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Damage-based optimization of large-scale steel structures

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Abstract. A damage-based seismic design procedure for steel frame structures is formulated as an optimization problem, in which minimization of the initial construction cost is treated as the objective of the problem. The performance constraint of the design procedure is to achieve "repairable" damage state for earthquake demands that are less severe than the design ground motions. The Park–Ang damage index is selected as the seismic damage measure for the quantification of structural damage. The charged system search (CSS) algorithm is employed as the optimization algorithm to search the optimum solutions. To improve the time efficiency of the solution algorithm, two simplifying strategies are adopted: first, SDOF idealization of multi-story building structures capable of estimating the actual seismic response in a very short time; second, fitness approximation decreasing the number of fitness function evaluations. The results from a numerical application of the proposed framework for designing a twelve-story 3D steel frame structure demonstrate its efficiency in solving the present optimization problem.

Keywords: damage-based design methodology; steel frame structures; Park-Ang damage index; charged system search algorithm; equivalent SDOF system; fitness approximation

1. Introduction

Confident prediction of seismic performance of structures under future earthquakes is an important task in earthquake engineering. The main objective of structural engineers is to design structures that are both economical and safe against probable earthquakes. To achieve this objective, the following criteria should be fulfilled (Moustafa 2011): (1) robust ground motion characterization for the site of the structure, (2) proper mathematical modeling of the material behavior, and (3) implementing structural damage descriptors that can reliably estimate possible structural damage under seismic excitations.

For over more than a decade now, performance-based seismic design has been at the forefront of research on earthquake-resistant design methodologies. The most distinctive feature of the new trend from conventional design methods is the explicit requirement of 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). Damage control in a structure is complex because there are several response parameters

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that can be instrumental in determining the level of damage that a particular structure suffers during an earthquake. Among these response parameters, the following seismic demands are relevant (Arjomandi *et al.* 2009): deformation (characterized either by the interstory drift ratio or by the maximum and cumulative deformation ductility ratios); plastic energy dissipation; and viscous (or hysteretic) damping energy dissipation. Various damage indexes, which establish analytical relationships between the maximum 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 performance-based design methodology is possible if, through the use of damage indexes, limits can be established to the maximum or cumulative response of a structure, as a function of the desired performance for the different levels of ground shaking. Once the response limits have been established, it is then possible to estimate the mechanical characteristics need to be supplied to the structure so that its response is likely to remain within the limits (Moustafa 2011). So far, the most commonly proposed approach for the performance-based design of structures –adopted in many standards and building codes– defines structural performance levels and the corresponding limit states using deformation-based damage indexes. This because of their straightforward physical interpretation and the simplicity in calculation. However, the main weakness of deformation-based damage indexes is neglecting the damage caused by the cumulative effect of seismic excitations (Ghosh *et al.* 2011). Many researchers have shown that the energy dissipated due to cyclic–plastic deformations in a structure during an earthquake, i.e. hysteretic energy, is a more reliable indicator of seismic structural damage. Ghosh and Collins (2006) and Moustafa (2011) in their studies on developing a damage-based design procedure suggested that more complex damage indexes, such as the Park–Ang damage index (Park and Ang 1985), which combines the cumulative energy demand with the ductility demand, would be even better measures of seismic damage potential.

The main issue in any earthquake-resistant design methodologies is the estimation of the seismic demand under the design ground motion (Ghosh *et al.* 2011). With the computing facilities available today, calculation of the Park–Ang damage index is not difficult, although it is computation-intensive, because the calculation involves a nonlinear static pushover analysis and a nonlinear time-history analysis of the multi-degree of freedom (MDOF) model of the structure under study. Moreover, the computational intensity is increased when this seismic demand need to be calculated in iterative procedures such as optimization, because optimization algorithms usually need to perform a large number of evaluations in order to obtain a good solution. The aim of this study is to develop a computationally efficient framework for the optimum damage-based design of large-scale steel structures. As mentioned above, structural optimization using the Park-Ang damage index is highly computation-intensive. 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.

Minimization of the initial material cost is considered by treating the total weight of the structural component as the objective function and the charged system search (CSS) algorithm (Kaveh and Talatahari 2010) is employed to solve the optimization problem. The CSS algorithm was inspired by the principles of physics and mechanics. CSS utilizes a number of charged particle (CP) which affects each other based on their fitness values and separation distances considering the governing laws of Coulomb and Gauss from electrical physics and the governing laws of motion from the Newtonian mechanics (Kaveh and Talatahari 2012 and Kaveh 2014).

The response of an MDOF structure can be related to the response of an equivalent single-degree-of-freedom (SDOF) system. This implies that response is controlled by a single mode, and that the shape of this mode remains essentially constant throughout the response history. Although both assumptions are incorrect, numerous studies have indicated that these assumptions lead to reasonable predictions of the maximum seismic response of MDOF systems (FEMA-274 1997). Such a simplification can be very useful in the Park–Ang damage index-based design methodologies, since the heavy computational burden imposed by time-history analysis of MDOF structures can be eliminated by the use of equivalent SDOF systems. The variation of damage index values for a series of SDOF systems with different structural properties subjected to multiple earthquakes with different characteristics forms damage spectra (Ghosh *et al.* 2011). Over the years, some studies have been carried out on finding methods to construct damage spectra for the Park-Ang damage index. For example, Fajfar and Gašperešič (1996) developed an equivalent SDOF system to obtain the Park–Ang damage index for reinforced concrete structures. Ghosh *et al.* (2011) proposed three equivalent SDOF idealization schemes in order to develop damage spectra for estimating the Park–Ang damage index demand of MDOF structures. Karbassi *et al.* (2014) presented damage spectra in the form of decision trees for reinforced concrete buildings based on the qualitative meaning of the Park-Ang damage index.

