OPTIMAL PERFORMANCE-BASED DESIGN OF STEEL BRACED FRAMES BY PSO AND FA METAHEURISTICS

Reza KAMYAB
Assistant Professor, ACECR, Kerman, Iran
r_kamyab_m@yahoo.com

Keywords: Performance-Based Design, Optimization, Steel Braced Frames, Metaheuristic

ABSTRACT

The main aim of the present study is performance-based optimum design (PBOD) of steel braced frames using particle swarm optimization (PSO) and firefly algorithm (FA) as two popular metaheuristics. Nonlinear pushover analysis is performed to evaluate the seismic capacity of the structures. PBOD employing nonlinear pushover analysis is an iterative process needed to meet code requirements. In the PBOD procedure developed in this study, the metaheuristics minimize the structural weight subjected to performance constraints at various performance levels. Two numerical examples are presented and the numerical results reveal that the FA possesses better performance compared with the PSO.

INTRODUCTION

In the seismic design process of a structural system the number of parameters which affect the structural performance and consequently the design is usually large. In this case, recognizing that the current design is the best solution or still there is room for finding cost-efficient solutions satisfying design code requirements is a quietly difficult task. In the face of increase in price of materials, finding cost-efficient structural designs, with improved performance, is one of the major concerns in the field of structural engineering. In order to achieve this purpose, structural optimization methodologies have been developed during the last decades. The performance-based design of steel structures in the framework of structural optimization is a topic of growing interest (Gholizadeh and Kamyab 2014, Kaveh et. al. 2012, Fragiadakis and Lagaros 2011). In the performance-based seismic design approach, nonlinear analysis procedures are efficiently employed to evaluate the nonlinear seismic response of structures. Pushover analysis is a simplified, static nonlinear procedure in which a predefined pattern of earthquake loads is applied incrementally to framework structures until a plastic collapse mechanism is reached. This analysis method generally adopts a lumped-plasticity approach that tracks the spread of inelasticity through the formation of nonlinear plastic hinges at the frame element's ends during the incremental loading process (Zou and Chan 2005).

In Performance-based design (PBD) design codes, such as FEMA-356 (2000), performance ratings are divided into three levels: Immediate Occupancy (IO), Life Safety (LS) and Collapse Prevention (CP). The IO level implies very light damage with minor local yielding and negligible residual drifts. In the Life Safety (LS) level, the structure tolerates sever damage, but it remains safe for the occupants to evacuate the building. The CP level is associated with extensive inelastic distortion of structural members and an increase in load or deflection results in collapse of the structure. The PBD methods tend to consider the nonlinear seismic response of structures. These methods directly address inelastic deformations to identify the levels of damage during severe seismic events. A nonlinear analysis tool is required to evaluate earthquake demands at the various performance levels. Pushover analysis is widely adopted as the effective tool for such nonlinear analysis because of its simplicity compared with dynamic nonlinear procedures. The purpose of the nonlinear static Pushover analysis is to assess structural performance in terms of strength and deformation capacity globally as well as at the element level. The outcome of pushover analysis is the inelastic capacity curve of the structure.

In order to replace the traditional PBD process with an automatic advanced procedure for seismic design of structures, optimization algorithms can be effectively used. In this case, pushover analysis can be incorporated in a structural optimization strategy to evaluate the structural performance at the various performance levels. In the last years, many researches have been done in the field of performance-based optimum design of structures. However, metaheuristics have been employed in a few numbers of these researches. There are large numbers of such metaheuristic techniques available in the literature nowadays (Kaveh *et*. *al*. 2012). In this work, two popular metaheuristic techniques, PSO and FA, are employed to achieve optimization task. The main features of the mentioned metaheuristics are similar but there are some differences between them.

A three and A nine story planner steel braced frame structures are optimized for various performance levels using PSO and FA metaheuristics and the numerical results reveal that the FA possesses better performance compared with the PSO.

PERFORMANCE-BASED OPTIMUM DESIGN

In performance-based design frameworks, a performance objective is defined as a given level of performance for a specific hazard level. In the present work, immediate occupancy (IO), life safety (LS) and collapse prevention (CP) performance levels are considered according to FEMA-356. Each objective corresponds to a given probability of being exceed during 50 years. A usual assumption (Fragiadakis and Lagaros 2011) is that the IO, LS and CP performance levels correspond respectively to a 20%, 10% and 2% probability of exceedance in 50 year period. In this work, the nonlinear static pushover analysis is utilized to quantify seismic induced nonlinear response of structures based on the displacement coefficient method (FEMA-356) procedure. The target displacement can be obtained from the FEMA-356 as follows:

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

where C_0 relates the spectral displacement to the likely building roof displacement; C_1 relates the expected maximum inelastic displacements to the displacements calculated for linear elastic response; C_2 represents the effect of the hysteresis shape on the maximum displacement response and C_3 accounts for P-D effects. T_e is the effective fundamental period of the building in the direction under consideration; S_a is the response spectrum acceleration corresponding to the T_e; g_a *is* ground motion acceleration.

