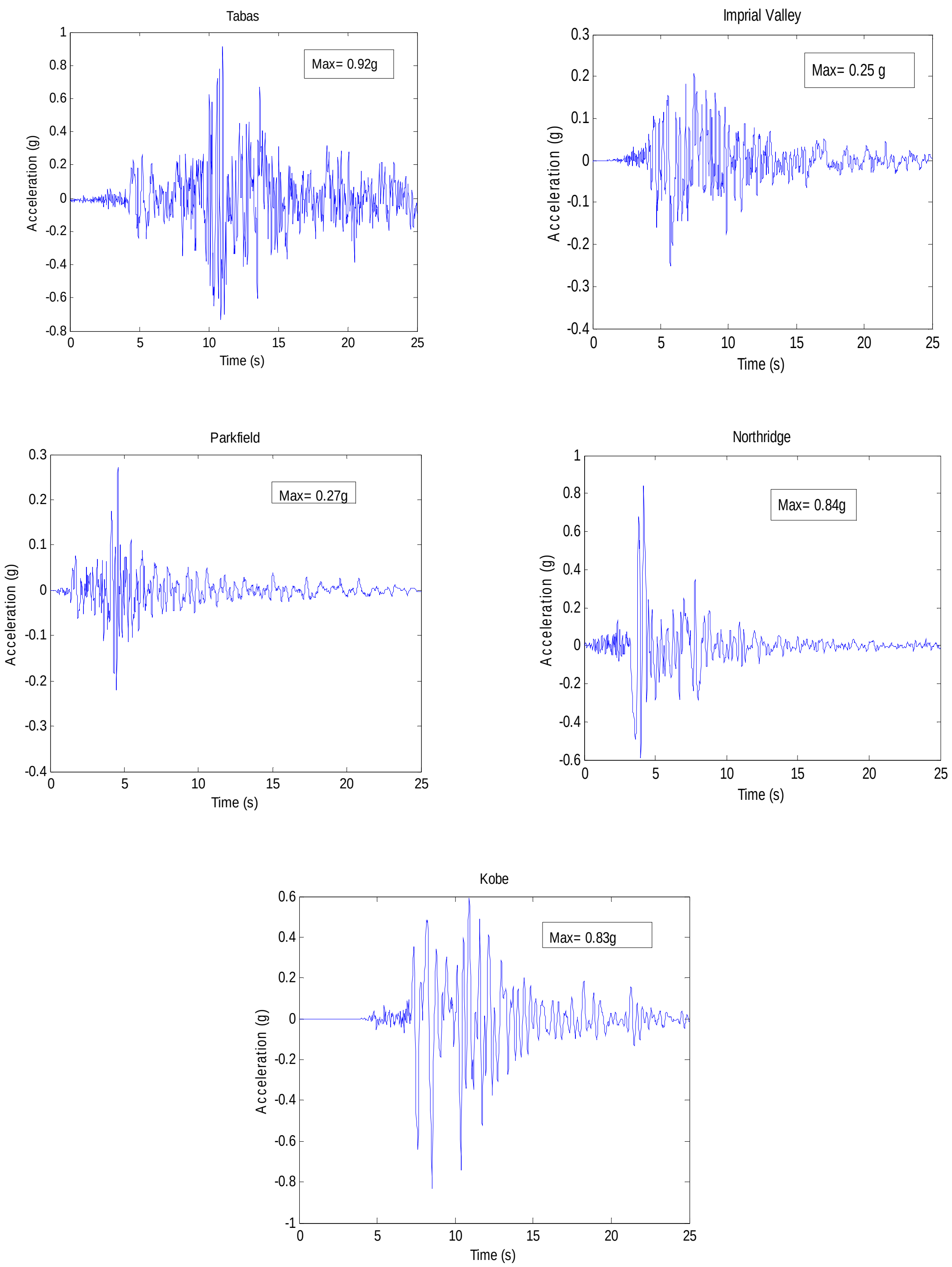


Fig. 1 Records of Tabas, Parkfield, Kobe, Imperial Valley and Northridge earthquakes