Fitness approximation is a strategy for decreasing the number of fitness function evaluations to reach an optimum solution (Jin 2005). Numerous studies focus on developing computationally efficient models to approximate the fitness value of computationally intensive fitness functions. 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 optimization algorithm to converge correctly. Thus, evaluation of some solutions using the original fitness function, termed as model management, is essential (Jin 2005). The fitness function of our optimization problem – the initial material cost– does not need any kind of structural analysis and it is easy to calculate. Whereas evaluation of the damage constraint for a candidate solution is highly time-consuming. The nonlinear static pushover analysis needed to calculate the Park-Ang damage index can be approximated through a model management procedure. Radial basis function (RBF) networks – emerging as a variant of artificial neural networks– have been successfully implemented as a reliable meta-model in approximating expensive functions for structures subjected to earthquake loading (see Gholizadeh and Salajegheh 2009; Kaveh *et al*. 2012). Fast training, reasonable accuracy, and simplicity make RBF network a useful tool for decreasing the computational burden of pushover analyses in solving our optimization problem.

2. Charged system search algorithm

The charged system search is a population-based search algorithm, where each candidate solution $\mathbf{X}_i$ is considered as a charged particle. Each CP is a charged sphere of radius a with a uniform volume charge density that can impose an electric force on other CPs. The quantity of the resultant force on each CP is determined using the laws of Coulomb and Gauss from electrostatics and the quality of the movement is determined using the laws of motion from the Newtonian mechanics. The concept of charged system search and its detailed implementation procedure can be found in (Kaveh and Talatahari 2010). In the following, the pseudo-code of the CSS algorithm is presented.

Step 1: *Initialization*. The magnitude of the charge for each CP is defined as:

$$q_i = \frac{fit(i) - fitworst}{fitbest - fitworst}, \qquad i = 1, 2, \ldots, N \tag{1}$$

where *fitbest* and *fitworst* are the best and the worst fitness of all the particles; *fit*(*i*) represents the fitness of the particle *i*; and *N* is the total number of CPs. The separation distance r_{ij} between two charged particles is defined as:

$$r_{ij} = \frac{\|\mathbf{X}_i - \mathbf{X}_j\|}{\|(\mathbf{X}_i + \mathbf{X}_j)/2 - \mathbf{X}_{best}\| + \varepsilon} \tag{2}$$

where $\mathbf{X}_i$ and $\mathbf{X}_j$ are respectively the positions of the *i*th and *j*th CPs. $\mathbf{X}_{best}$ is the position of the best current CP; and ε is a small positive number to avoid singularities. The initial positions of CPs are determined randomly in the search space and the initial velocities are assumed to be zero.

Step 2: *CM creation*. A number of the best CPs and the corresponding fitness values are saved in a memory called charged memory (CM).

Step 3: *Force determination.* First, the probability of moving each CP towards the others is determined using the following function:

$$p_{ij} = \begin{cases} 1 & fit(i) < fit(j) \;\; or \;\; \dfrac{fit(i) - fit(j)}{fit(i) - fitbest} > rand \\ 0 & \end{cases} \tag{3}$$

where *rand* is a random number uniformly distributed in the range of 0 to 1. The above probability function states all good CPs attract bad CPs and only some of bad CPs attract good ones. Then, the value of the resultant force acting on each CP is calculated by:

$$F_j = q_j \sum_{i, i \neq j} \left(\frac{q_i}{a^3} r_{ij} . i_1 + \frac{q_i}{r_{ij}^2} . i_2 \right) p_{ij} (\mathbf{X}_i - \mathbf{X}_j), \qquad \left\langle \begin{array}{l} j = 1, 2, \ldots, N \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < a \\ i_1 = 0, i_2 = 1 \Leftrightarrow r_{ij} \geq a \end{array} \right. \tag{4}$$

In the above equation, the magnitude of the attractive electrical forces imposed by the CPs located inside the sphere is proportional to the separation distance and for the CPs located outside the sphere is inversely proportional to the square of the separation distance. The default value for the radius of all charged spheres is 1.0.

Step 4: *Solution construction*. Each CP moves to the new position under the action of the resultant force as:

$$\mathbf{X}_{j,new} = Fix(rand_{j1}.k_a.\frac{F}{m_j}.\Delta t^2 + rand_{j2}.k_v.\mathbf{V}_{j,old}.\Delta t + \mathbf{X}_{j,old}) \tag{5}$$

The new velocity is calculated by:

$$\mathbf{V}_{j,new} = \frac{\mathbf{X}_{j,new} - \mathbf{X}_{j,old}}{\Delta t} \tag{6}$$

where m_j is the mass of the *j*th CP and its magnitude is equal to the magnitude of the charge of the particle; Δt is the time step and is set to unity; $rand_{j1}$ and $rand_{j2}$ are two random numbers uniformly distributed in the range of 0 to 1; k_a and k_v are respectively the acceleration and velocity coefficients, obtained as:

$$k_v = 0.5(1 - iter / iter_{\max}), \qquad k_a = 0.5(1 + iter / iter_{\max}) \tag{7}$$

in which *iter* is the current iteration number and $iter_{\max}$ is the maximum number of iterations; *Fix*(**X**) is a function which rounds each component of **X** to the nearest integer. If any component of **X** violates the boundaries, it is regenerated using the harmony search-based handling approach as:

$$\mathbf{X}_{i,j} = \begin{cases} \text{w.p. CMCR} & \Rightarrow \text{select a new value from CM,} \\ & \Rightarrow \text{w.p (1-PAR) do nothing,} \\ & \Rightarrow \text{w.p. PAR choose a neighboring value,} \\ \text{w.p. (1-CMCR)} & \Rightarrow \text{select a new value randomly,} \end{cases} \tag{8}$$

where $\mathbf{X}_{i,j}$ is the *i*th component of the *j*th CP; "w.p." is the abbreviation for "with the probability"; the CMCR, varying between 0 and 1, sets the rate of choosing a value from the values saved in the CM, and (1− CMCR) sets the rate of randomly choosing a value from the allowable range. The pitch adjusting process is performed only after a value is chosen from the CM. The value (1−PAR) sets the rate of doing nothing, and PAR sets the rate of choosing a value from neighboring the best CP.