In this study, the OPENSEES platform is utilized to conduct the pushover analyses.

Optimal design of structures is the solution procedure to find the design variables such that the weight of the structure to be minimized subject to design constraints. For a steel structure consisting of *ne* members that are collected in *ng* design groups, if the variables associated with each design group are selected from a given profile list of steel sections (In the present study, design variables are selected from W-shaped sections), a discrete optimization problem can be formulated as follows:

$$\text{Find: } X = \{x_1 \quad x_2 \quad \ldots \quad x_i \quad \ldots \quad x_{ng}\}^{\mathrm{T}} \tag{2}$$

$$\text{To minimize: } w(X) = \sum_{i=1}^{ng} \rho_i A_i \sum_{j=1}^{nm} L_j \tag{3}$$

$$\text{Subject to: } g_k(X) \le 0,\ k = 1,2,\cdots,nc \tag{4}$$

where X is a vector of design variables; x_i is an integer value expressing the sequence numbers of steel sections assigned to *i*th group; *w* represents the weight of the frame, ρ_i and A_i are weight of unit volume and cross-sectional area of the *i*th group section, respectively; *nm* is the number of elements collected in the *i*th group; L_j is the length of the *j*th element in the *i*th group; $g_k(X)$ is the *k*th behavioral constraint; *nc* is the number of behavioral constraint.

In this present work, the constraints of the optimization problem are handled using the concept of exterior penalty functions method (EPFM). The general approach of penalty function methods is to minimize the objective function as an unconstrained function but to provide some penalty to limit constraint violations. In this case, the pseudo objective function is expressed as follows:

$$\Phi(X,r_p)=w(X)\left(1+r_p\sum_{k=1}^{nc}\left(\max\{0,g_k(X)\}\right)^2\right) \tag{5}$$

where Φ and r_p are the pseudo objective function and positive penalty parameter, respectively.

Two types of constraints should be checked during the optimization process. The first type includes the checks of each structural element for gravity loads. In this case, the following load combination is considered:

$$Q_G^1=1.2Q_D+1.6Q_L \tag{6}$$

where Q_D and Q_L are dead and live loads, respectively.

If the first type constraints are not satisfied then the candidate design is rejected, else a nonlinear pushover analysis based on the displacement coefficient method is performed in order to estimate the PBD constraints values at various performance levels.

The following component gravity force is considered for combination with seismic loads (FEMA-356):

$$Q_G^2=1.1(Q_D+Q_L) \tag{7}$$

The inter-story drift constraints at various performance levels can be expressed as follows:

$$g_s^i(X)=\frac{-_s^i}{-_{all}^i}-1\le 0\quad,\quad i=\text{IO};\text{LS};\text{CP},\quad s=1,2,\ldots,ns \tag{8}$$

where $-_s^i$ and $-_{all}^i$ are respectively the *s*th story drift and its allowable value of a steel braced frame associated with *i*th performance level.

The axial deformation constraints of braces at various performance levels are as follows:

$$g_b^i(X)=\frac{\Delta_b^i}{\Delta_{all}^i}-1\le 0\quad,\quad i=\text{IO};\text{LS};\text{CP},\quad b=1,2,\ldots,nb \tag{9}$$

where Δ_b^i and Δ_{all}^i are respectively the *b*th brace axial deformation and its allowable value associated with *i*th performance level.

To determine the target displacement, S_a should be calculated for the three performance levels. The calculation of spectral acceleration S_a^i for each design spectrum *i* can be expressed as:

$$S_a^i=\begin{cases}F_aS_s^i(0.4+3T/T_0) & \text{if } 0<T\le 0.2T_0^i\\ F_aS_s^i & \text{if } 0.2T_0^i<T\le T_0^i\\ F_vS_1^i/T & \text{if } T>T_0^i\end{cases}\quad,\quad i=\text{IO},\text{LS},\text{CP} \tag{10}$$

$$T_0^i=\frac{F_vS_1^i}{F_aS_s^i} \tag{11}$$

where T is the elastic fundamental period of the structure, which is computed here from structural modal analysis; S_s^i and S_1^i are the short-period and the first sec.-period response acceleration parameters, respectively; T_0^i is the period at which the constant acceleration and constant velocity regions of the response spectrum intersect; F_a and F_v are the site coefficient determined respectively from FEMA-273, based on the site class and the values of the response acceleration parameters S_s^i and S_1^i, according to Table 1 (Kaveh *et. al*. 2010).