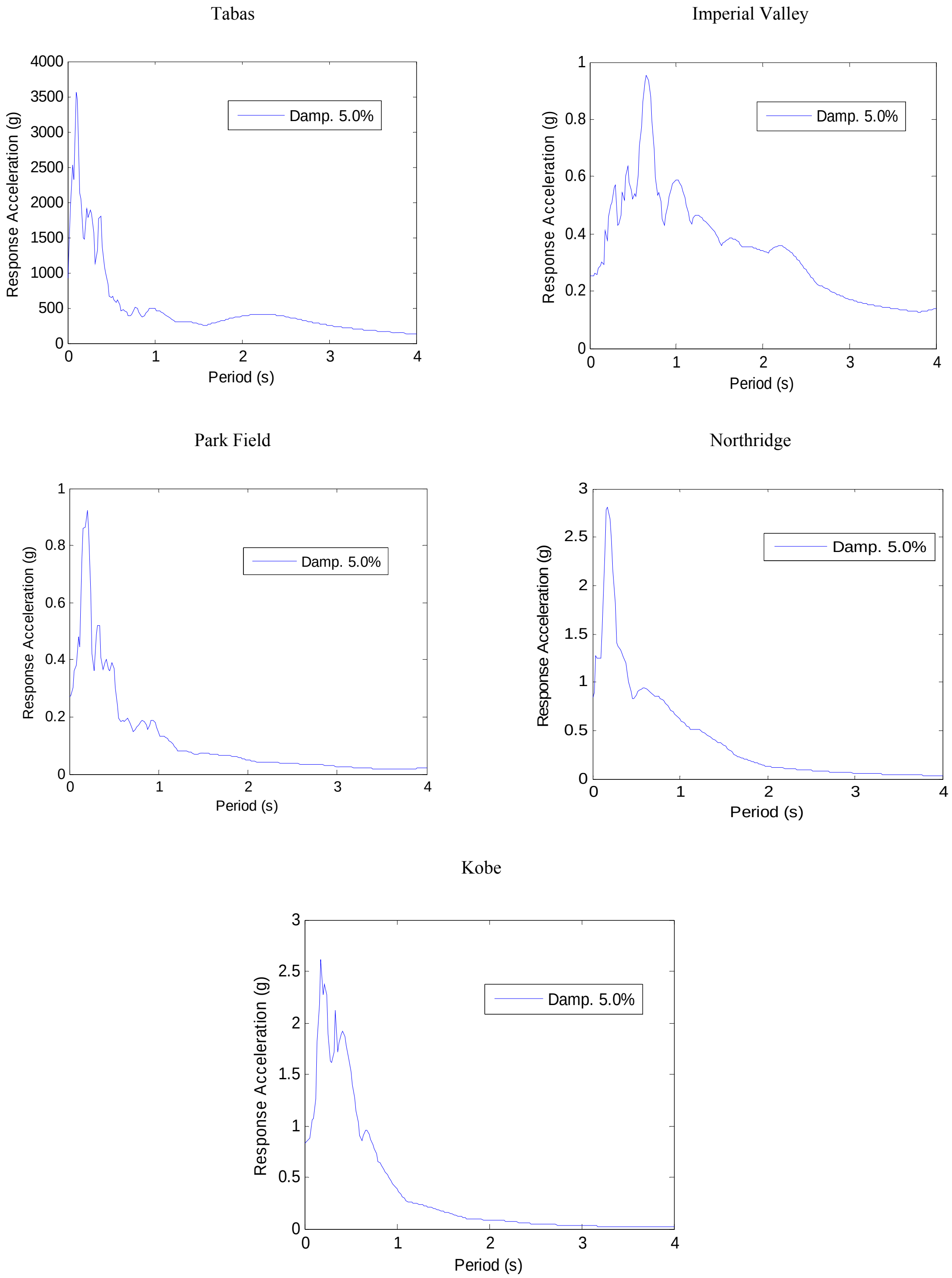


Fig. 2 Acceleration response spectrums of Tabas, Parkfield, Kobe, Imperial Valley and Northridge earthquakes

Table 1 Sections used in the structure

Member type	Section	Member type	Section
Type 1 column (stories 1, 2 and 3)	IPB16 IPB18 IPB20 IPB22	Type 2 beam (stories 4 and 5)	IPE16 IPE20 IPE18 IPE22
Type 2 column (stories 4 and 5)	IPB10 IPB12 IPB14 IPB16	Type 1 bracing (stories 1, 2 and 3)	2L10 2L12 2UNP10 2UNP12
Type 1 beam (Stories 1, 2 and 3)	IPE18 IPE20 IPE22 IPE24	Type 2 bracing (stories 4 and 5)	2L8 2L10 2UNP8 2UNP10

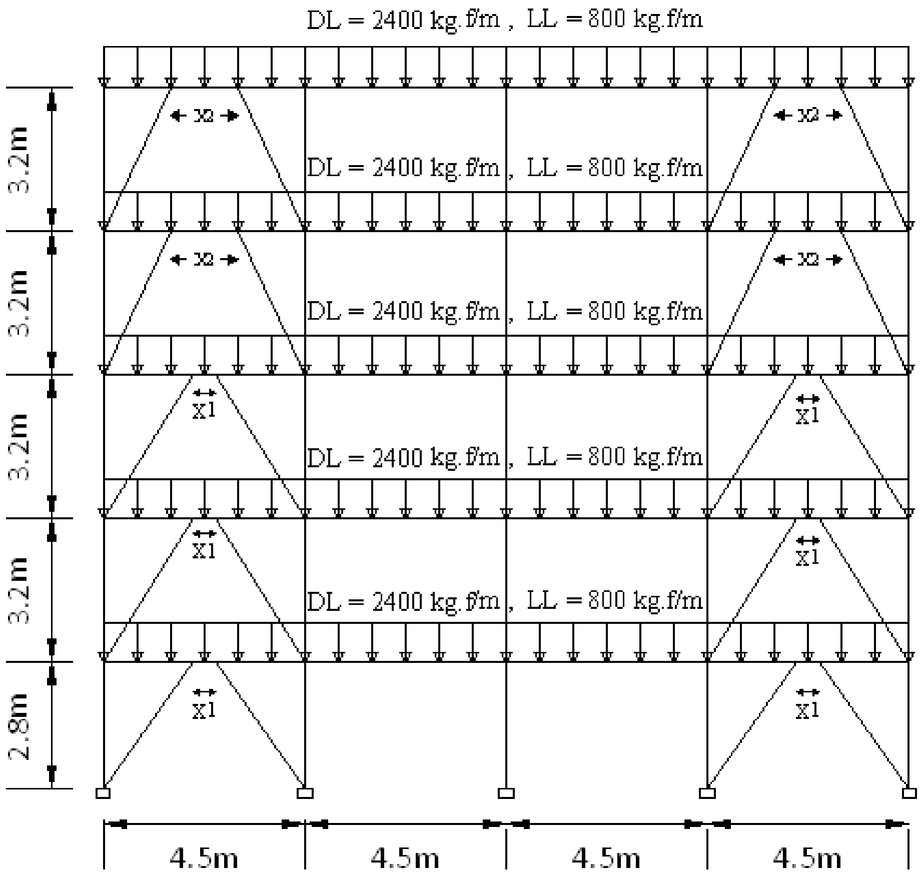


Fig. 3 Geometry and variables of the frame

1. Controlling the constraints corresponding to the beams, columns and excentric beams

$$if\ \ \frac{P_r}{\Phi_c P_n} < 0.2 \ \Rightarrow\ \frac{P_r}{2\Phi_c P_n} + \frac{M_r}{\Phi_b M_n} \le 1 \tag{1}$$

$$if\ \ \frac{P_r}{\Phi_c P_n} \ge 0.2 \ \Rightarrow\ \frac{P_r}{\Phi_c P_n} + \frac{8}{9}\left(\frac{M_r}{\Phi_b M_n}\right) \le 1 \tag{2}$$

Where P_r is the required compression strength of the beam, column or excentric beam. P_n is the nominal compression strength of the beam, column or excentric beam, Φ_c is the strength coefficient in compression which is equal to 0.9, M_r is the required bending strength of the beam, column or excentric beam and M_n is the nominal bending strength of the beam, column or excentric beam.

2. Controlling the constraints for bracing members

$$\lambda \le 4.23\sqrt{\frac{E}{F_y}} \tag{3}$$

$$P_{cr} \le \Phi_c . P_{cn} \tag{4}$$

$$P_{tr} \le \Phi_t . P_{tn} \tag{5}$$

Where λ is the slenderness ratio, E is the modulus of elasticity, F_y is the yield stress of the steel, P_{cr} is the required compression strength, Φ_c is the strength coefficient in compression which is 0.9, P_{cn} is the nominal value of the compression strength, P_{tr} is the required tensile strength, Φ_t is the strength coefficient in tension which is 0.9 and P_{tn} is the nominal tensile strength of the section.