Step 5: *CM updating*. If the fitness values of some CPs in the new positions are better than the worst solutions saved in the CM, the better solutions are saved in place of the worst ones in the CM.

Step 6: *Terminating criterion control*. Steps 3-5 are repeated until a terminating criterion is satisfied.

2.1. Constraint handling

In this paper, a relatively simple scheme is adopted to handle the given constraints. Whenever two solutions are compared to update the CM, first, they are checked for constraint violation. If both are feasible, between the new solution and the solution saved in the CM, the one having the better fitness value is preferred. If one is feasible and the other is infeasible, the feasible is preferred. If both are infeasible, the one with the lowest amount of constraint violation is preferred. This is similar to the approach adopted by (Coello *et al*. 2004) to handle the constraints.

3. Park-Ang 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. A robust damage measure 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:

$$DI = \frac{d_m - d_y}{d_u - d_y} + \frac{\beta}{V_y d_u} \int \mathrm{d}E_h \tag{9}$$

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 non-negative non-dimensional parameter calibrated experimentally. In this equation, if the ultimate strength, V_u, is calculated to be smaller than V_y, V_y is replaced by V_u.

Ideally Eq. (9) 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 broadly similar to that of a vertical cantilever fixed at the base. The modified Park-Ang damage index for multi-story frames is defined as:

$$DI = \frac{D_m - D_y}{D_u - D_y} + \frac{\beta}{V_y D_u} \int \mathrm{d}E_h \tag{10}$$

where D_m is the maximum roof displacement from nonlinear time-history analysis of the MDOF model; 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. (10) is termed the "global" Park-Ang damage index, because it considers only the roof displacement and the total energy demand for the structure (Gosh *et al.* 2011).

According to the definition of the damage index in Eq. (10), 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 states and the Park–Ang damage index values are shown in Table 1. The five classes of damage states 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).

Knowing the damage state of a building under future earthquakes provides invaluable economical information that helps investors or insurance companies to make the best decisions. In this study, the performance objective of the design procedure is to achieve "repairable" damage state for earthquake demands that are less severe than the design ground motions. Calculation of the Park-Ang damage index for a structure is usually done under a target ground motion time-history 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-356 (2000)– such that the value of the 5%-damped response spectrum does not fall below the design response spectrum for the site for periods between 0.2T seconds and 1.5T seconds, where T is the

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

fundamental period of the structure.

In order to estimate different terms of Eq. (10), the structural model must be pushed until a failure point is reached and also a nonlinear dynamic analysis must be performed. In the proposed framework, the nonlinear dynamic analysis is performed using an equivalent SDOF system which is based on the nonlinear static pushover analysis of the MDOF model of the structure. The details of this procedure will be explained in the next section. On the basis of 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. In addition, the factor β is considered to be 0.15.)

4. Equivalent SDOF system

An equivalent SDOF system is a simplistic representation of the actual MDOF model of a structure, based on the properties of the real structure, such that the equivalent SDOF system is capable of representing certain responses of the MDOF system (Ghosh *et al.* 2011). The formulation of the equivalent SDOF system assumes that the deflected shape of the MDOF system can be represented by a shape vector, $\{\Phi\}$, which remains constant throughout the response history, regardless of the level of deformation. The method employed in this study for transformation of the MDOF system to an equivalent SDOF system is in accordance with the specifications of FEMA-274 (1997). The governing differential equation of a MDOF system is:

$$[M]\{\ddot{X}\}+[C]\{\dot{X}\}+\{Q\}=-[M]\{1\}\ddot{x}_g \tag{11}$$

where $[M]$ and $[C]$ are the mass and damping matrices; $\{X\}$ is the relative displacement vector; $\{Q\}$ denotes the story force vector; and $\ddot{x}_g$ is the ground acceleration history. Let the assumed shape vector $\{\Phi\}$ be normalized with respect to the roof displacement, x_t; that is, $\{X\}=\{\Phi\}x_t$. Substituting this expression for $\{X\}$ in Eq. (11) yields:

$$[M]\{\Phi\}\ddot{x}_t+[C]\{\Phi\}\dot{x}_t+\{Q\}=-[M]\{1\}\ddot{x}_g \tag{12}$$

Define the SDOF reference displacement x^r as:

$$x^r=\frac{\{\Phi\}^T[M]\{\Phi\}}{\{\Phi\}^T[M]\{1\}}x_t \tag{13}$$

Pre-multiplying Eq. (12) by $\{\Phi\}^T$ and substituting for x_t using Eq. (13) results in the governing differential equation for the response of the equivalent SDOF system:

