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Optimum design of steel frame structures considering construction cost and seismic damage

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Abstract. Minimizing construction cost and reducing seismic damage are two conflicting objectives in the design of any new structure. In the present work, we try to develop a framework in order to solve the optimum performance-based design problem considering the construction cost and the seismic damage of steel moment-frame structures. The Park-Ang damage index is selected as the seismic damage measure because it is one of the most realistic measures of structural damage. The non-dominated sorting genetic algorithm (NSGA-II) is employed as the optimization algorithm to search the Pareto optimal solutions. To improve the time efficiency of the proposed framework, three simplifying strategies are adopted: first, simplified nonlinear modeling investigating minimum level of structural modeling sophistication; second, fitness approximation decreasing the number of fitness function evaluations; third, wavelet decomposition of earthquake record decreasing the number of acceleration points involved in time-history loading. The constraints of the optimization problem are considered in accordance with Federal Emergency Management Agency's (FEMA) recommended seismic design specifications. The results from numerical application of the proposed framework demonstrate the efficiency of the framework in solving the present multi-objective optimization problem.

Keywords: performance-based design; steel moment-frame structures; Park-Ang damage index; non-dominated sorting genetic algorithm; simplified nonlinear modeling; fitness approximation; wavelet analysis

1. Introduction

Damage prediction in structures under future earthquakes is very important in design of structures. The basic objective of the structural engineer is to design structures that are both economical and safe against probable earthquakes. Generally, a certain degree of damage is to be expected; otherwise the design would be too costly (Park and Ang 1985). It is shown that an optimum design with respect to the minimum construction cost is far from being optimum with respect to the damage that the structure might experience during earthquakes (Liu *et al*. 2005). An optimum seismic design can achieve balanced minimization of the two general conflicting objective functions: the primary investment and the seismic vulnerability.

A practical way to predict damage in structures is to calculate the damage index. Various

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damage indexes, which establish analytical relationships between the maximum and/or cumulative response of structural components and the level of damage they exhibit, have been proposed with the objective of quantifying structural damage in structures subjected to seismic excitations. These indexes can provide useful information on structural damage, considering the underlying assumptions and application limits introduced by their developers (Arjomandi *et al*. 2009). A very well-known damage index in the literature is the one developed by Park and Ang (1985). This index is a combination of ductility and energy absorption capacity parameters. The effectiveness of using the Park–Ang damage index has been supported by many researchers from the mid-1980s (e.g., Park *et al.* 1987, Kunnath *et al.* 1992, Datta and Ghosh 2008).

This study aims to develop a practical framework for the optimum performance-based design of steel moment-frame structures with an acceptable computational time. Minimization of the initial cost and the Park-Ang damage index are considered as two separate objectives of the optimization problem. The meta-heuristic algorithm employed in this study belongs to a subclass of evolutionary algorithms. NSGA-II (Deb *et al*. 2002) is a well-known, fast sorting and elite multi-objective genetic algorithm. The wide application of this algorithm in engineering problems proves its great abilities in covering the Pareto front and solving the multi-objective optimization problems (see Deb 2009, Talbi 2009). However, the main problem in utilizing any evolutionary algorithm is the need to perform a large number of fitness function evaluations in order to obtain a good solution. Our optimization problem is even much more computationally intensive, because the calculation of the Park–Ang damage index involves a nonlinear time-history analysis of the multi-degree of freedom (MDOF) model of the structure under consideration. Consequently, the required computation time for solving our optimization problem -especially for large-scale structures- may exceed several hundreds of hours. In this study, we try to incorporate the available techniques in the literature into a simple framework in order to make the solution of our problem possible in a timely manner.

During recent years, extensive studies have been carried out to find methods for tackling similar problems, their results can improve the time efficiency of our solution algorithm. Some of these studies are focused on developing simplified structural models of steel moment-frames with fewer degrees of freedom compared to models with member-by-member representation in order to quickly predict earthquake responses of structures. Nakashima *et al*. (2001) developed a generic frame model for the simulation of earthquake responses of steel moment-frames in which all beams at each floor level are condensed into one rotational spring, and all columns in each story are condensed into one representative column. In this model, overturning moment and axial deformations in columns are neglected. Lignos *et al*. (2011) successfully developed and tested a simplified nonlinear model of steel moment-frames against static and time-history loadings for different demand parameters such as interstory drift ratios, story shear forces, and absolute floor accelerations. In this model, a single bay frame represents the original multi-bay moment-frame so that overturning moment and column axial deformation effects are adequately represented. The experimental results demonstrated that the proposed simplification in modeling, to a great extent, maintains accuracy in predicting the desired response parameters. Simplified modeling seems to be valuable in performance-based design optimization, where response parameters need to be computed many times during the optimization algorithm. By using these models, the computation time for optimization procedure can reduce dramatically, because they require the solution of significantly fewer degrees of freedom in comparison with member-by-member frame models.

Moreover, numerous studies aim to develop computationally efficient models to approximate the fitness value of highly time-consuming fitness function. It would be ideal if an approximate model (meta-model) can fully replace the original fitness function, however, researchers have come to realize that it is generally necessary to combine the approximate model with the original fitness function to ensure the evolutionary algorithm to converge correctly (Jin 2005). Thus, re-evaluation of some individuals using the original fitness function, termed as evolution control, is essential. Radial basis function (RBF) networks -emerging as a variant of artificial neural networks- have been successfully implemented as a reliable meta-model in predicting expensive fitness function for structures subjected to earthquake loading (see Gholizadeh and Salajegheh 2009, Kaveh *et al*. 2011). Fast training, reasonable accuracy, and simplicity make RBF network a powerful tool for decreasing computational burden of fitness evaluations in solving computationally intensive optimization problems.

Finally, some studies focus on producing surrogate earthquake records for original earthquake records that have larger time steps but with almost similar effects on structures. In this field, wavelet analysis has shown to be very effective. Wavelet decomposition can divide an earthquake signal into two parts: low frequency approximation part and high frequency detail part. Low frequency part is the most influential part of the original signal on the response of structures and it can efficiently be used in dynamic analysis of structures to decrease the number of points of earthquake record involved in the time-history loading (see Salajegheh and Heidari 2005, Gholizadeh and Samavati 2011, Kaveh *et al*. 2012). In this paper, all the introduced simplifying strategies (simplified structural modeling, fitness approximation and wavelet analysis) will be implemented in the proposed framework in order to improve the time efficiency of the optimization procedure.

2. Performance-based design procedure

Performance-based engineering is an emerging philosophy for design, rehabilitation and maintenance of new and/or existing engineering structures aims at overcoming the limits of current design codes that are based on deterministic structural analyses and prescriptive procedures intended to preserve life safety (Foley *et al*. 2007). The most distinctive feature of the new trend from conventional design practice is the explicit requirement of deformation-based structural performance under different hazard levels to achieve structural designs that not only reliably protect human lives after rare ground motions, but decrease damage after more frequent ground motions (Foley *et al*. 2007). The damage state associated with each hazard level is defined by deformation indices as a measure of distortion severity that a structure will experience during significant earthquake events of that particular level. FEMA-350 (2000), *Recommended Seismic Design Criteria for New Steel Moment-Frame Buildings*, evaluates structural performance at two levels of seismic hazard:

- Maximum considered earthquake (MCE) ground motions with less than 2% probability of exceedance in 50 years;
- Frequent earthquake (FE) ground motions with 50% probability of exceedance in 50 years.

Under FEMA-350, each building and structure must be assigned to one of three Seismic Use Groups (SUGs). Buildings are assigned to the SUGs based on their intended occupancy and use. Most commercial, residential and industrial structures such as those studied in this paper are assigned to SUG I. FEMA-350 states that all buildings should, as a minimum, be designed in accordance with the applicable provisions of the prevailing building code, e.g., AISC-LRFD (2010) specifications; in case the building is to attain a performance other than what the building code implies, the performance evaluation procedure may be followed according to FEMA-350. In the two-step procedure of FEMA-350 for performance evaluation, at each step one performance objective is verified. Each performance objective consists of the specification of a structural performance level and a corresponding hazard level, for which that performance level is to be achieved. Performance objectives for SUG-I structures are as follows:

- Collapse prevention building performance level for earthquake demands that are less severe than the MCE ground motions;
- Immediate occupancy building performance level for earthquake demands that are less severe than the FE ground motions.