3. Controlling the drift of the stories and the roof

$$if\ \ T < 0.7\sec \Rightarrow \overline{\Delta}_M < 0.025\ h_s \tag{6}$$

$$if\ \ T \ge 0.7\sec \Rightarrow \overline{\Delta}_M < 0.020\ h_s \tag{7}$$

Where T is the period of the structure, $\overline{\Delta}_M$ is the relative lateral displacement of the story considering the P-Δ effect and h_s is the height of the story.

4. Controlling the constraint for link beams: $\gamma_p \le 0.08\ rad$

In this paper the maximum length of the link beams is constrained in a manner that the shear behavior governs the design as recommended by the codes of practice.

$$e \le 1.6\frac{M_p}{V_p} \text{ and } \gamma_p \le 0.08\ rad \tag{8}$$

$$V_u \leq \Phi_v . V_n \tag{9}$$

Where e is the length of the link beam, M_p is the plastic moment of the link beam, V_p is the plastic shear of the link beam, γ_p is the maximum amount of the rotation of the link beam, V_u is the factored shear applied to the beam, V_n is the nominal amount of the shear strength in the beam and Φ_v is the strength reduction factor which is equal to 0.9.

If we do not want the shear govern the design, then instead of Eq. (8) we can use the following general equations. In this case Eq. (10) represents the shear behavior and Eq. (11) is the corresponding bending behavior. For bending-shear behavior, with condition presented in Eq. (12), γ_p can be found by interpolation.

$$if \;\; e \leq 1.6 \frac{M_p}{V_p} \Rightarrow \gamma_p \leq 0.08 \; rad \tag{10}$$

$$if \;\; e \geq 2.6 \frac{M_p}{V_p} \Rightarrow \gamma_p \leq 0.02 \; rad \tag{11}$$

$$1.6 \frac{M_p}{V_p} \leq e \leq 2.6 \frac{M_p}{V_p} \tag{12}$$

In this way a collection of varied answers with different weights and damage levels will be obtained that are acceptable from the viewpoint of the code, and the neural network can then be trained using these answers.

3. Damage index

Converting structural damage potential into numerical values has been one of the most conflicting problems in earthquake engineering. Evaluating this potential in a reliable way will have lots of usage in designing and rehabilitation of structures. One of the indexes used in this field is the damage index. Structural performance and linear states can be described by this index. This index can be normalized between zero and 1 in an ideal way. For the zero index there is no expectation of damage while for index 1 there is a potential for collapse. Other performance levels like immediate occupancy (IO), life safety (LF) and collapse prevention (CP) are arranged between zero and 1. An index is normally based on parameters such as force, deformation and the amount of dissipated. In the technical literature different damage indexes are used and that of the Park and Ang (1985) has been one of the most popular ones, described in terms of deformation and energy

$$DI_{pa} = \frac{U_{\max}}{U_{mon}} + \beta \frac{E_H}{F_y U_{mon}} \tag{13}$$

Where,

$U_{\max}$: the maximum deformation of the member under loading,

U_{mon}: the maximum deformation capacity under one-way loading,

E_H: the dissipated energy during loading,
β: a constant parameter.

4. Selection of the objective function

In a practical optimization problem usually more than one objective is needed to be achieved. These objectives are necessary for optimal design procedure to obtain improved designs that can be utilized in real engineering world. In a seismic design optimization procedure, suitable objective functions can be considered as economical concern and seismic risk in future probable earthquakes. In the single-objective optimization problems, structural weight is normally considered as the objective function. In multi-objective optimization problems, weight is again considered as the first objective while there is not a unique agreement on the other objectives. Maximum strain energy, maximum natural frequency of free vibration, minimum displacement in some specific structure points, maximum stiffness (Li *et al.* 1999) and maximum dissipated energy in structure due to material hysteretic behavior (Ohsaki *et al.* 2007) are some examples of other objectives considered in researches. In this study other surveys were done for choosing some more acceptable objectives. Each objective eventually should either describe weight index (cost) or damage in probable earthquakes, For example; the structural stiffness is increased in order to decrease the displacements which are a part of damage, or as an example about maximizing energy, consider two structures with same weights. Under a ground motion one of them remains in linear state while the other one passes it and thus dissipate some energy so in this manner the first structure is more satisfactory if it doesn't have more displacements. On the other hand the damage sustained by a member, depends on dissipated energy-member capacity ratio and not just only on dissipated energy. All these terms can simultaneously be seen in damage index formula. Both energy and displacement terms are presented in this formula. Energy is demonstrated in the numerator of the fraction, divided by area of structure behavior curve. Consequently, there are just two main objectives so that the rest like stiffness, frequency and energy are considered as some parts of the two main objectives. It means other objectives should be related to weight or damage when they are assessed so it seems more reasonable to throw them away and directly use weight and damage indexes instead. In seismic design based on standards, damage and performance concepts are not clearly mentioned and designing approach finish just based on minimizing initial cost. In this study structure weight is considered as an index for initial cost. Structure weight variations are achieved by choosing a variety of standard steel sections, also link beam variations cause braces length to vary, then in this way structure weight can again change. The considerable point about other objectives, i.e., structural and non-structural damages, is that designing structures with high yield strengths can't ensure decreasing damages; especially non-structural's, since in this way structure will experience high accelerations even during mild excitations that worry inhabitants and also cause great non-structural damages; especially in strong ground motions. In addition, high yield strength causes great base shear and then huge forces in base level columns that makes it difficult to design foundation. All these concerns should be considered in designing structures (Liu *et al.* 2005).

5. Relating input and output variables by neural network

A neural network is trained and utilized to find the relationship between the input and output variables. Decreasing the amount of calculations and increasing the speed of data processing are some advantages of using a neural network in a multi-objective genetic algorithm in comparison to other methods (Liu *et al.* 2005). In the present multi-objective genetic algorithm, by choosing 100 as the first generation population and 10 as the generations number, optimization procedure takes about 10 minutes of computational time by utilizing a Dell Vostro 1510 Laptop. Also by using neural network, convergence can easily be achieved. In the other words, an optimization process may need thousands of structural analysis that is both expensive and time-consuming, especially in non-linear time history analyses. By the use of neural network, the problem with analyses can be eliminated and a simple formulation is substituted using much less number of analyses, i.e. initially 120 analyses and then decreasing to 19 analyses after applying further modifications. The neural network includes 12 input variables i.e. inertia moment (I), beam, column and brace section areas in each type (A) and link beam length in each type (L) in which link beam length is a continues one and the rest are discrete. The neural network includes 3 output variables i.e. average inter-story drift in each structure, dissipated energy in each story, and average plastic hinges rotations of link beams in each story. The neural network used in this study is a GRNN one. As it was mentioned 120 structures are modeled and analyzed, in which 100 and 20 models used for training the network and checking the answers, respectively. Maximum error of average inter-story drift is about 2.5 percent and average error is about 1percent, also maximum error of dissipated energy in each story is about 5.2 percent while its average is about 2 percent and for link beams plastic hinges rotations, maximum and average errors are respectively about 4.5 and 1.8 percent. The 20 examples that are modeled for checking the answers are presented in Figs. 4 and 5 in which neural network and PERFORM3D energy and rotation outputs are compared.