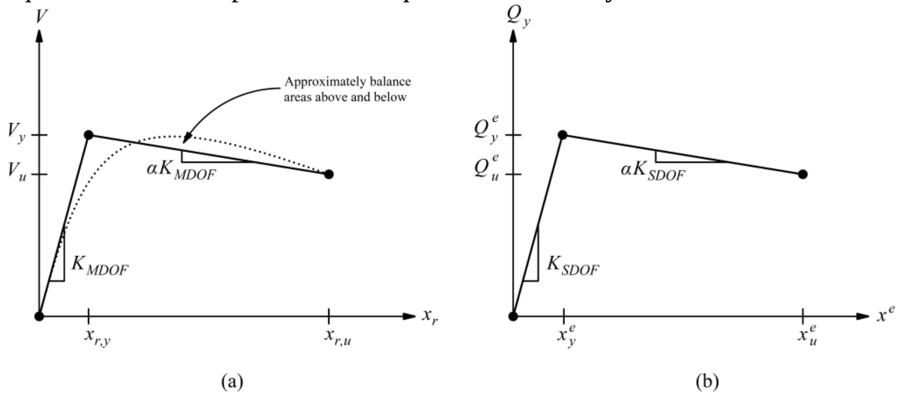

Fig. 1 Force-displacement relationships: (a) MDOF structure; (b) equivalent SDOF system (FEMA-274 1997

$$M^r \ddot{x}^r + C^r \dot{x}^r + Q^r = -M^r \ddot{x}_g \tag{14}$$

where

$$M^r = \{\Phi\}^T [M]\{1\}$$
$$Q^r = \{\Phi\}^T \{Q\} \tag{15}$$
$$C^r = \{\Phi\}^T [C]\{\Phi\} \frac{\{\Phi\}^T [M]\{1\}}{\{\Phi\}^T [M]\{\Phi\}}$$

If the same shape vector is also assumed for the nonlinear static pushover analysis of the structure, the force-displacement relationship of the equivalent SDOF system can be determined from the results of the pushover analysis of the MDOF model (FEMA-274 1997). In this method, the lateral force distribution for the pushover analysis is obtained as:

$$\{f\} = [M]\{\Phi\} \tag{16}$$

The nonlinear relationship obtained from the pushover analysis between base shear force and roof displacement must be replaced with an idealized relationship that is defined by a yield point ($V_y, x_{t,y}$), an elastic stiffness K_{MDOF}, a post yield stiffness ratio α, and a failure point ($V_u, x_{t,u}$). 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 such that the yield strength does not exceed the maximum base shear force at any point along the nonlinear curve (see Fig. 1(a)). Using the data of the idealized relationship, the reference SDOF yield displacement, x_y^r, and the ultimate displacement, x_u^r, can be calculated as:

$$x_y^r = \frac{\{\Phi\}^T [M]\{\Phi\}}{\{\Phi\}^T [M]\{1\}} x_{t,y} \qquad x_u^r = \frac{\{\Phi\}^T [M]\{\Phi\}}{\{\Phi\}^T [M]\{1\}} x_{t,u} \tag{17}$$

The reference SDOF yield force is obtained as:

$$Q_y^r = \{\Phi\}^T \{Q_y\} \tag{18}$$

where $\{Q_y\}$ is the story force vector at yield, that is,

$$V_y = \{1\}^T \{Q_y\} \tag{19}$$

The elastic stiffness of the equivalent SDOF system is calculated as:

$$K_{SDOF} = Q_y^r / x_y^r \tag{20}$$

The reference SDOF ultimate force is defined as:

$$Q_u^r = Q_y^r + \alpha K_{SDOF} (x_u^r - x_y^r) \tag{21}$$

The force-displacement relationships for the MDOF system and the equivalent SDOF system are shown in Fig. 1. After characterizing the equivalent system, the Park-Ang damage index demand for the actual structure can be obtained from a nonlinear time-history analysis of the equivalent system as per Eq. (14). For this purpose, the displacement and the support reaction force response history of the SDOF system must be transformed respectively to the roof displacement and the base shear force response history of the MDOF structure. This transformation can be written in the form,

$$R_{MDOF} = \frac{\{\Phi\}^T [M]\{1\}}{\{\Phi\}^T [M]\{\Phi\}} R_{SDOF} \tag{22}$$

where R_{SDOF} represents the quantities in the equivalent SDOF system and R_{MDOF} represents the corresponding quantities in the MDOF structure (Fajfar and Gaspersic1996).

Properties of the equivalent SDOF system depend on the assumed shape vector and how the pushover analysis is conducted. Various alternative equivalent system schemes have been proposed over the years. Ghosh *et al.* (2011) provided a detailed comparison between two common equivalent SDOF system schemes, judged by their closeness to the MDOF system response, for a variety of scenarios where considerable higher mode effects are expected. The first scheme assumes that the fundamental mode dominates the structural response to the extent that other modes' contributions could be neglected. Thus, the equivalent system is constructed assuming $\{\Phi\} = \{\Phi_1\}$, where $\{\Phi_1\}$ is the fundamental mode shape of the structure (normalized to a roof displacement equals to 1). This scheme involves the implicit assumption that the structure retains the elastic (fundamental) mode shape even when it displays an inelastic response. The second scheme applies the concept of modal pushover analysis through using multiple modal equivalent systems. In this scheme, an equivalent system is constructed for each mode shape and then the nonlinear dynamic responses of the modal equivalent systems are combined using the SRSS or CQC modal combination methods. Ghosh *et al.* (2011) concluded that although it may intuitively seem that the second scheme is more accurate, the first scheme provides better estimates for the global Park-Ang damage index, across the low- to high-rise building frames considered.