Table 1. Performance level site parameters for site class of D

Performance Level	Hazard Level	S_s (g)	S_1 (g)	F_a	F_v
IO	20% / 50-years	0.658	0.198	1.27	2.00
LS	10% / 50-years	0.794	0.237	1.18	1.92
CP	2% / 50-years	1.150	0.346	1.04	1.70

PARTICLE SWARM OPTIMIZATION

The PSO has been proposed by Eberhart and Kennedy (1995) to simulate the motion of bird swarms. The particle swarm process is stochastic in nature; it uses a velocity vector to update the current position of each particle in the swarm. The velocity vector is updated based on the memory gained by each particle, conceptually resembling an autobiographical memory, as well as the knowledge gained by the swarm as a whole. Thus, the position of each particle in the swarm is updated based on the social behaviour of the swarm which adapts to its environment by returning to promising regions of the space previously discovered and searching for better positions over time. Numerically, the position of the *i*th particle, X_i, at iteration $t + 1$ is updated as follows:

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{12}$$

where V_i^{t+1} is the corresponding updated velocity vector given as follows:

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 \left(P_i^t - X_i^t\right) + c_2 r_2 \left(G_{best} - X_i^t\right) \tag{13}$$

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{k_{max}}.k \tag{14}$$

where V_i^t is the velocity vector at iteration t, r_1 and r_2 represents random numbers between 0 and 1; P_i^t is the best ever particle position of particle i, and G_{best}^t is the global best position in the swarm up to iteration t. The remaining terms are problem dependent parameters; c_1 and c_2 are cognitive and social parameters, respectively; ω is the inertia weight which plays an important role in the PSO convergence behaviour; ω_{max} and ω_{min} are the maximum and minimum values of ω, respectively; k_{max}, and k are the number of maximum iterations and the number of present iteration, respectively.

FIREFLY ALGORITHM

The FA is a new meta-heuristic optimization algorithm inspired by the flashing behaviour of fireflies. The FA is a population-based algorithm, which may share many similarities with PSO. Fireflies communicate, search for pray and find mates using bioluminescence with varied flashing patterns. In order to develop the firefly algorithm, natural flashing characteristics of fireflies have been idealized using the following three rules (Yang 2009):

a. All of the fireflies are unisex; therefore, one firefly will be attracted to other fireflies regardless of their sex.
b. Attractiveness of each firefly is proportional to its brightness, thus for any two flashing fireflies, the less bright firefly will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly.
c. The brightness of a firefly is determined according to the nature of the objective function.

The attractiveness of a firefly is determined by its brightness or light intensity which is obtained from the objective function of the optimization problem. However, the attractiveness β, which is related to the judgment of the beholder, varies with the distance between two fireflies. The attractiveness β can be defined by (Yang 2010, Miguel *et al*. 2013):

$$\beta = \beta_0 e^{-\gamma . d^2} \tag{15}$$

where d is the distance of fireflies, β_0 is attractiveness at d = 0, and γ is the light absorption coefficient.

The distance between two fireflies i and j at X_i and X_j respectively, is determined as follows:

$$d_{ij} = \left\| X_i - X_j \right\| = \sqrt{\sum (x_{i,k} - x_{j,k})^2} \tag{16}$$

where $x_{i,k}$ is the k-th parameter of the spatial coordinate x_i of the i-th firefly.

In the FA, the movement of a firefly i towards a more attractive (brighter) firefly j is determined by the following equation (Yang 2010):

$$X_i^{t+1} = X_i^t + \beta_0 e^{-\gamma . d_{ij}^2} (X_j^t - X_i^t) + \lambda (r - 0.5) \tag{17}$$

where the second term is related to the attraction, while the third term is randomization with λ being the randomization parameter between 0 and 1; r is a random number generator uniformly distributed in [0, 1].

NUMERICAL RESULTS

In order to illustrate the efficiency of the proposed methodology, a three and a nine story planner steel braced frame structures are optimized for various performance levels using PSO and FA metaheuristics. For both the PSO and FA the number of particles is considered to be 50 and the maximum number of iterations is restricted to 500.

The three story planner steel braced frame structure and its element grouping details are shown in Fig 1.

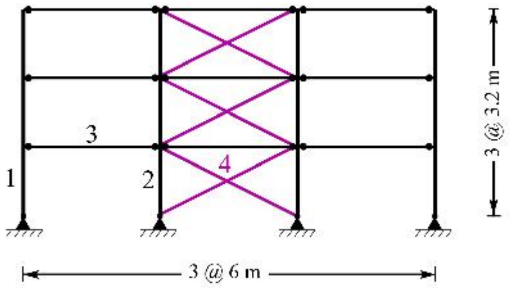

Figure 1. Three story steel braced frame

The results of optimization for the three story planner steel braced frame structure are compared in Table 1.