5.1. Further modification to the neural network

Structural period is an index of both demand and stiffness. This feature makes it possible to train the neural network in an easy but much effective manner. Structural period can fairly estimate general responses such as average inter-story drift or total dissipated energy in a structure since period generally presents entire demand and stiffness, also it can be composed with some other features such as story stiffness in a specific story for calculating some local responses like inter-story drift or dissipated energy in that story. In structures design base on energy, input energy demand is estimated by structural period so it is possible to consider any structure, with any kind of shape or structural system type, just by period index. By using period, a variety of variables are omitted and replaced by just one variable. On the other hand, just in this manner an especial problem (structure) can be converted to a total problem (structure) with further elements and more complicated geometry but the only problem is calculating structures dynamic period. An algorithm, based on modal analysis, are utilized in order to calculate structures exact period so for estimating inter-story drift by neural network, 12 input variables are replaced by one variable (period). By using the mentioned algorithm the periods of modeled structures are gained between 0.47s and 0.65s. Consequently, 19 structures (from 0.47s to 0.65s) are used in the neural network rather than the initial 120 structures. In Table 2 the results of neural network are compared in two different training schemes. Maximum neural network error by using period is about 2.5 percent and its average is about 1 percent. Another approach for decreasing the calculations amount and omitting the inter-story drift neural network is calculating the drift by using link beams plastic hinges rotation and structure geometry

$$\delta_p = \frac{e.h}{L}\gamma_p \tag{14}$$

Where,

e: length of the link beam

h: story height

L: span length

γ_p: maximum link beam rotation

δ_p: maximum real inter-story displacement

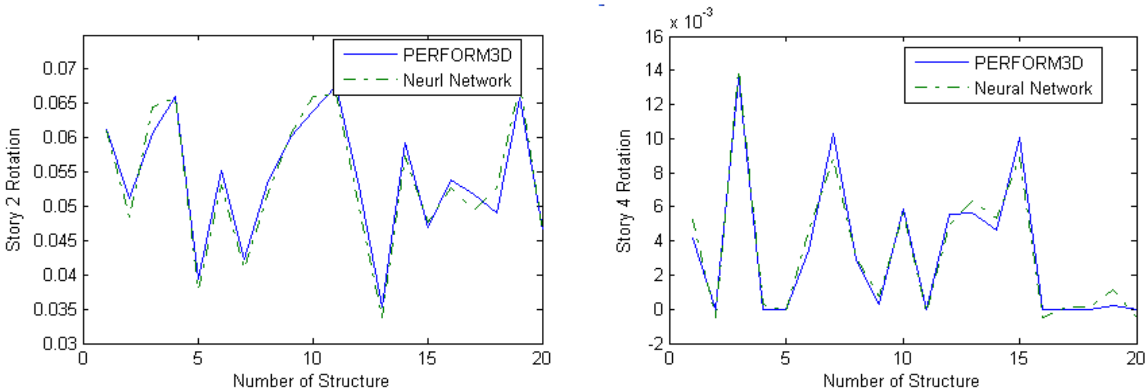


Fig. 4 Comparison of the results of the neural network and the actual results of the plastic hinges rotations in the structure

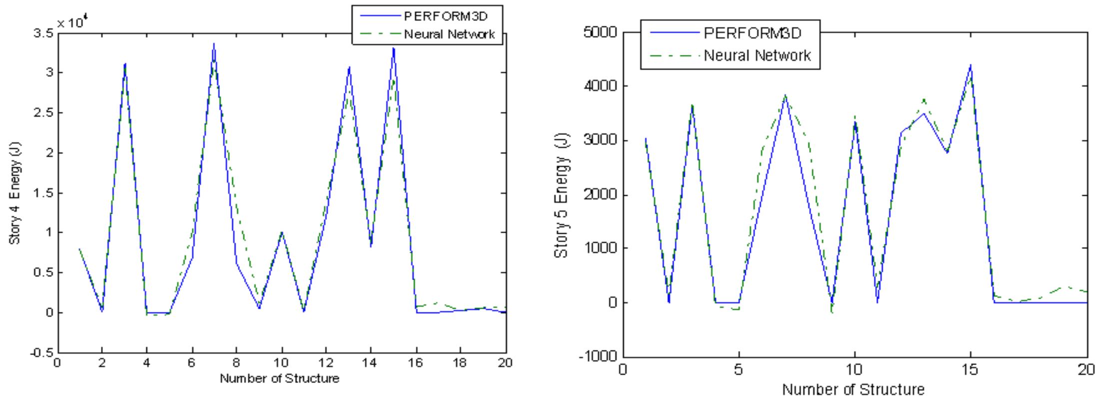


Fig. 5 Comparison of the results of the neural network and the actual results for dissipated energy in the structure

Table 2 Comparison of the neural network results for two different training schemes

	Mean value of the story drift	
Number of variables and number of structures used as input data of the networks	Mean Error (%)	Maximum Error (%)
One variable (T) and 19 structures	1	2.5
12 variables (all sections) and 100 structures	1.4	3.5

In Fig. 6 the results of the inter-story drift are presented for two different types of training.