Buildings that achieve immediate occupancy (IO) level are expected to sustain minimal or no damage to their structural elements; and only minor damage to their nonstructural components, so immediate re-occupancy of the building is safe. At collapse prevention (CP) level, buildings may pose a significant hazard to life safety resulting from failure of nonstructural components. However, since the building does not collapse, gross loss of life could well be avoided. Many buildings that achieve this level are complete economic losses (FEMA-350 2000). Although nonstructural components damage is extremely important, the present methods for the estimation of potential seismic damage only consider structural components.

In order to evaluate the performance of a structure through the mentioned seismic hazard levels, it is necessary to construct a mathematical model of the structure that can represent its strength and deformation characteristics, and then to conduct a nonlinear static analysis to predict the values of various demand parameters at each hazard level. In this study, for the structural modeling and analysis process, OpenSees® (2013) was utilized. OpenSees® is an open-source software for simulating the seismic response of structural and geotechnical systems. This software was developed to serve as a computational platform for research in performance-based earthquake engineering at the Pacific Earthquake Engineering Research Center.

2.1 Nonlinear static analysis

The development of nonlinear static analysis, also known as pushover analysis, is based on the assumption that the response of a structure is related to the response of an equivalent single degree of freedom system with properties proportional to the first mode of the structure. In this procedure, the mathematical model of the structure is subjected to a pattern of monotonically increasing lateral forces or displacements until either the lateral displacement of the control node exceeds a specified target displacement or a mathematical instability occurs (FEMA-350 2000). The control node is located at the center of mass at the roof of the structure. The target displacement is intended to approximate the total maximum displacement likely to be experienced by the actual structure, at the hazard level corresponding to the selected performance objective (FEMA-350 2000). According to FEMA-350, the target displacement should be calculated in accordance with the recommendations of FEMA-273 (1997). This document calculates the target displacement as follows

$$\delta_t = C_0 C_1 C_2 C_3 S_a \frac{T_e^2}{4\pi^2} g \tag{1}$$

where C_0, C_1, C_2 and C_3 are modification factors: C_0 relates spectral displacement of an equivalent SDOF system to the roof displacement of the MDOF system; C_1 relates expected maximum inelastic displacements to the displacements calculated for linear elastic response; C_2 represents the effect of pinched hysteretic shape, stiffness degradation and strength deterioration on maximum displacement response; C_3 accounts for the increased displacements due to dynamic P-Δ effects.

In Eq. (1), S_a is the response spectrum acceleration at the effective fundamental period (T_e) and damping ratio of the structure, normalized by *g*. In order to compute the target displacement at each seismic hazard level, S_a must be read from the corresponding response spectrum. FEMA-273 offers equations for calculating the response spectrum of FE and MCE ground motions in which the required seismic input data can be found on the ground-shaking hazard maps provided by this document. The effective fundamental period is defined as

$$T_e = T_i \sqrt{\frac{K_i}{K_e}} \tag{2}$$

where T_i is the elastic fundamental period in seconds, calculated by modal analysis; K_i is elastic and K_e is effective lateral stiffness, computed using the relationship obtained from the pushover analysis between base shear force and displacement of the control node (FEMA-273 1997). The nonlinear force-displacement relationship must be replaced with an idealized relationship as shown in Fig. 1. This relationship is bilinear, with initial slope K_e and post-yield slope αK_e. Line segments on the idealized force-displacement curve are located using an iterative graphical procedure that approximately balances the area above and below the curve (see Fig. 1). The effective lateral stiffness is taken as the secant stiffness calculated at a base shear force equal to 60% of the effective yield strength V_y. The post-yield slope is determined by a line segment that passes through the actual curve at the calculated target displacement. Moreover, the effective yield strength must not exceed the maximum base shear force at any point along the actual curve (FEMA-273 1997).

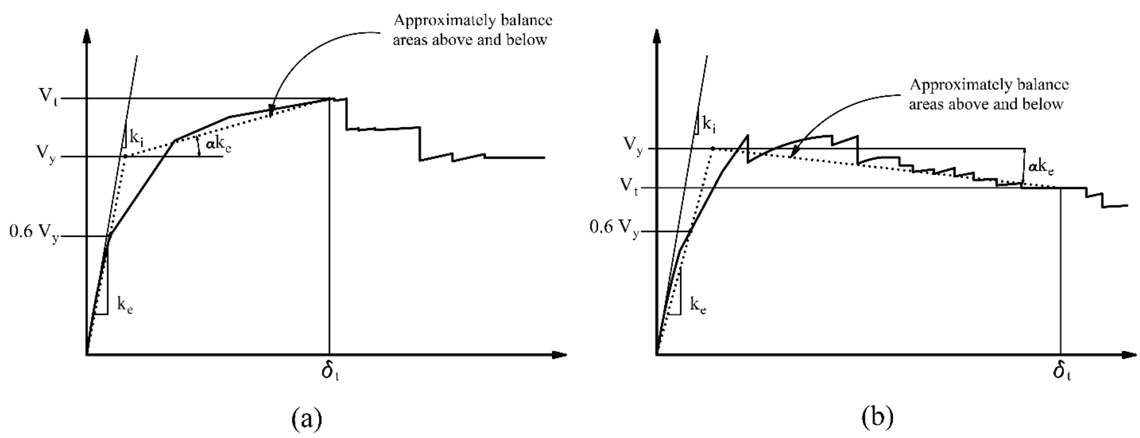


Fig. 1 Idealized force-displacement curves (FEMA-273 1997): (a) Positive post-yield slope; (b) Negative post-yield slope

Determination of the target displacement depends on the results from the pushover analysis. Therefore, a trial-and-error procedure is usually used to compute the target displacement. The structural model is pushed until a failure point is reached. The relation between base shear force and the lateral displacement of the control node is established for control node displacements ranging between zero and the failure displacement. The value of displacement at the failure point, as an initial guess, is set to the target displacement and based on the corresponding idealized force-displacement curve, a new value for the target displacement is calculated. If the new value is close enough to the initial guess, the new value is the target displacement. Otherwise, a new idealized force-displacement curve must be found for the obtained target displacement, and again, a new value for the target displacement must be calculated. This process continues until the new value is close enough to the candidate one.

2.2 General requirements and performance evaluation

The seismic provisions of FEMA-350 for the design of new steel moment-frame structures state in order to check the validity of any design alternative, firstly, the required strength of structural members and connections must be verified by AISC-LRDF specifications. Strength checks can be found in any textbook about the design of steel structures. In this study, the equivalent lateral force procedure of ASCE-7 (2010) is used for seismic design of structures. In the next stage, a pushover analysis is performed to check whether the acceptance criteria at the IO and CP performance levels are met.

FEMA-350 presents a probabilistic procedure that evaluates structural performance in terms of confidence levels for specified structural response parameters, including, interstory drift ratio, column axial compression force and column (splice) tension force. These structural response parameters are related to the amount of damage experienced by individual structural components as well as the structure as a whole. For each performance level, FEMA-350 specifies acceptance criteria (median estimates of capacity) for each of these response parameters. Acceptance criteria have been developed on a reliability basis, incorporating demand and resistance factors related to the uncertainty inherent in the evaluation process and variation inherent in structural response, so that a confidence level can be estimated with regard to the ability of a structure to meet the desired performance objectives (FEMA-350 2000).

Although column axial compression and tension, and connection drift ratio are important response measures in assessing performance of steel frames, due to the limitations of the current study, they were not included in our calculations. If one assumes global behavior is limited by interstory drift as the controlling response parameter -as done in the present work- the FEMA-350 methodology requires at least 50% confidence in attaining IO performance and 90% confidence in achieving CP performance objectives. Consequently, in this study for the mid-rise special steel moment-frames, the maximum allowable interstory drift ratio of 1.5% and 5% are considered at the IO and CP performance levels, respectively. In other words, in order to check the acceptance criteria for each performance objective, the maximum interstory drift ratio of the structure, when displacement of the control node reaches the target displacement of the corresponding hazard level, should be compared to these allowable values.

3. Optimization Algorithm: NSGA-II

The NSGA-II algorithm and its detailed implementation procedure can be found in (Deb *et al*. 2002). In the following, a general description of NSGA-II is provided. Once the population is initialized, two fitness values are assigned to each individual. Firstly, NSGA-II uses a "non-dominated sorting" algorithm for fitness assignment in which all individuals that are not dominated by any other individual are assigned front number 1; all individuals only dominated by the individuals in front number 1 are assigned front number 2, and so on. Secondly, a value called "crowding distance" is calculated for each individual; it is a measure of how close an individual is to its neighbors. A higher fitness value is assigned to individuals located on the sparsely populated part of a front (Deb 2009).