The two demand parameters needed for the calculation of the Park-Ang damage index are the roof displacement (D_m) and the hysteretic energy (E_h) demand. The first scheme underestimates the actual E_h, and it gets even worse for taller structures. Using the second scheme reduces the estimation errors because it adds the higher mode contributions to the E_h demand of the first scheme. Roof displacement demands, on the other hand, tend to overestimate the actual demand, which becomes much worse when higher mode contributions are combined with the D_m demand from the fundamental mode. Consequently, contributions from higher modes increase both the E_h and D_m demands in the second scheme, and in turn the value of the damage index. While a balancing of the underestimation of the E_h and the overestimation of the D_m demand in the first scheme, results in smaller errors (Ghosh *et al.* 2011). Obviously, the differences between these two schemes are considerable for tall buildings where higher mode effects are significant. Our numerical experiments also confirmed that the first scheme works better. So, in this study, the first scheme, which is based on a single pushover analysis using the fundamental mode shape, is employed to construct the equivalent SDOF systems.

5. Approximation procedure

In the present optimization problem, constraint validation is the most time-consuming part of the solution algorithm. Although equivalent SDOF systems are used instead of MDOF models for nonlinear dynamic analysis of structures, however, if all of the required damage index calculations are performed by nonlinear static pushover analysis, the optimization algorithm may need many hours even for small structures to complete the solution process. An alternative is to use approximations instead of exact evaluations to substantially reduce the computation time.

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 exact evaluation model (Jin and Sendhoff 2004). To alleviate this problem, two main measures can be taken (Jin 2005). 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 the model, and use of active data sampling. Secondly, the approximate model should be used together with the exact model. In the most cases, the exact model is available, although it is computationally intensive. Therefore, it is very important to use the exact model efficiently. This known as model management in the optimization literature. In the next two subsections, these two concerns are reviewed in our specific optimization problem.

5.1 Meta-model selection and training

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 several cases RBF neural networks have been successfully applied as a reliable meta-model in predicting expensive 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.* 2012). In the present study, generalized regression (GR) neural networks are employed to approximate the results of the pushover analyses. 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).

In evaluation of each candidate solution, a pushover analysis is needed for two purposes: first, to calculate the capacity terms of the Park-Ang damage index, and second, to determine the force-displacement relationship of the equivalent SDOF system. The output data of the GR networks should be selected such that they serve these two purposes. 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 with the yield force of the equivalent SDOF system (Q_y^r) are selected 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 good representative of the 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. It is well known that periods represent lateral stiffness of structures very well. On the other hand, the periods of a structure can be determined by a modal analysis in a very short time. These properties of periods make them a proper choice for the input data of the GR networks in our problem. 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, some of the pushover analyses required in the solution algorithm could be approximated by the trained GR networks.

5.2 Model management

Application of meta-models in the optimization algorithms 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 instead of exact evaluation models. Firstly, it should be ensured that the optimization algorithm converges to the global optimum or a near optimum of the exact model. Secondly, the computational cost should be reduced as much as possible. Thirdly, in the process of the 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 meta-model is employed together with the exact model (Jin 2005).

In addition, when meta-models are involved in the optimization, it is very important to determine which candidate solutions should be evaluated using the exact model in order to guarantee faster and correct convergence of the optimization algorithm (Jin and Sendhoff 2004). In this paper, the fuzzy c-means (FCM) clustering algorithm is applied to group the charged particles of the CSS algorithm into a number of clusters. In each cluster, only the representative of the cluster –the particle that is closest to the cluster center– is evaluated using the expensive exact model (i.e. the output data of the representative particle is calculated by performing a nonlinear static pushover analysis). The output data 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 and Sendhoff 2004) to choose the candidate solutions to be evaluated by the original fitness function, rather than choosing them randomly. However, in there, the k-means algorithm was applied for 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 model management should be made based on the properties of the problem under study; this is achievable through trial and error. In our problem, at each iteration of the CSS algorithm, once all the particles move to their new positions, FCM algorithm calculates k membership grades for each of them (k is the total number of clusters). Then, each particle is assigned to a particular cluster for which the corresponding grade of membership is maximum. For each cluster, the particle that has the highest membership grade is selected as the representative of the cluster. The representative particle is evaluated by the exact model and its properties –i.e. the first m periods and the results of the pushover analysis (D_y, V_y, D_u, V_u, Q_y^r)– are stored in an archive. In this way, all the particles evaluated by the exact model from the start of the optimization, are stored in the archive. In the next step, the output data of all the remaining particles are estimated by the meta-models that are trained using the data stored in the archive.

The solutions stored in the archive 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 approximate the output data of all the remaining particles 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 ith solution stored in the archive to the nth cluster is obtained as (Miyamoto *et al.* 2008):

$$\omega_n(x_i) = \frac{1}{\sum_{j=1}^{k} \left(\frac{d(center_n, x_i)}{d(center_j, x_i)} \right)^2} \tag{23}$$

where $d(center_n, x_i)$ denotes the Euclidean distance between the center of the nth cluster and the ith 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 nth cluster and lower values show that x_i may not belong to the nth 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 GR network 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 the meta-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 0.2, the accuracy of the new network is acceptable and it is used for estimating the output data of all remaining particles in the *n*th cluster. Otherwise the remaining particles are evaluated by performing a pushover analysis for each of them. In this method, only one GR network 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*, the number periods stored in the archive, *m*, and the number of solutions selected from the archive, *p*, are respectively set to 0.1 total number of charged particles, 10, and 60.