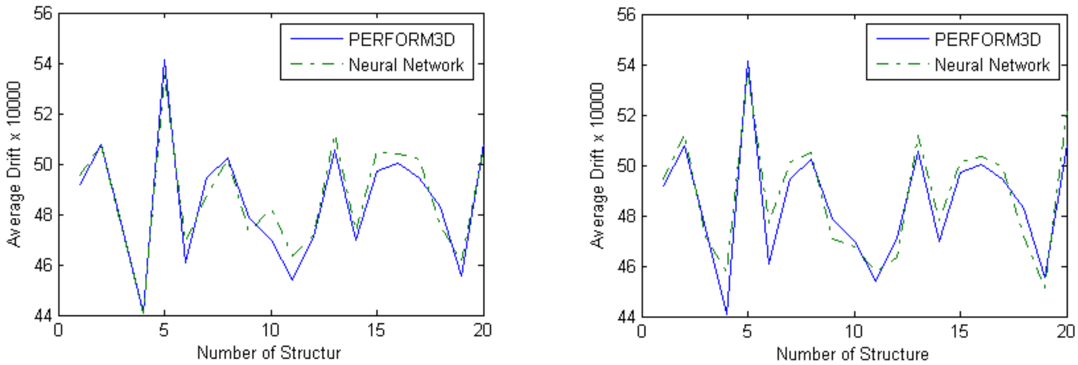


Fig. 6 Comparison of the results of neural network for two different training schemes; (a) Training of the network using a single variable (period), (b) Training of the network using a twelve variable

6. Multi-objective optimization by genetic algorithm

A multi-objective genetic algorithm is utilized as an explorer engine for optimizing the structural design. This algorithm is able to locate a group of optimal seismic designs based on the selected multiple objectives. In comparison to most conventional methods based on single-objective optimization and used to discrete or custom populations, genetic algorithms (GA) are problem-independent methods and do not need Sensitive Information for guiding the search procedure. These features make them very effective tools for solving structures optimization problems in which discrete variables of beam and column sections are selected from standard steel sections catalogs (Huang and Arora 1997), and nowadays GAs are widely utilized in structural optimization problems because of the above mentioned merits (Adeli and Cheng 1993). NSGA-II as a modified version of NSGA, is a popular non-dominated sorting genetic algorithm in which GA uses simulated binary crossover operator (Park and Ang 1985, Deb and Agarwal 1995) for crossover and poly-nominal mutation (Deb and Agarwal 1995, Raghuwanshi and Kakde 2004). Solution fitness is defined by using non-dominated sorting technique (Goldberg 1989a) and another parameter called crowding distance (Deb 2001).

6.1. Description of the multi-objective algorithm

In this study the existing algorithm is modified to be compatible with a structural problem. Initial population is chosen as usual by considering the problem range. Each generation is sorted based on non-domination. Individuals are assigned fitness values based on the objective functions values. The first front in each generation is assigned 1 and the second one as 2 and so on. In order to avoid the near answers, crowding distance is utilized. The crowding distance makes it sure to have a variety of answers. In the next step parents are chosen based on a binary tournament in which the fitness values and crowding distance are compared. The population used in NSGA-II is suitable only for continuous ones and can not be used for other kinds of populations. Some changes are performed in this algorithm to make it applicable for other types of populations such as continuous, discrete and custom. A genetic algorithm that works for discrete populations as well as continuous or custom ones is applied to the algorithm to make it compatible with the problem. In this study there are both discrete and continuous variables, link beam length as a continuous variable and beam and column sections as discrete ones that are selected from standard steel sections catalogs.

The multi-objective optimization algorithm used here is mostly similar to NSGA-II. The main difference between the two algorithms is related to their genetic operators. The algorithm includes below parts.

Population Initialization. The population is initialized based on the problem range and constraints.

Non-Dominated Sorting. The initialized population is sorted based on non-domination.

Crowding Distance. Once the non-dominated sort is completed the crowding distance is assigned. Since the individuals are selected based on rank and crowding distance, all the individuals in the population are assigned a crowding distance value. Crowding distance is assigned front wise and comparing the crowding distance between two individuals in different front is not necessary.

All structures used for the neural network are designed models based on code to prevent undesirable situations such as soft story. Normalizing the constraints of the problem adding three weight (f_1), damage (f_2) and drift (f_3) functions, the final general objective function together with a constant penalty coefficient is obtained as follows

$$PF_i = f_i(1+\alpha\sum_{m=1}^{nc}\max[0, g_m]) \qquad i = 1,2,3 \tag{15}$$

Where nc is the number constraints and g_m shows the violations of the constraints. Here we have used the adaptive coefficient for the penalty function introduced by (Barbosa and Lemonge 2003) and employed in (Kaveh *et al.* 2008). The capability of this coefficient is investigated in (Goldberg 1989a). Eq. (15) together with using this coefficient, results in the following relationships

$$F_i = f_i + \sum_{m=1}^{nc}\alpha_m v_m \qquad i = 1,2,3 \tag{16}$$

$$\alpha_m = |\langle W\rangle| \frac{\langle v_m\rangle}{\sum_{l=0}^{nc}[\langle v_l\rangle]^2} \tag{17}$$

Where

$$v_m = \max[0, g_m] \qquad m = 1:nc \tag{18}$$

In these relationships, the sign $\langle\ \rangle$ means the average value in all strings of each generation.

6.2. Pareto optimal areas and discussion of the results

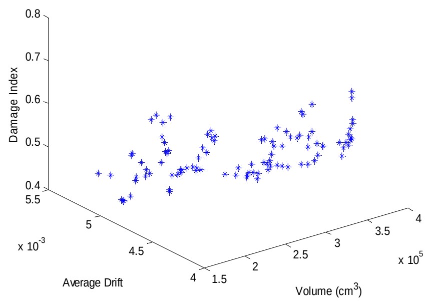
Running the algorithm with determined objective functions and constraints results in a variety of answers with different weights and damage levels that are acceptable based on the used code of practice, providing a multiple decisions possible for the design engineer. These merits are only related to multi-objective algorithms. Three common components are considered in the algorithm used in this study:

1. The constraints related to the code;
2. Comprehensive objective functions;
3. A suitable numerical algorithm that results in optimal solution.

In Table 3, the results of the first 10 optimal structures are presented, and in Fig. 7 the pareto optimal areas are shown in both 2 and 3 dimensions for the first 100 optimal structures. The results in the Table 3 show the importance of considering both non-structural and structural damages. For instance, in the second optimal structure it can be seen that the structure has the maximum damage index as the structural or cumulative damage, and the minimum inter-story drift as the non-structural or non-cumulative damage. In design codes it is usual to check the maximum drifts or plastic deformations. Considering the fact that structures experience cumulative damages by dissipating energy in their cyclic behavior under ground motions and poor relationship between cumulative damage and final deformation in some cases, it seems to be necessary to estimate the cyclic damage of the structures.

Table 4 is related to the neural network error that is obtained from a comparison of the first 10 optimal structures obtained by neural network with those obtained by PERFORM3D. Finally, in Fig. 8 the results of the first 10 optimal structures obtained by the neural network and those obtained by PERFORM3D are compared. This comparison is made to become sure that the constraints in the last generation are controlled and they are lower than the allowable values.

When the pareto optimal areas are obtained, it is possible to compare the characteristics of optimal and non-optimal structures. Some of these characteristics include distribution pattern of inter-story drift, distribution pattern of dissipated energy and distribution pattern of damage index in structure's height. Another importance of this comparison is from the viewpoint of designs codes. For instance, unique distribution of inter-story drift is one of the codes suggestions. In Fig. 9 this quality is shown for 8 structures that 4 structures belong to the optimal areas and 4 structures are non-optimal. It can be seen the optimal structures have not only lower average inter-story drift but also a better distribution in the height.