Parent selection is made using a "binary tournament selection" based on the assigned fitness values. This selects, between two random individuals, the one with the lowest front number, if the two individuals are from different fronts. While the individuals are from the same front, the individual with the highest crowding distance is selected. Then, the selected individuals generate offsprings using genetic operators. The offspring population is combined with the current generation's population, replacement is performed to set the individuals of the next generation. Since all previous and current best individuals are included, elitism is ensured. The combined population is now sorted based on the non-domination rule. The new generation is filled with fronts, one after another, until the population size exceeds the given size. If by adding all the individuals from the *i*th front, the population size exceeds, then individuals in the *i*th front are selected based on their crowding distance in a descending order until the population is formed. This process is repeated to generate the subsequent generations, until the termination criteria is met (Deb 2009).

In this study, the genetic operators are differential evolution (DE) operator for crossover and polynomial mutation operator (for details, see Deb 2009, Talbi 2009). The role of crossover operator is to inherit some genetic materials of parents to generate offsprings, whereas mutation alters one or more gene values in a chromosome from its initial state. The mutation and crossover operators are complementary, i.e., mutation maintains genetic diversity from one generation of a population of algorithm chromosomes to the next while crossover preserves genetic inheritance between generations (Talbi 2009).

In order to handle the given constraints, a relatively simple scheme is adopted. Whenever two individuals are compared for sorting population in different fronts, first, they are checked for constraint violation. If both are feasible, the non-domination rule is directly applied to decide the winner. If one is feasible and the other is infeasible, the feasible dominates. If both are infeasible, the one with the lowest amount of constraint violation dominates the other. This is the approach that was utilized by (Deb *et al*. 2002, Coello *et al*. 2004) to handle the constraints.

4. Damage index

Structural damage has a physical interpretation from the structural engineering view point, losing the ability to resist external forces and ultimately becoming unstable. Damage control in a structure is complex, because there are several response parameters that can be instrumental in determining the level of damage that a particular structure suffers during an earthquake. Over the years, several damage indexes have been proposed with the objective of quantifying structural damage in structures that are subjected to seismic excitations (Arjomandi *et al*. 2009). A frequently-used damage index in the literature is the one proposed by Park and Ang (1985). Consistent with the dynamic behavior, Park and Ang expressed seismic structural damage as a linear combination of the damage caused by excessive deformation and the damage caused by repeated cyclic loading effect. The Park–Ang damage index has been used in various forms over the last three decades, according to the specific requirements. One of the most important modifications of this index was suggested by Kunnath *et al.* (1992). They reformulated the original index as

$$DI = \frac{d_m - d_y}{d_u - d_y} + \frac{\beta}{V_y d_u} \int \mathrm{d}E_h \tag{3}$$

where d_m is the maximum deformation (demand) under dynamic loading; d_u is the ultimate deformation (capacity) under monotonic static loading; d_y is the yield displacement; $\mathrm{d}E_h$ is the incremental hysteretic energy (demand); V_y is the yield strength; and β is a positive constant that weights the effect of cyclic loading on structural damage. In this equation, if the ultimate strength, V_u, is smaller than V_y, V_y is replaced by V_u.

Ideally Eq. (3) should be applied to a cantilevered beam with d_m and d_y representing its displacements at the free end. This concept was extended by Gosh *et al.* (2011) to a regular multi-story frame, since the behavior of the regular frame subjected to horizontal earthquake excitation is similar to that of a vertical cantilever fixed at the base. The modified Park-Ang damage index for multi-story frames is defined as

$$DI = \frac{D_m - D_y}{D_u - D_y} + \frac{\beta}{V_y D_u} \int \mathrm{d}E_h \tag{4}$$

where D_m is the maximum roof displacement from nonlinear time-history analysis; D_y is the yield roof displacement from the idealized force-displacement pushover curve; and D_u is the roof displacement capacity. The definition as per Eq. (4) is termed the “global” Park-Ang damage index, because it considers only the roof displacement and the total energy demand for the structure.

According to the definition of the damage index in Eq. (4), under elastic response, the value of *DI* remains zero, and once the DI exceeds 1.0, the building is assumed to be in complete damage state. The interpretation of different values of *DI* and the relations between the damage levels and the Park–Ang damage index values are shown in Table 1. The five classes of damage levels in Table 1, are usually classified into three general levels. Up to a *DI* value of 0.4, the building is considered “repairable” with small economical loss. For *DI*s from 0.4 to 1.0, the building is in “beyond repair” damage state with high economical loss, it requires to destroy and replace the building after the earthquake. For *DI*s bigger than one, the building is “collapsed” with loss of life (Karbassi *et al.* 2014).

In order to estimate different terms of Eq. (4), the structural model must be pushed until a failure point is reached and also a nonlinear time-history analysis must be performed. According to the recommendation of Park and Ang (1985) for gradually failing members, in this study, the failure point is defined as the point when the strength drop is 20% of the maximum strength. Based on experimental tests, it was reported that the factor β ranges between 0.025 and 0.2 with an average value of 0.15 as suggested by Park *et al.* (1987). In this study, the factor β is considered as 0.15.

Calculation of the Park-Ang damage index for a structure is usually done under a target ground motion that is historically significant in the region of the structure. The target ground motion time-history should be scaled –in accordance with the recommendations of FEMA-273 (1997)– such that the value of the 5%-damped response spectrum does not fall below the response spectrum for the design earthquake for periods between 0.2T seconds and 1.5T seconds, where T is the fundamental period of the structure. In order to reduce the computational burden of the calculation, the effective duration of the target ground motion can be used in the time-history analysis instead of considering the whole earthquake record. The effective duration of a ground motion determines the start and the end of a strong shaking phase that is the time interval between the accumulation of 5% and 95% of ground motion energy, where ground motion energy is defined by the Arias intensity (Towhata 2008). The end of the duration is the time until which the maximum response has already been recorded (Kaveh *et al.* 2012). The effective duration of an earthquake record can be easily computed by software such as SeismoSignal® (2002). In this study, the concept of the effective duration is applied to shorten the duration of the target earthquake record, however, the start of the duration is considered to be from the start of the record. Moreover, in order to further decrease the number of points of the earthquake record involved in the time-history loading, a wavelet decomposition procedure is adopted. Details of this procedure is provided in section 7.

5. Simplified nonlinear modeling

Simplified modeling investigates the minimum level of multi-degree-of-freedom modeling sophistication that results in a negligible loss of accuracy in predicting demand parameters. This approach has shown to be highly effective in reducing the computational effort for estimating seismic demands of steel moment-frame structures (see Nakashima *et al.* 2001). In the method developed by Lignos *et al*. (2011), as shown in Fig. 1, a multi-bay steel moment-frame is condensed to a single bay simplified frame with properties tuned to represent the original frame. Lumping together a multi-bay frame into a single bay frame is accomplished by the following rules

$$\sum EI_i/L_i = EI/L \tag{5}$$

Table 1 Relations between damage index values and damage states (Park and Ang 1985).

Damage extent	Damage index	State of building
Slight	<0.1	No damage
Minor	0.1 – 0.25	Minor damage
Moderate	0.25 – 0.4	Repairable
Severe	0.4-1.0	Beyond repair
Collapse	>1.0	Loss of building

$$\sum M_{p,i} = M_p \tag{6}$$

where I_i and L_i is the moment of inertia and the length of the i-th beam in a story, respectively, and EI/L and M_p are the stiffness and the plastic moment of the single bay beam. For steel columns

$$\sum EI_i = 2EI \tag{7}$$

$$\sum M_{pc,i} = 2M_{pc} \tag{8}$$

where $M_{pc,i}$ is the plastic moment of the i-th column of the multi-bay frame and M_{pc} is the plastic moment of the single bay columns in presence of axial load. For higher steel moment-frames in which overturning moment and axial deformations in columns are important, these effects can be included by setting L of the single bay frame equal to the distance between end columns of the multi-bay frame, and setting the cross-sectional area of the single bay columns equal to the area of the end columns of the multi-bay frame. This simplification is based on the assumption that overturning effects are resisted mostly by the exterior columns of a steel moment-frame (Lignos *et al*. 2011). In the simplified model, a leaning column carrying gravity loads is linked to the frame by axially rigid truss elements, to simulate P-Delta effects of the existing gravity columns on the response of the lateral resisting frame. The approximations considered in this method are reasonable if all bays of the frame are of about equal width, and they are more approximate when spans of the frame vary considerably (Lignos *et al*. 2011).