6. 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 parts:

- *Initial constraints*: The constraints of this part are fulfilled by modifying candidate solutions. 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, columns and braces 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. The directions of application of seismic forces used in the design should be those which will produce the most critical load effects. In the orthogonal combination procedure of ASCE-7, members are designed for the effects from 100% of the forces acting in one direction plus 30% of the forces acting in the perpendicular direction. The combination requiring the maximum component strength must be used.
- *Damage constraint*: This part checks the Park-Ang damage index of candidate solutions. The performance objective of the design procedure is to achieve “repairable” damage state under the scaled target ground motion. Therefore, if the damage index of a candidate solution is calculated to be less than 0.4, it is a feasible solution to our problem, otherwise it is an infeasible one. For this part, constraint violation is reported by a factor that guides optimization process as mentioned in Sect. 2.1. Based on FEMA-356 (2000), the load combination of

$1.1(1.0D + 0.25L) + 1.0E$ should be applied to the mathematical model during the pushover analysis.

The main procedure, which is based on the CSS algorithm, is as follows:

Main procedure {

1. Set parameters.

2. Determine the initial positions of CPs randomly.

3. Evaluate CPs at the initial positions.

3.1. for each CP do.

3.1.1. Check the initial constraints.

3.1.2. Compute the initial cost.

3.1.3. Perform a nonlinear static pushover analysis.

3.1.4. Store the properties of the CP in an archive (i.e. the first *m* periods and the results of the pushover analysis).

3.1.5. Construct an equivalent SDOF system.

3.1.6. Perform a nonlinear time-history analysis under the target earthquake record.

3.1.7. Check the damage constraint.

4. Create a CM.

5. Calculate the resultant force vector acting on each CP.

6. Determine the new position of each CP under the action of the resultant force vector.

7. Evaluate CPs at the new positions.

7.1. for each CP do.

7.1.1. Check the initial constraints.

7.1.2. Compute the initial cost.

7.2. Perform FCM clustering algorithm and cluster the CPs into *k* clusters.

7.3. Perform *model management*.

7.4. for each CP do.

7.4.1. Construct an equivalent SDOF system.

7.4.2. Perform a nonlinear time-history analysis under the target earthquake record.

7.4.3. Check the damage constraint.

8. Update the CM.

9. Stop if termination criterion is met, otherwise go to step 5.

}.

Model management is done as follows:

Model management {

1. for each cluster do

1.1. Find the representative particle, i.e. the particle with the highest membership grade.

1.2. Perform a nonlinear static pushover analysis for the representative particle.

1.3. Store the properties of the representative particle 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 accuracy of the GR network is acceptable, estimate the output data of all remaining particles by the GR network; otherwise perform a nonlinear static pushover analysis for each of them.

}.

7. 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® (2013). 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. Three different models are used in this study for analyzing the given structure. In the first part, an MDOF 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, again, a MDOF model of the structure is constructed, however, this time 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 analysis. The rotational behavior of the springs 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 the both MDOF models, braces are modeled with "truss" elements. In the third part, an equivalent SDOF model of the structure is constructed and a nonlinear dynamic analysis is performed to calculate the Park-Ang damage index demand of the structure. 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 and constructing GR networks, respectively, fuzzy logic and neural network toolboxes of MATLAB® are utilized.

In what follows, a test problem is presented and solved using the developed program. The structure considered is a twelve-story steel frame structure with rectangular plan, in which all stories have the same floor plan. Fig. 3 shows 3D, plan and elevation views of this structure. As observed in the plan view, two two-bay moment frames in the X direction, along with two three-bay braced-moment frames and a one-bay moment frame in the Y direction, serve as the lateral load resisting systems; the rest are gravity frames with simple beam connections. The MDOF model of this structure consist of 156 joints and 396 members including 144 columns, 84 fixed beams, 120 simple beams and 48 braces. All members of the structure 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.

Columns in a story are divided into two groups: columns lie in Z-X plane such that the strong axis bending takes place about Y axis and columns lie in Z-Y plane such that the strong axis bending takes place about X axis. Similarly, beams are divided into four groups: X-direction fixed beams (resp. simple beams) lie in Z-X plane such that the strong axis bending takes place about Y axis and Y-direction fixed beams (resp. simple beams) lie in Z-Y plane such that the strong axis bending takes place about X axis. All four braces in a story are in one group. Each group of columns, fixed beams and braces has the same section number over two adjacent stories. This results in a total of 30 different groups of members, each corresponding to an independent design variable. Since simple beams do not participate in resisting the lateral loads and they only take the gravity loads that are constant and equal for all the floors, the section number of the simple beams does not need to be variable throughout the optimization process.

The structure is assumed to be located in Los Angeles, California, and the type of soil profile is considered to be *C* at the site of the structure. The moment frames of the structure are designed as special moment frames based on the requirements specified in AISC seismic provisions (2010). The rigid diaphragm effect is assumed for all the floors. In order to determine the rotational behavior of the plastic hinges in the MDOF model, the empirical relationships developed by Lignos and Krawinkler (2011) for I-shaped cross-sections are employed.

The modulus of elasticity is equal to 2.1e6 kg/cm^2 and the yield stress of steel is 2400 kg/cm^2. The dead load and the transient live load are respectively considered to be D = 400 kg/m^2 and L = 250 kg/m^2. The joint masses 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 all joints of each floor. In addition to the gravity loads, the self-weight of each element is divided into two equal mass portions and added to the mass of the end joints of the element.

Loma Prieta ground motion, see Fig. 3(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 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 (Towhata 2008). In order to reduce the computational burden, the target earthquake record can be analyzed to the end of the effective duration instead of considering the whole earthquake record. The effective duration of Loma Prieta ground motion, calculated by SeismoSignal® (2012), stops at second 17.5 leading to 3500 points with a time step of 0.005 sec, see Fig. 3(b). Both the records shown in Fig. 3 have been scaled to the design response spectrum as specified by FEMA-356.