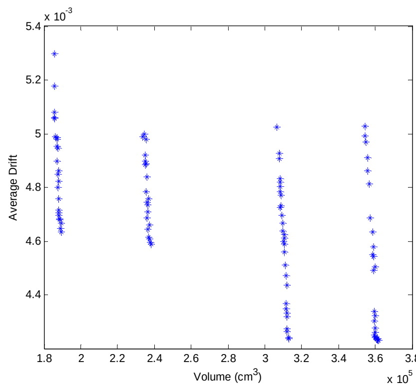


Fig. 7 Pareto optimal areas for the first 100 structures (2 and 3 dimensions)

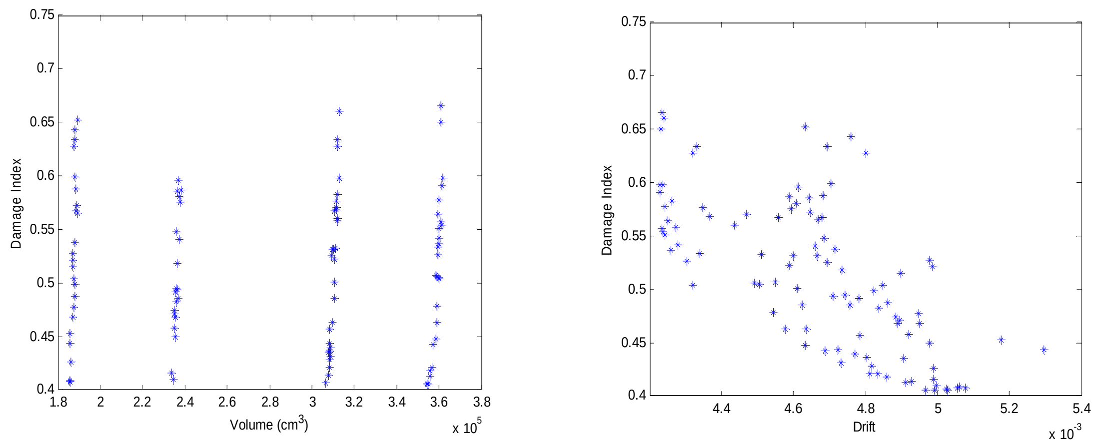


Fig. 7 Continued

Table 3 Details of the first 10 optimal structures

	1st struct.	2nd struct.	3rd struct.	4^{th} struct.	5^{th} struct.	6^{th} struct.	7^{th} struct.	8^{th} struct.	9^{th} struct.	10^{th} struct.
Type 1 beams (IPE)	22	22	20	20	22	22	20	22	22	22
Type 2 beams (IPE)	18	18	20	20	20	20	20	20	20	20
Type 1 columns (IPB)	18	20	20	20	18	18	20	18	18	18
Type 2 columns (IPB)	12	12	12	12	12	14	14	12	12	12
Sections of type 1 bracings	2UNP10	2L12	2UNP10	2UNP10	2L12	2UNP10	2UNP10	2L12	2L12	2L12
Sections of type 2 bracings	2UNP8	2L10	2L10	2L10	2UNP8	2L10	2UNP8	2L10	2UNP8	2UNP8
Length of type 1 link beam (cm)	59	30	60	30	57.7	59.5	31.1	55.3	30	35
Length of type 2 link beam (cm)	59.8	35	56.2	34.9	42.7	59	35.3	59	34	42
Volume$\times10^{-4}$ (cm^3)	18.5	36.2	23.4	23.8	30.7	23.3	18.9	35.5	31.3	31.2
Drift$\times10^{4}$	53.4	42.3	50.1	45.8	49.6	52.1	46.4	49.6	42.4	43.9
Damage Index	0.446	0.668	0.403	0.597	0.414	0.405	0.583	0.424	0.600	0.546

Table 4 The network errors obtained by comparison of the output of the network and those of PERFORM3D

	Max (%)	Mean (%)
Mean value of story drift	2.5	1.5
Plastic rotation of the link beam – 1^{st} story	6	2.5
Plastic rotation of the link beam – 2^{nd} story	3	1.3
Plastic rotation of the link beam – 3^{rd} story	4.5	1.5
Plastic rotation of the link beam – 4^{th} story	4	2
Plastic rotation of the link beam – 5^{th} story	4.5	1.8
Plastic hinge rotation of the entire stories	4.5	2
Dissipated energy in the 1^{st} story	6	2.5
Dissipated energy in the 2^{nd} story	6	3
Dissipated energy in the 3^{rd} story	5.5	2.8
Dissipated energy in the 4^{th} story	5	2
Dissipated energy in the 5^{th} story	4.5	1.5
Dissipated energy in all the stories	6	2.5