The simplified model, as shown in Fig. 2(b), consists of elastic beam-column elements with rotational springs at their ends. The rotational springs capture the nonlinear behavior of the frame consistent with the concentrated plasticity concept. The rotational behavior of the plastic hinges follows a bilinear hysteretic response based on the modified Ibarra-Krawinkler deterioration model. Detailed information about this model and the modes of deterioration it simulates are available in (Ibarra and Krawinkler 2005, Lignos and Krawinkler 2011). In this study, the input parameters for the rotational behavior of the plastic hinges are determined using the empirical relationships developed by Lignos and Krawinkler (2011), derived from an extensive database of steel component tests. For the sake of simplicity, in this paper, cyclic deterioration is ignored in studying the nonlinear behavior of structures.

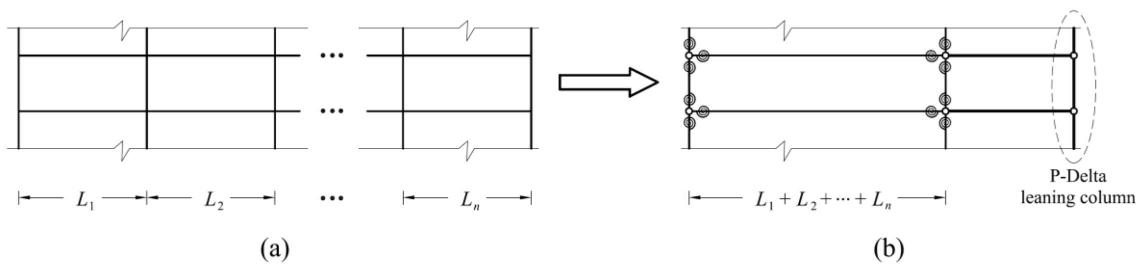


Fig. 2 Simplified nonlinear modeling: (a) member-by-member model of an n-bay steel moment-frame in a story; (b) simplified nonlinear model of the frame in that story

Since each frame member is modeled as an elastic element connected in series with rotational springs at either end, the stiffness of these components must be modified so that the equivalent stiffness of this assembly is equivalent to the stiffness of the actual frame member. Using the approach described in appendix B of (Ibarra and Krawinkler 2005), the rotational springs are made n times stiffer than the rotational stiffness of the elastic element in order to avoid numerical problems and allow all damping to be assigned to the elastic element. In order to ensure that the equivalent stiffness of the assembly is equal to the stiffness of the actual frame member, the stiffness of the elastic element must be $(n+1)/n$ times greater than the stiffness of the actual frame member. In this study, this is accomplished by making the elastic element's moment of inertia $(n+1)/n$ times greater than the actual frame member's moment of inertia. Ibarra and Krawinkler (2005) suggested a value of $n=10$ for the stiffness modifications.

Moreover, to match the nonlinear behavior of the assembly with that of the actual frame member, the strain hardening coefficient (the ratio of post-yield stiffness to elastic stiffness) of the plastic hinge must be modified, as well. If the strain hardening coefficient of the actual frame member is denoted by $\alpha_{s,mem}$, and the strain hardening coefficient of the spring by $\alpha_{s,spring}$, then $\alpha_{s,spring} = \alpha_{s,mem} / (1+n(1-\alpha_{s,mem}))$. More information about the modified Ibarra-Krawinkler deterioration model, its features and implementation, is available on the online supporting documentation provided by OpenSees® developers.

6. Fitness approximation strategy

In the present optimization problem, fitness function evaluation is the most time-consuming part of the solution algorithm. If all of the required damage index calculations are performed by nonlinear time-history analyses, the solution algorithm may need several hours even for small structures; because evolutionary algorithms usually need a large number of fitness function evaluations to obtain a good solution. The solution of this problem lies in the use of computationally efficient approximations of the fitness function, a strategy utilized for solving optimization problems with expensive objective functions (Jin 2005).

In many real-world problems, due to lack of data and high dimensionality of the search space, it is very difficult to obtain a perfect global functional approximation (meta-model) for the original fitness function (Jin and Sendhoff 2004). To alleviate this problem, two main measures can be taken. Firstly, the quality of the approximate model should be improved as much as possible. Several factors may influence the improvement of the model quality, such as selection of the model, careful selection of the input and the output data set employed for training of the model, and use of active data sampling. Secondly, the approximate model should be used together with the original fitness function. In the most cases, the original fitness function is available, although it is computationally intensive. Therefore, it is very important to use the original fitness function efficiently. This is known as model management in conventional optimization or evolution control in evolutionary computation (Jin 2005). In the next two subsections, these two concerns are reviewed in our specific optimization problem.

6.1 Meta-model selection

Neural networks are adaptive statistical models which can be trained and used for predicting the response of a function. A neural network consists of an interconnected group of simple processing elements called artificial neurons, which exhibit complex global behavior determined by the pattern of connections among them. Advanced neural networks have shown to be effective in modeling most complicated non-linear relationships between inputs and outputs (Buhmann and Ablowitz 2003).

In many cases RBF neural networks have been successfully applied as a reliable meta-model, in predicting expensive fitness functions for structures that are subjected to seismic excitations. The obtained results demonstrate that with respect to the model precision and the required computational time, the RBF networks perform well (see Gholizadeh and Salajegheh 2009, Kaveh *et al.* 2011). In the present study, generalized regression (GR) neural networks are employed for fitness approximation. GR networks are an advanced variant of RBF networks that are also known as normalized RBF networks. They consist of a radial basis layer and a special extra linear layer that performs normalization on the output set. Detailed information about different variants of RBF networks can be found in (Buhmann and Ablowitz 2003).

The first objective of the optimization problem –the weight of the structure– does not need any kind of structural analysis and it is easy to calculate. Whereas calculation of the second objective –the Park-Ang damage index of the structure– requires a nonlinear time-history analysis. As defined by Eq. (4), the maximum roof displacement, D_m, and the cumulative hysteretic energy, E_h, are determined from nonlinear time-history analysis of the structure. In this study, these two parameters are considered as the output data of the GR networks.

Selection of the input data should be done as follows; firstly, they should represent the considered structure properly; secondly, they should be a proper representative of the nonlinear behavior of the structure under lateral loads; finally, the trained network by these input data should be able to predict the output data with an acceptable precision. In this study, four parameters defining the yield point (D_y, V_y) and the failure point (D_u, V_u) of the idealized force-displacement curve –obtained from pushover analysis of the structure– are selected as the input data of the GR networks. Through an active data sampling method, a GR network can be trained to process the input data of a candidate solution and predict the output data for it. Consequently, the value of the Park-Ang damage index can be estimated for the candidate solution using the output data.

6.2 Evolution control

Application of approximate models in the evolutionary optimization procedures is not straightforward, because it is very difficult to construct a meta-model that is globally accurate due to high dimensionality, ill distribution, and limited number of training samples (Jin 2005). There are three major concerns in using meta-models for fitness approximation. Firstly, it should be ensured that the evolutionary algorithm converges to the global optimum or a near optimum of the original fitness function. Secondly, the computational cost should be reduced as much as possible. Thirdly, in the process of evolutionary optimization, the range of the solutions may change significantly and the model trained by the initial data may converge to a false optimum; therefore, in most cases it is absolutely essential that the approximate model is employed together with the original fitness function (Jin 2005).

In addition, when approximate models are involved in evolution, it is very important to determine which individuals should be evaluated using the original fitness function in order to guarantee faster and correct convergence of the evolutionary algorithm (Jin and Sendhoff 2004). In this paper, the fuzzy c-means (FCM) clustering algorithm is applied to group the individuals of a population into a number of clusters. In each cluster, only the representative of the cluster -the individual that is closest to the cluster center- is evaluated using the expensive original fitness function (i.e., the Park-Ang damage index of the representative individual is calculated by performing a nonlinear time-history analysis). The fitness of other individuals is estimated using a GR network, specifically constructed and trained for that cluster. This is the method that was employed in (Jin *et al.* 2004) to choose the individuals to be evaluated by the original fitness function, rather than choosing them randomly. However, in there, the k-means algorithm was applied for individual clustering.

FCM is a data clustering technique in which each data element belongs to a cluster to some degree that is specified by a membership grade. These grades indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership grades, and then using them to assign data elements to one or more clusters. See (Miyamoto *et al.* 2008) for more information about this algorithm and its implementation.