Table 2 Properties of the optimum design for the twelve-story steel frame structure.

X-direction fixed beams		Y-direction fixed beams		Columns lie in Z-X plane		Columns lie in Z-Y plane		Braces	
Group no.	Cross section no.	Group no.	Cross section no.	Group no.	Cross section no.	Group no.	Cross section no.	Group no.	Cross section no.
1	W360×58*	2	W360×33	13	W1000×296	14	W1000×296	25	W360×110
3	W530×92	4	W360×39	15	W920×201	16	W840×226	26	W360×91
5	W690×140	6	W530×66	17	W840×193	18	W920×201	27	W360×110
7	W360×44	8	W360×51	19	W690×170	20	W920×201	28	W360×91
9	W530×82	10	W360×44	21	W690×170	22	W690×170	29	W360×72
11	W530×72	12	W360×44	23	W690×170	24	W690×140	30	W360×72
X-direction simple beams		Y-direction simple beams		Initial material cost		Park-Ang damage index		Damage state	
Group no.	Cross section no.	Group no.	Cross section no.	256.0663 ton		0.3967		Repairable	
31	W360×44	32	W360×110						

* Units are in SI system

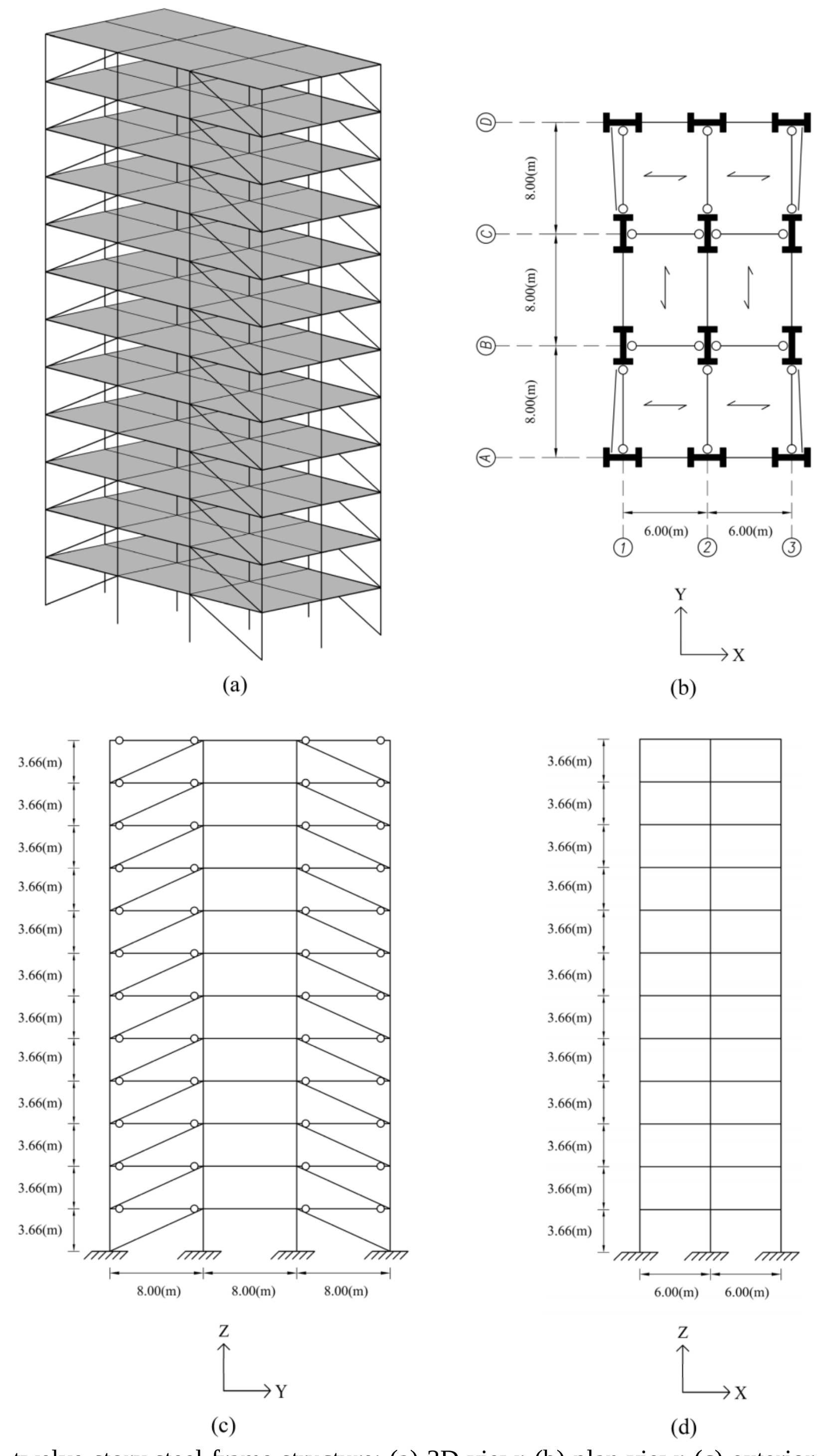

Fig. 2 A twelve-story steel frame structure: (a) 3D view; (b) plan view; (c) exterior elevation view in Z-Y plane; (d) exterior elevation view in Z-X plane