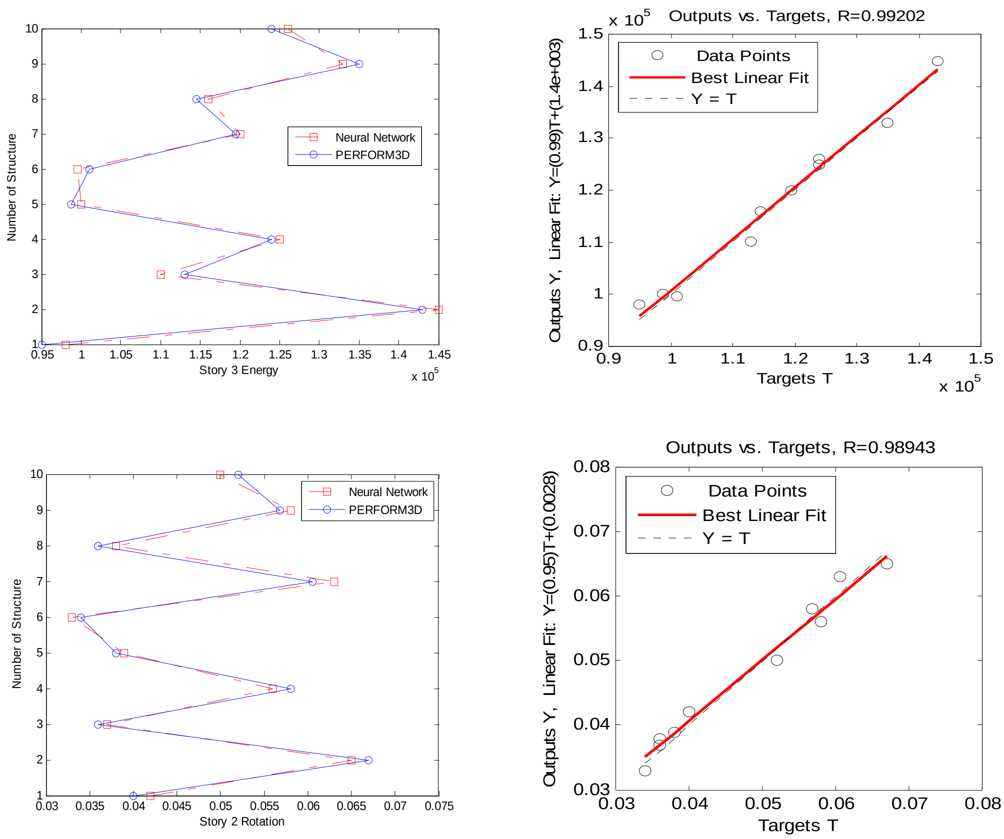


Fig. 8 Comparison of the outputs for the first 100 structures using neural networks and the PERFORM3D Program

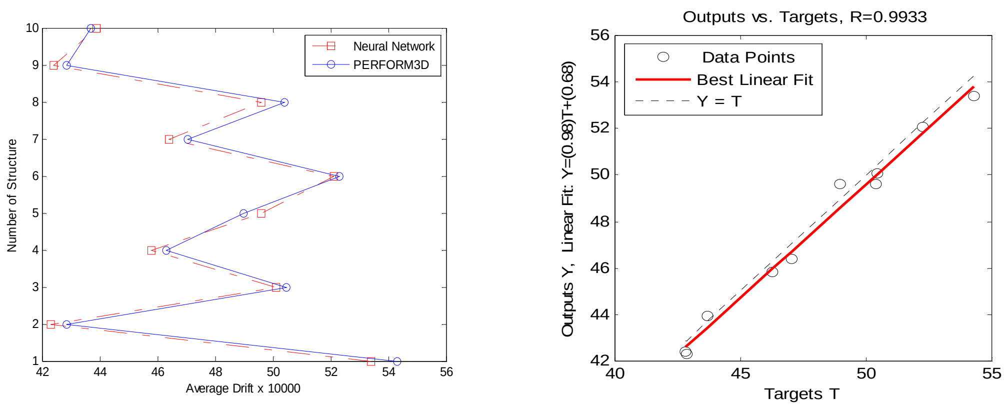


Fig. 8 Continued

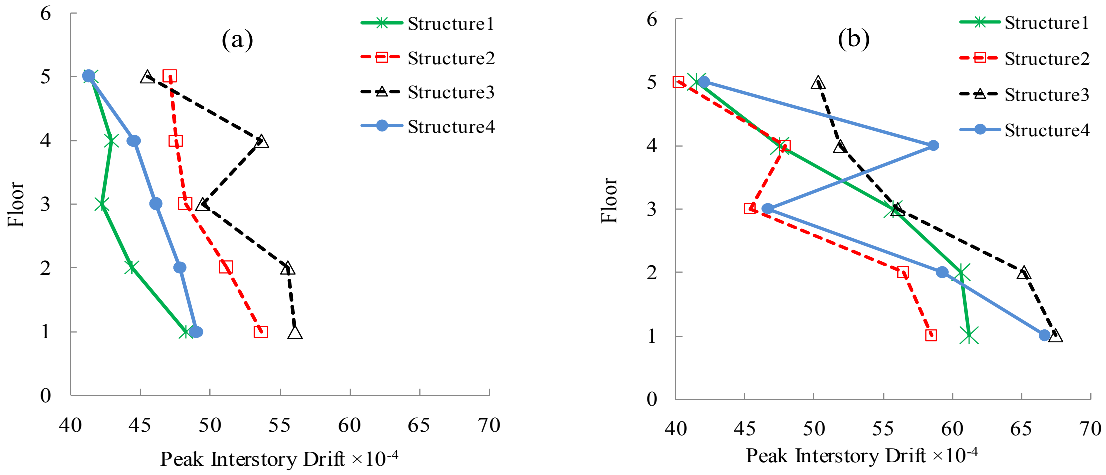


Fig. 9 Maximum inter-story distribution of 8 structures. (a) 4 structures of pareto optimal areas (b) 4 structures of non-optimal areas

6.3. A supplementary example

In this section a 7-story bending frame is considered, each story having the height of 3m and span length of 5m, as shown in Fig. 10. According to what was explained in Section 5-1, the period index which is a function of the demand and stiffness of the structure (suitable for general responses), together with the stiffness of the stories (suitable for local response), form the input of the neural network. Considering the sections for the beams and columns of this frame, the period of the structure falls between 1.32 and 1.59. Therefore, instead of using a large number of structures and many inputs for the neural network, only 27 structures with period in the range of 1.32 and 1.59 are utilized. Also 8 structures are employed for controlling the validity of the results of the neural network. Thus a sum of 35 structures are modeled using the PERFORM3D program for controlling the learning of the neural network. The base acceleration for design and the type of ground are considered as 0.25 and 1.00, respectively. Nonlinear modeling is performed by using FEMA356 pre-standard and the rules form concentric plastic hinges. The P-Delta effect of the interior gravity loads is considered and strain hardening for all the hinges is taken as 3 per cent. The seismic loads applied to the structures are those of Tabas, Parkfield, Kobe, Imperial Valley and Northridge. The record and response of these earthquakes are shown in Figs. 1 and 2. A non-linear time history analysis are performed for these models and the dissipated energy, the average inter-story drifts, dissipated energy, plastic deformation and then the damage index are calculated. The first three stories have the same type and the other two stories have identical type, and the two upper stories have the same type. The design variables in all the 35 structures are the sections of the beams and columns and for each member 4 sections are used as indicated in Table 5.