The decision about the evolution control should be made based on the properties of the problem under study, this is achievable through trial and error. In our problem, at each generation of the NSGA-II algorithm, once all the individuals are generated by the genetic operators, FCM algorithm calculates *k* membership grades for each of them (*k* is the total number of clusters). Then, each individual is assigned to a particular cluster for which the corresponding grade of membership is maximum. For each cluster, the individual that has the highest membership grade is selected as the representative of the cluster. The representative individual is evaluated by the original fitness function and its properties –i.e., the results of the pushover analysis (D_y, V_y, D_u, V_u) and the results of the nonlinear time-history analysis (D_m, E_h)– are stored in an archive. In this way, all the individuals that are evaluated by the original fitness function from the start of the optimization, are stored in an archive. In the next step, the fitness of all the remaining individuals are estimated by the meta-models that are trained using the data stored in the archive.

Since the present problem is a multi-objective optimization problem, the solutions on the Pareto front may differ greatly from each other. Consequently, the trained network with these widely ranged input data has low precision in estimating the response or even may generate completely wrong answers. As much as the input data of a GR network are similar to the properties of an arbitrary solution, its estimate of the response to the arbitrary solution is more accurate (Samarasinghe 2006). In the present study, for improving the quality of the estimations, an active data sampling method is developed. In this method, in order to evaluate the fitness of all the remaining individuals in a cluster, first, a membership grade is calculated for each of the solutions stored in the archive to determine the grades these solutions belong to that particular cluster. The grade of membership of the *i*th solution stored in the archive to the *n*th cluster is obtained by (Miyamoto 2008)

$$\omega_n(x_i) = \frac{1}{\sum_{j=1}^{k}\left(\frac{d(center_n, x_i)}{d(center_j, x_i)}\right)^2} \tag{9}$$

where $d(center_n, x_i)$ denotes the Euclidean distance between the center of the *n*th cluster and the *i*th solution, x_i, in the input data space. $\omega_n(x_i)$ returns values from 0 to 1, in which higher values mean that x_i is more closer to the center of the *n*th cluster and lower values show that x_i may not belong to the *n*th cluster.

When the membership grades are computed for the whole archive, *p* solutions with the highest grades are selected from the archive and then a new GRNN is constructed and trained by 70% of these similar accurate solutions and the remaining 30% is used to validate the network. The purpose of validation is to ensure generalization ability of an approximate model and see how well it performs on unseen data. A model that does not fit the data enough has limited representation, causing lack of fit, and one that fits the data too much models noise as well as leading to overfitting; both situations increase generalization error (Samarasinghe 2006). The RRMSE (relative root mean squared error) measure is used to check the validation of the new network. If the RRMSE on the validation data is lower than 0.25, the accuracy of the new network is acceptable and it is used for estimating the fitness of all remaining individuals in the *n*th cluster, otherwise the remaining individuals are evaluated by the original fitness function. In this method, only one GRNN is constructed and trained for each cluster, which is effective for reducing computational burden of the solution algorithm. The value of *p* should be determined in a way that first, the trained network should be able to estimate output data precisely; second, the network should not be over trained. In this study, the total number of clusters, *k*, and the number of solutions selected from the archive, *p*, are respectively set to 0.2 number of offsprings generated at each generation, and 60.

7. Wavelet analysis

Wavelet analysis is an advanced mathematical set of tools and techniques for signal-processing which has aroused great attention in many fields of science and engineering. By a wavelet decomposition, we can denoise a signal from high-frequency components to understand behavior of the primary signal better. The theory and methods of wavelet analysis are widely available in literature. In this paper, only the application of wavelet analysis in our problem is explained; additional information can be found in (Strang and Nguyen 1996).

Wavelet transform is a method for decomposing data, functions and signals into different frequency bands (Salajegheh and Heidari 2005). A wavelet transform can be simply constructed by a tree of filter banks as shown in Fig. 3. In this figure, “downsampling” is an operation that keeps the even indexed elements of the input signal. The key scheme for a wavelet transform is to decompose a signal into two parts: the low-frequency part and the high-frequency part. This scheme is achieved by a set of filters (a low- and a high-pass filter), which separate the input signal into different frequency bands. The low-pass filter removes the high-frequency bands of the input signal and produces an approximate signal; the high-pass filter removes the low-frequency bands and produces a signal including the details of the input signal (Kaveh *et al*. 2012). In other words, by constructing a wavelet transform with these two filters, the input signal is decomposed into an approximation and a detail signal. As shown in Fig. 3, the output of a wavelet transform is two sets of coefficients, (*cA*) and (*cD*), respectively include the low- and the high-frequency content of the input signal. In Fig. 3, the length of each filter is equal to 2*N* that N is the order of the wavelet function used for the filter. If *n* is the length of the input signal, the signals *F* and *G* are both of length $n + 2N - 1$; and the length of cA and cD are equal to floor $\left(\frac{n-1}{2}\right) + N$, almost half of the input signal length.

The time-history response of structures is mostly affected by the low-frequency content of earthquake records (Salajegheh and Heidari 2005). This content can be efficiently used for time-history analysis of structures –as a surrogate for the original earthquake record– in order to decrease the number of acceleration points involved in time-history loading and subsequently reduce the computational demand of this type of analysis. The decomposition process can be repeated for the low-frequency content to achieve the desired scale of the earthquake record. This multilevel decomposition process is called wavelet decomposition tree (Gholizadeh and Samavati 2011). In this study, the decomposition process proceeds in two levels (see Fig. 4), i.e., the approximate version of the original earthquake record in the last step (cA_2) is used for analysis of structures. Consequently, the number of points involved in time-history loading is decreased to 0.25 of the original record. According to the results of our previous study (Kaveh *et al*. 2012), Daubechies wavelet function (Db2) is selected to operate as the filter and decompose the earthquake record. When cA_2 is used, the time-step of analysis must be updated as (Kaveh *et al*. 2012)

$$dt = dt \times \frac{length(\ddot{x}_g)}{length(cA_2)} \tag{10}$$

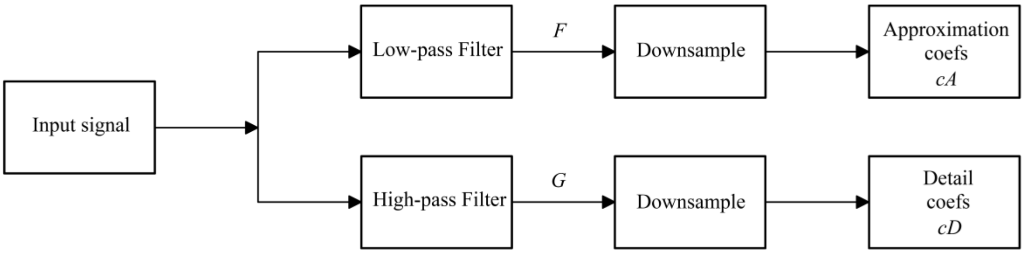


Fig. 3 General algorithm for discrete wavelet transform

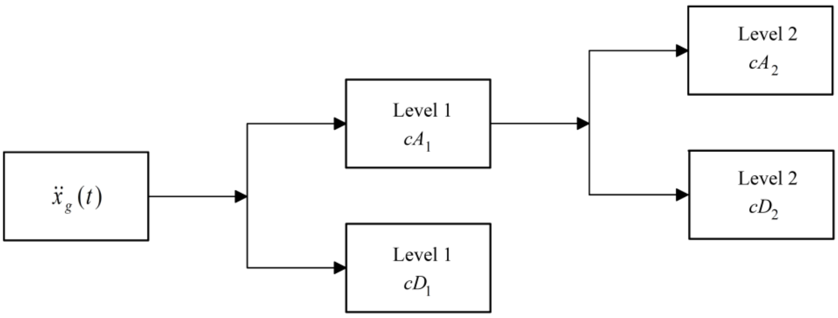


Fig. 4 A two-level wavelet decomposition of an earthquake record

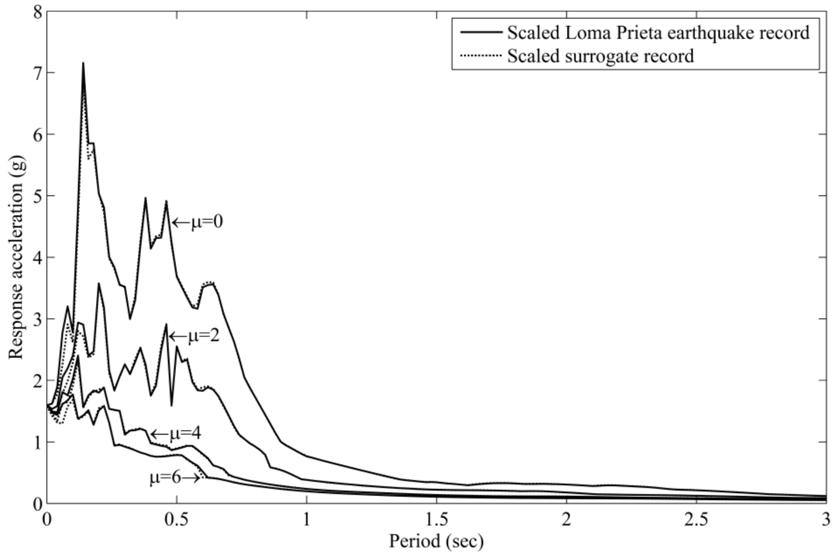


Fig. 5 5%-damped inelastic response spectra of the scaled Loma Prieta earthquake record and the scaled surrogate record