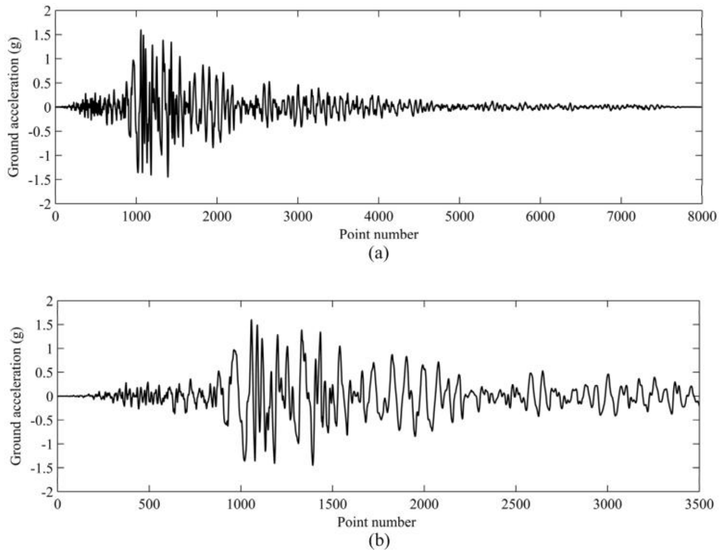

Fig. 3 Loma Prieta ground motion (station: Gilroy Array #7, 1989): (a) Scaled record; (b) Scaled record in the effective duration

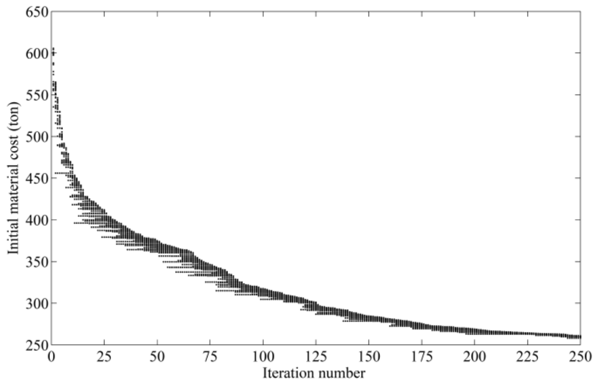

Fig. 4 Convergence history of the CSS algorithm

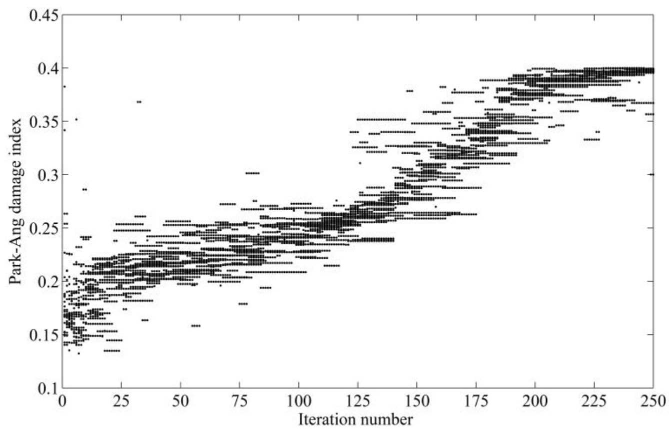

Fig. 5 Variation of the Park-Ang damage index for the solutions saved in the CM

Because of the stochastic nature of the solution algorithm, this problem was solved three times. In each run of the program, a population of 100 CPs was employed for the CSS algorithm and the optimization process was terminated after 250 iterations. The properties of the best obtained solution, i.e. the design with minimum initial cost, are summarized in Table 2. The convergence history of the best run is shown in Fig. 4. This figure demonstrate fitness of the solutions saved in the CM at the end of each iteration of the CSS algorithm. In addition, the variation of the damage index for the solutions saved in the CM is shown in Fig. 5.

The computational time required by the developed program to solve this optimization problem was approximately 50 hours, using an Intel® Core™ i7 @ 2.0 GHz processor equipped with 8 GBs of RAM. As a rough estimate, without using the employed simplifying strategies (the SDOF idealization and the approximation procedure), the solution algorithm requires 55 times more computational time. This value was estimated by calculating the time required for one iteration of the CSS algorithm in the case that none of the simplifying strategies are adopted.

8. Conclusions

This paper proposed a framework for the damage-based optimum design of steel frame structures. The performance objective of the design procedure was to prevent high economical loss for earthquake demands that are less severe than the design ground motions. For quantitative assessment of seismic damage in structures, the Park-Ang damage index was selected as the seismic damage measure. Calculation of the Park–Ang damage index is time-consuming – especially for large-scale structures– because the calculation involves a nonlinear static pushover analysis and a nonlinear time-history analysis of the MDOF model of structures. In order to alleviate this problem, two simplifying strategies were adopted. Firstly, an equivalent SDOF idealization scheme was employed to estimate the time-history response of the MDOF structures under the target ground motion. In this scheme, a multi-story frame structure is condensed to an SDOF system with properties tuned to represent the original frame. The force-displacement relation of the condensed system is determined based on the pushover analysis of the MDOF structure using the fundamental mode shape. Secondly, an approximation procedure was implemented to approximate the results of the pushover analysis. In this procedure, GR networks served as meta-models and a specific model management scheme was developed. In order to determine which candidate solutions should be evaluated by the pushover analysis and which by the meta-model, the FCM clustering algorithm was used to choose the competent solutions rather than choosing them randomly. Careful selection of the solutions evaluated by the exact model, guarantees faster and correct convergence of the optimization algorithm.

A computer program was developed based on the proposed frame work and operated for the design of a twelve-story steel frame structure. It was demonstrated that by the use of the proposed framework, a considerable saving in computational effort can be achieved. This issue is more important specifically in the optimum design of large-scale structures.

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