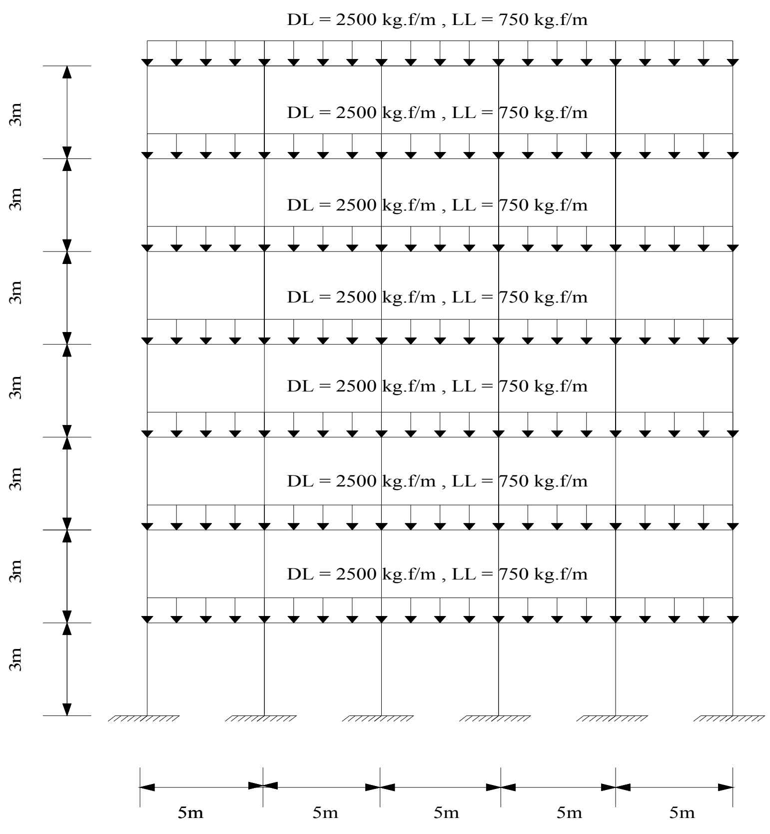


Fig. 10 Geometry of the frame

Table 5 Sections used in the structure

Member type	Section	Member type	Section
Type 1 column (stories 1, 2 and 3)	IPB24 IPB26 IPB28 IPB30	Type 1 beam (stories 1, 2 and 3)	IPE33 IPE36 IPE40 IPE45
Type 2 column (stories 4 and 5)	IPB18 IPB20 IPB22 IPB24	Type 2 beam (stories 4 and 5)	IPE30 IPE33 IPE36 IPE40
Type 3 column (stories 6 and 7)	IPB12 IPB14 IPB16 IPB18	Type 3 beam (stories 6 and 7)	IPE27 IPE30 IPE33 IPE36

Each of the 35 structures used for the neural network is designed according to the design code and all the results obtained from the multi-objective optimization are controlled for satisfying the limitations of the code.

Mechanical properties of the frame are as follows:

$$E = 2e8(kN/m^2)\,,\ \rho = 76.82(kN/m^3),\ \text{and}\,\nu = 0.3$$

The constraints employed in different generations of the GA are as follows:

1. The control of the limitation corresponding to beams and columns using Eqs. (1) and (2).
2. Control of the stories and roof drifts utilizing Eqs. (6) and (7).

After training the neural network and comparison of the mean values for 8 controlled structures with the results of the PERFORM3D program, the errors involved are according to Table 6, which are negligible for engineering problems.

In this way the relation between the structural period and the disapated energy, plasic deformations and mean value of the inter-story drifts is obtained and according to Eq. (13) the relationship between the structural period and damage index is specified. This relationship together with the relation of period-drift are itilized in the multi-objective Genetic optimization. The results obtained for 10 first optimal structures of the pareto front are depicted in Table 7.

Table 6 The network errors obtained by comparison of the output of the network and those of PERFORM3D

	Max (%)	Mean (%)
Mean value of story drift	4.5	2
Plastic rotation of the beam - 1st story	5.5	1.5
Plastic rotation of the beam – 2nd story	4.5	2.5
Plastic rotation of the beam – 3rd story	4	3
Plastic rotation of the beam – 4th story	4	2.5
Plastic rotation of the beam – 5th story	6	2.2
Plastic rotation of the beam – 6th story	5.5	2
Plastic rotation of the beam – 7th story	6	2.5

Table 6 Continued

Plastic hinge rotation of the entire stories	5	1.5
Dissipated energy in the 1^{st} story	4	2.5
Dissipated energy in the 2^{nd} story	4.5	2
Dissipated energy in the 3^{rd} story	5	3
Dissipated energy in the 4^{th} story	6	1.5
Dissipated energy in the 5^{th} story	4	2
Dissipated energy in the 6^{th} story	4	2.8
Dissipated energy in the 7^{th} story	4.5	2
Dissipated energy in all the stories	5.5	2.5

Table 7 Details of the first 10 optimal structures

	1st struct.	2nd struct.	3rd struct.	4^{th} struct.	5^{th} struct.	6^{th} struct.	7^{th} struct.	8^{th} struct.	9^{th} struct.	10^{th} struct.
Type 1 beams (IPE)	33	40	40	36	33	33	36	40	33	36
Type 2 beams (IPE)	36	30	33	36	30	36	30	36	36	40
Type 3 beams (IPE)	27	27	33	27	36	33	27	33	36	27
Type 1 columns (IPB)	30	28	28	30	26	30	28	30	30	28
Type 2 columns (IPB)	22	24	24	22	24	24	20	22	22	24
Type 3 columns (IPB)	16	18	18	16	14	16	18	18	14	16
Volume$\times 10^{-4}$ (cm^3)	51.8	65.7	72.4	70.3	63.4	70.6	64.8	75.1	70.3	71.6
Drift$\times 10^{4}$	60.1	51.2	58.4	50.2	58.4	59.1	55.3	53.2	52.4	51.9
Damage Index	0.416	0.572	0.37	0.512	0.44	0.39	0.45	0.39	0.491	0.482

7. Conclusions

In this study a multi-objective optimization technique is developed and applied to optimal design of frame structures. The objective functions are comprised of the construction cost in terms of section weights, damage index, and drift as non-structural damage. It is shown why these functions can fairly result in optimal design under a dynamic loading. Though the presented approach is applied to 2D problems, its application can easily be extended to 3D structures with no substantial changes in the formulation. Relating structural features to a specific index like structural period removes the 3D and geometric complications and makes it possible to use the present method in real engineering problems. Using neural networks to formulate the input and output variables, decreases the amount of calculations and computational time considerably while the errors involved are acceptable for such engineering problems. Utilizing a minimum number of structures for training neural network becomes possible by relating the structural features to their periods since in this way it only sufficient to model structures with the periods in a small range instead of modeling a vast number of structures. Using this approach, the number of models is decreased, also the calculations related to the neural network become both easier and more accurate. The only acceptable objectives considered are minimizing weight and damage under ground motions and other objectives should somehow be related to these two. In this study non-linear dynamic analyses are used since only this kind of analysis can simulate the real behavior of the structure under ground motions and calculate damage function and dissipated energy terms.

Acknowledgements

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