The wavelet decomposition process is invertible and the input signal can be reconstructed by convolving the obtained approximation and detail coefficients. This process is known as inverse wavelet transform, simply defined by reversing the trajectory of the wavelet transform algorithm. In order to compute the actual response of structures under the original earthquake record, the reverse process is required (Kaveh *et al*. 2012). However, as wavelet transform is a linear transform, the reverse process cannot be employed to recover the nonlinear time-history response of structures.

As mentioned in Sect. (4), in order to calculate of the Park-Ang damage index, the target ground motion time-history should be scaled according to the specifications of FEMA-273 (1997). In this study, Loma Prieta ground motion is selected as the target earthquake record to predict the damage index. The 5%-damped inelastic response spectra of the scaled Loma Prieta earthquake record and the scaled surrogate record for ductility ratio of 0, 2, 4, and 6 are shown in Fig. 5. The mean value of errors in estimating the inelastic response spectra of the original earthquake record using the surrogate record is 0.0489, calculated by the RRMSE measure. Although the effect of higher modes might be significant on the nonlinear time-history response of MDOF structures, but the considerable overlaps between the obtained inelastic response spectra –as shown in Fig. 5– suggest that the surrogate record could reasonably predict the actual roof displacement response-history of MDOF structure.

In order to verify the efficiency of the two-level wavelet decomposition tree, 100 simplified models for the ten-story moment-frame introduced in the numerical study section were generated randomly and analyzed subjected to both the scaled Loma Prieta earthquake record and the scaled surrogate record. The mean RRMSE for estimating the maximum roof displacement and the cumulative hysteretic energy using the surrogate record was respectively 0.1328 and 0.2356. While the analysis time for this record was approximately 1/4 of that was required for the original record. These values confirm that by implementing the developed wavelet decomposition method, considerable improvement in computational effort is achieved at the expense of a small loss of accuracy.

8. The proposed framework

Now, all of the components introduced in the previous sections are incorporated in a simple framework which makes it possible to solve our optimization problem. In this problem, all the constraints are classified into two main groups:

- *Initial constraints*: The constraints of this group are fulfilled by modifying the given solution. These constraints are as follows: (1) column-beam moment ratio should be satisfied at beam-to-column connections in accordance with AISC seismic provisions (2010). This condition is checked at each joint and if it is not fulfilled, the section number of the columns connecting to the joint is increased one number and then it is checked again. This process continues until all joints fulfill this constraint. (2) Lower columns should have the same or larger section number than the upper columns. This constraint is checked from the last story and gradually modifies the section of columns in order to satisfy this constraint. (3) The design strength of beams and columns should be checked following AISC-LRFD (2010) specifications. If the strength ratio of each member of structure is more than one, its section number is increased by one and this process continues until all members fulfill this constraint. The equivalent lateral force procedure of ASCE-7 (2010) is considered for earthquake loading. According to ASCE-7, the seismic load combination is $1.2D + 1.0L + 1.0E$, where D and L represent dead load and transient live load, and E represents earthquake load.
- *Final constraints*: This group contains checking of the requirements specified in Sect. 2.2 for performance evaluation. Based on FEMA-350 (2000), in order to verify the acceptance criteria for the desired performance objectives, the load combination of $1.0D + 0.25L + 1.0E$ must be applied to the mathematical model during pushover analysis. For this group, constraint violation is reported by a factor that guides optimization process as mentioned in Sect. 3.

The main procedure, which is based on the NSGA-II algorithm, is as follows:

Main procedure {

1. *Set parameters.*
2. Initialize a population.
    - 2.1. Generate a random individual.
    - 2.2. *Evaluate* the new individual.
    - 2.3. Calculate the Park-Ang damage index for the new individual.
        - 2.3.1. Perform a nonlinear time-history analysis under the surrogate record.
    - 2.4. Store the properties of the new individual in an archive (i.e. D_y, V_y, D_u, V_u, D_m, and E_h).
3. Sort the initial population based on non-domination and calculate crowding distances.
4. Select parents using binary tournament selection.
5. Generate offsprings by performing genetic operators.
    - 5.1. Generate a new individual.

5.2. *Evaluate* the new individual.
6. Perform FCM clustering algorithm and cluster the offsprings into *k* clusters.
7. Perform *evolution control strategy*.
8. Form an intermediate population from merging the current population with the offsprings.
9. Sort the intermediate population based on non-domination and calculate crowding distances.
10. Perform replacement on the intermediate population to determine the new population.
11. Stop if termination criterion is met, otherwise go to step 4.

}.

The first step is done as follows:

Set parameters {

1. Set the NSGA-II user defined parameters, e.g. population size, number of offsprings, number of generations, etc.
2. Select the input parameters required for structural modeling, analysis and design.
3. Define the effective duration of the target earthquake record.
4. Perform the two-level wavelet decomposition tree for the effective duration and generate a surrogate record.

}.

Evaluation of the new individual is performed as:

Evaluate {

1. Construct a member-by-member model.
2. Check the initial constraints.
3. Compute the initial cost.
4. Construct a simplified nonlinear model.
5. Check the final constraints.
   5.1. Perform a pushover analysis.
   5.2. Determine target displacements respectively under FE and MCE hazard level ground motions.
   5.3. Check acceptance criteria respectively at IO and CP performance levels and record the amount of constraint violation.

}.

And, evolution control is done as follows:

Evolution control strategy {

1. for each cluster do
   1.1. Find the representative individual, i.e. the individual with highest membership grade.
   1.2. Calculate the Park-Ang damage index for the representative individual.
      1.2.1. Perform a nonlinear time-history analysis under the surrogate record.
   1.3. Store the properties of the representative individual in the archive.
   1.4. Calculate the membership grade for each solution stored in the archive.
   1.5. Select *p* solutions with the highest membership grades from the archive.
   1.6. Train a GR network by 70% of the selected solutions and validate by the remaining 30%.
   1.7. If the accuracy of the GR network is acceptable, estimate the damage index of all remaining individuals by the network, otherwise use the original fitness function.

}.

9. Numerical study

A computer program was developed by coding the proposed framework in MATLAB® (2011), in which structural analysis is done by the combination of MATLAB® and OpenSees®. Actually, first, the required data for analysis of structures, including structural modeling and loading, are provided by MATLAB® and then by the use of these data, OpenSees® performs analysis. Two different models are used in this study for analyzing the given structure. In the first part, a member-by-member model of the structure is constructed using "elasticBeamColumn" element of OpenSees®; then a linear static analysis is performed to calculate design strength of the structural components under LRFD load combination. In the second part, a simplified nonlinear model of the structure is constructed with "elasticBeamColumn" elements connected by "zeroLength" elements that serve as rotational springs to represent the nonlinear behavior of the structure. Then, OpenSees® performs a pushover and a nonlinear time-history analysis needed for structural performance evaluation and the calculation of the Park-Ang damage index. In order to model structural damping, Rayleigh damping model of OpenSees® is applied by assuming the damping ratio of 5% for the first and the second mode of the structure. For FCM clustering, constructing GR networks and wavelet decomposition of the target earthquake record, respectively, fuzzy logic, neural network and wavelet toolboxes of MATLAB® are employed.

In what follows, a test problem is presented and solved using the developed program. Assume a ten-story steel frame structure with the floor plan shown in Fig. 6, in which all stories have the same plan. As observed in Fig. 6, two four-bay moment-frames in the East-West direction and four two-bay moment-frames in the North-South direction serve as the lateral load resisting system. The goal of this example is performance-based optimal design of the moment-frame located at grid A(1-5). The member-by-member model of this frame, shown in Fig. 7(a), consists of 90 elastic beam-column elements in which all columns and beams are grouped into 13 sets, each corresponding to an independent design variable.

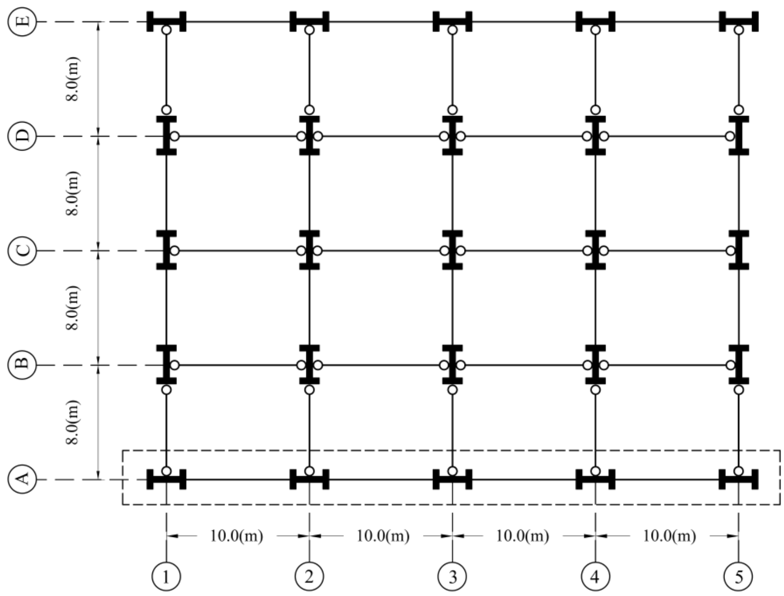
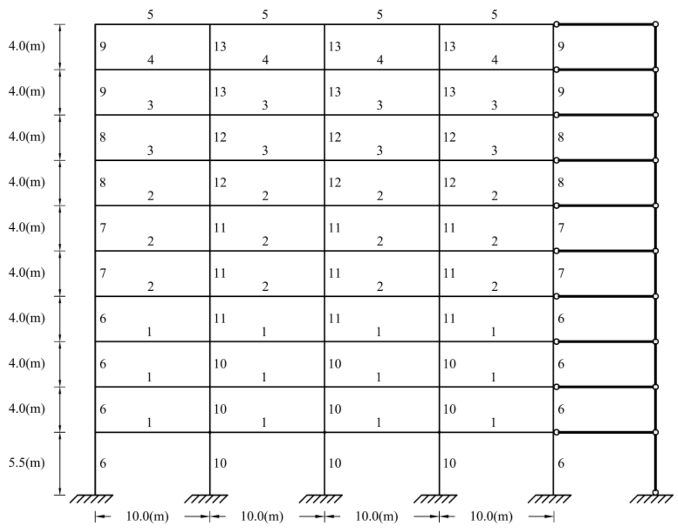
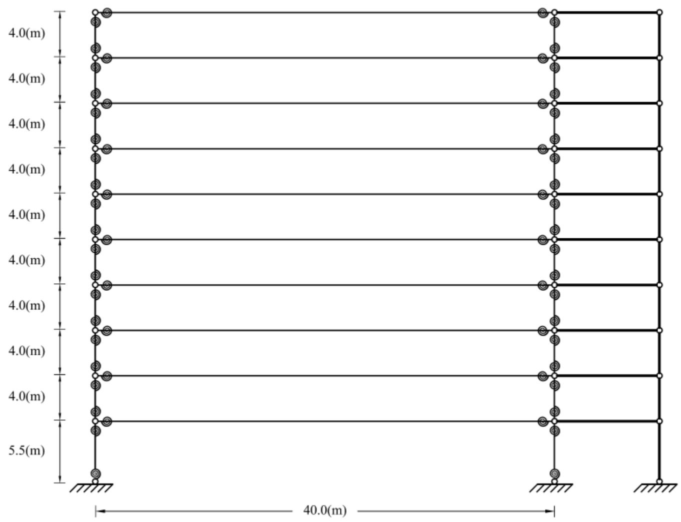


Fig. 6 Plan view of a ten-story steel moment-frame structure with the same floor plan for all stories

The simplified nonlinear model of this frame, demonstrated in Fig. 7(b), consists of 30 elastic beam-column elements with rotational springs at their ends. In this model, lumping together the columns and the beams of each story is done following the rules explained in section 5. In the both models, a leaning column, carrying half of the gravity loads acting on the existing three gravity frames in the East-West direction, is linked to the frame by rigid truss elements to simulate P-Delta effects. This frame is designed as a special moment-frame based on the requirements specified in AISC seismic provisions (2010). This structure is located in Los Angeles, California, and the type of soil profile is assumed to be *C* at the site of the structure.



(a)



(b)

Fig. 7 Models of the moment-frame located at grid A(1-5) of the floor plan: (a) member-by-member model; (b) simplified nonlinear model

All members of the frame have I-shaped cross-sections which are selected from a database of 129 W-sections containing 23 W1000, 22 W920, 13 W840, 17 W690, 18 W530, and 36 W360 sections. Details of these standard W-sections are available in the manuals of the American Institute of Steel Construction. In order to determine the rotational behavior of the plastic hinges in the simplified model, the empirical relationships developed by Lignos and Krawinkler (2011) for I-shaped cross-sections are employed.

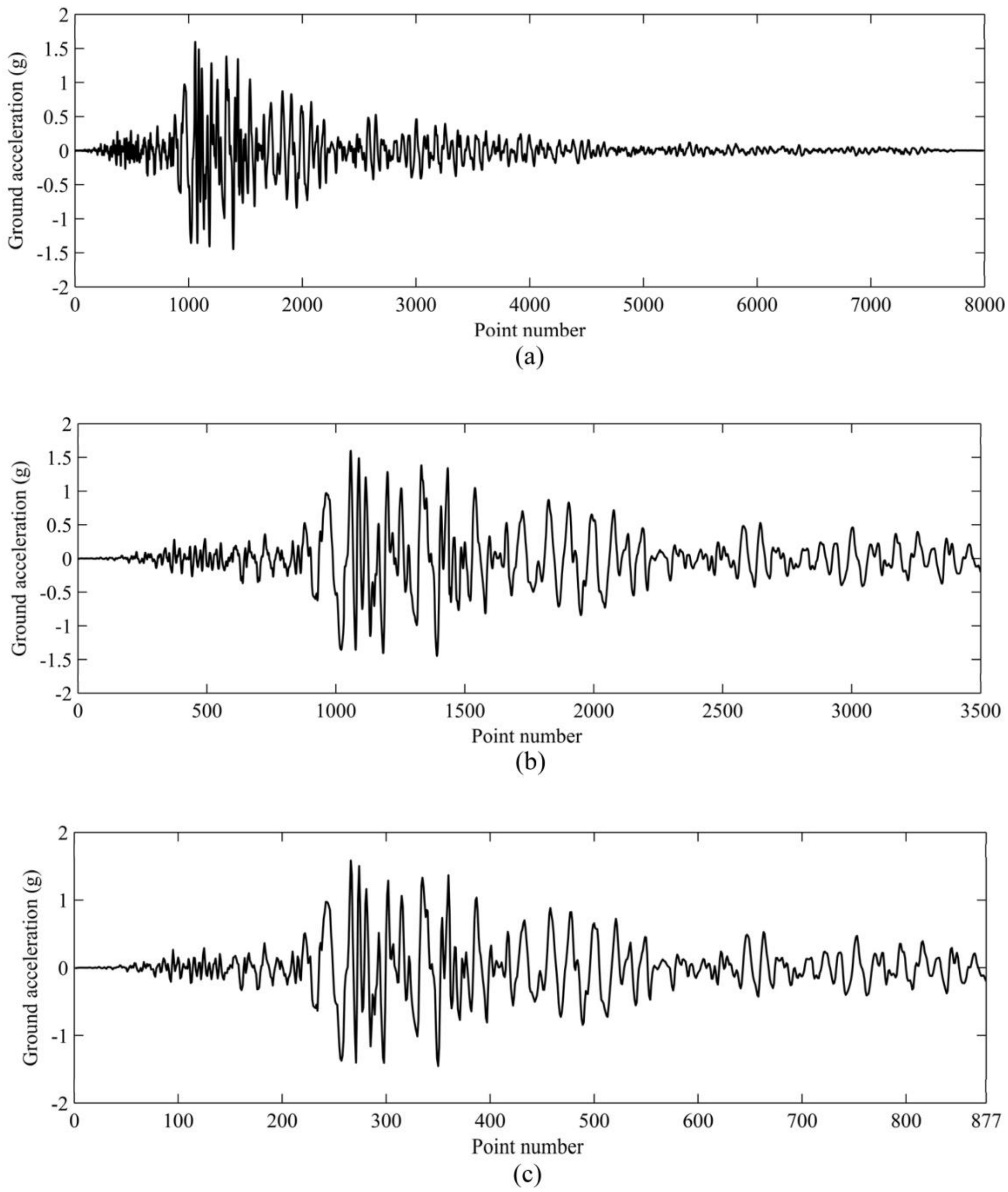


Fig. 8 Loma Prieta ground motion (station: Gilroy Array #7, 1989): (a) Scaled original record, (b) Scaled original record in the effective duration and (c) Scaled filtered record

The modulus of elasticity is equal to 2.1e6 kg/cm^2 and the yield stress of steel is 2400 kg/cm^2. The permanent load is considered to be D = 400 kg/m^2 and the transient live load is taken as L = 250 kg/m^2. The joint masses, for the simplified model, are computed by MATLAB® and given as input data to OpenSees®. The load combination for computing joint masses from the gravity loads is $1.0D + 0.2L$. In distributing the gravity loads, it is assumed that all loads are distributed uniformly between the two joints of each floor. In addition to the gravity loads, the self-weight of each element in the member-by-member model is divided into two equal mass portions and added to the mass of the corresponding joint in the simplified model.

Loma Prieta ground motion, see Fig. 8(a), is selected as the target earthquake record for the calculation of the Park-Ang damage index. Details of this earthquake record is available in the PEER Strong Motion database (PEER 2010). The effective duration of Loma Prieta ground motion, calculated by SeismoSignal®, stops at second 17.5 leading to 3500 points with a time step of 0.005 sec, see Fig. 8(b). Implementation of the Db2 function for the wavelet decomposition decreases the number of points to 877 with a time step of 0.02 sec, see Fig. 8(c). This filtered record is a surrogate for the target earthquake record that is used for the damage calculation throughout the optimization. All the records shown in Fig. 8 are scaled to the design response spectrum as recommended by FEMA-273.

Because of the stochastic nature of the solution algorithm, this problem was solved three times. The obtained Pareto fronts are shown in Fig. 9 for Park-Ang damage index against initial material cost (the total weight of structural components). These Pareto fronts demonstrate the rank-1 solutions obtained in the last generation of the NSGA-II algorithm for each run of the program. In all runs, a population of 150 individuals was evolved for 250 generations. In Fig. 9, Pareto optimal solutions are shown in three different colors according to their damage state. *DI* values less than 0.4 are classified as "repairable" damage state and are shown in green; from 0.4 to less than 1.0, as "beyond repair" damage state, in yellow; and larger than 1.0, as "collapsed", in red. Although the damage states of these optimal solutions are in different states under the target earthquake record, however, all of them are feasible solutions because they satisfies all of the initial and final constraints specified in section 8.

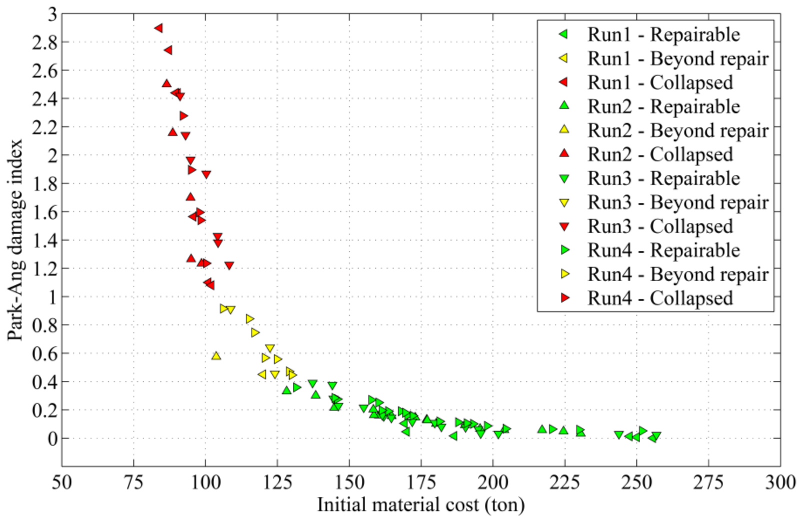


Fig. 9 One of the PLVM of the undamaged structure

Table 2 Properties of two characteristic designs of the ten-story moment-frame

	Cross section number												
Group no.	1	2	3	4	5	6	7	8	9	10	11	12	13
Design A*	W360 ×72***	W530 ×85	W360 ×64	W360 ×39	W530 ×72	W840 ×226	W840 ×226	W920 ×201	W920 ×201	W920 ×491	W840 ×226	W920 ×201	W920 ×201
Design B**	W690 ×419	W530 ×150	W840 ×359	W530 ×101	W360 ×101	W920 ×970	W920 ×787	W1000 ×591	W530 ×300	W920 ×725	W920 ×656	W920 ×656	W1000 ×554

	Fitness function evaluation		
	1st objective function	2nd objective function	Damage state
Design A	84.028 ton	2.897	Collapsed
Design B	255.597 ton	0.0004	Repairable

* Indicates the design with minimum initial cost

** Indicates the design with minimum Park-Ang damage index

*** Units are in SI system

The computational time required by the developed program to solve this multi-objective optimization problem was approximately 41 hours, using an Intel® Core™ i7 @ 2.0 GHz processor equipped with 8 GBs of RAM. As a rough estimate, without using the employed simplified modeling, the solution algorithm requires about 189 hours; without the developed fitness approximation strategy, about 166 hours; and without the two-level wavelet decomposition method, about 120 hours. If none of these simplifying strategies is adopted, the solution algorithm requires 55 times more computational time. These values were estimated by calculating the time required for one generation of the genetic algorithm in the cases that one or all of the simplifying strategies are not adopted, and multiplying it by the number of generations.

In order to compare the properties of the different optimal designs achieved in the Pareto fronts, two characteristic designs are investigated. These designs are the extreme points correspond to the single-objective optimal designs where minimization of the initial material cost and the Park-Ang damage index are respectively the objective functions. The properties of these two designs are listed in Table 2.

10. Conclusions

This paper proposed a framework, in accordance with FEMA-350 specifications, for the performance-based multi-objective optimal design of steel moment-frame structures. Minimization of the initial material cost and the Park-Ang damage index were considered as two separate objectives of the optimization problem. Obtaining the Pareto front of the possible optimal designs of a structure for these objectives, provide invaluable economical information that helps investors or insurance companies to make the best decisions. They can select among the Pareto optimal designs the one that is the most economical in terms of financial resources. This issue is more important specifically in large-scale construction projects. In the present study, we have tried to consider most of the relevant constraints included in the guidelines, so that the results may be useful for engineers in real-life projects.

For improving the time efficiency of the solution algorithm, three different strategies were adopted. Firstly, a simplified modeling method was employed to reduce the level of structural modeling sophistication needed for the seismic analysis of structures. In this method, a multi-bay steel moment-frame is condensed to a single bay moment-frame with properties tuned to represent the original frame. The simplified models require the solution of significantly fewer degrees of freedom than models with member-by-member representation. Secondly, a fitness approximation strategy was implemented to decrease the number of fitness evaluations. In this strategy, GR networks served as a meta-model for fitness approximation and a specific evolution control scheme was developed. In order to determine which individuals should be evaluated using the original fitness function and which by the meta-model, the FCM clustering algorithm was used to choose the competent individuals rather than choosing the individuals randomly. Careful selection of the individuals participating in fitness evaluation, guarantees faster and correct convergence of the evolutionary algorithm. Thirdly, a two-level wavelet decomposition method was used to decrease the number of involved acceleration points in the time-history loading to 0.25 of the target earthquake record. By using the filtered record instead of the target earthquake record, the damage index calculation requires about four times less computational time.

A computer program was developed based on the proposed frame work and operated for the design of a ten-story steel moment-frame structure. It was demonstrated that by the use of the proposed framework, a considerable saving in computational effort can be achieved, besides providing a convenient Pareto fronts of possible optimal solutions.

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