Table 1. Optimization results for three story braced frame

Group No.	FA	PSO
1	W8X31	W16X36
2	W24X76	W24X76
3	W10X22	W10X22
4	W14X61	W8X67
Weight (kN)	28.727	30.475

Also, the convergence histories of PSO and FA are shown in Fig 2. The results demonstrate the efficiency of the FA compared with PSO.

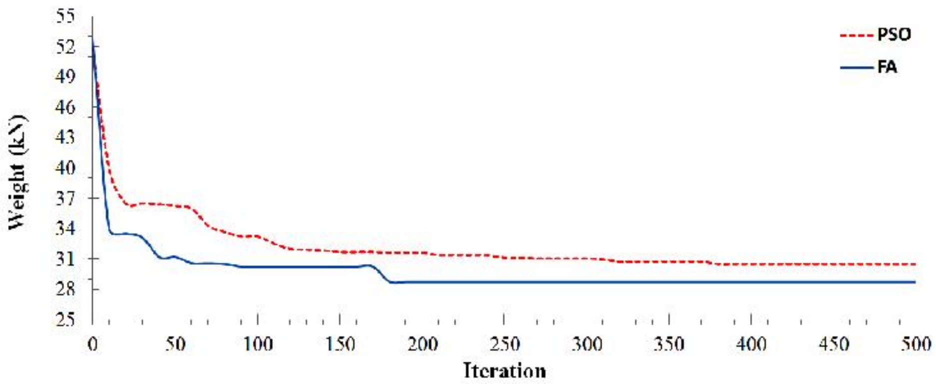

Figure 2. Convergence histories of PSO and FA for three story steel braced frame

The nine story planner steel braced frame structure and its element grouping details are shown in Fig 3.

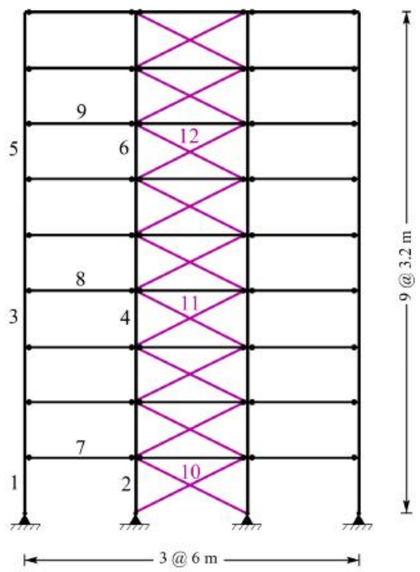

Figure 3. Nine story steel braced frame

The results of optimization for the nine story planner steel braced frame structure are compared in Table 2.

Table 2. Optimization results for nine story braced frame

Group No.	FA	PSO
1	W8X35	W8X35
2	W27X194	W40X235
3	W8X31	W8X31
4	W30X116	W33X118
5	W24X55	W24X55
6	W21X44	W21X48
7	W10X22	W10X22
8	W10X22	W8X28
9	W8X28	W8X28
10	W8X67	W21X83
11	W14X48	W24X55
12	W12X30	W12X30
Weight (kN)	88.5	95.9

Fig 4 depicts the convergence histories of PSO and FA. The results indicate that the FA converges to a better solution in comparison with PSO.

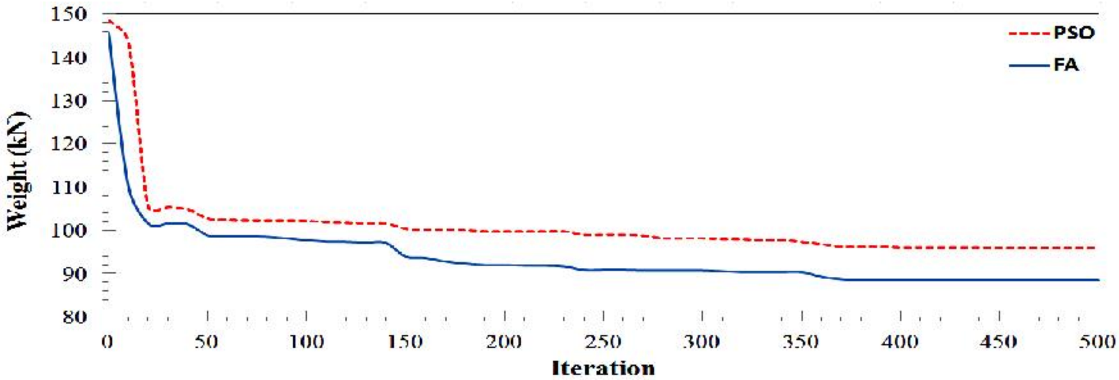

Figure 4. Convergence histories of PSO and FA for nine story steel braced frame

CONCLUSIONS

This paper tackles the problem of performance-based optimum design of steel braced frames utilizing PSO and FA metaheuristic optimization algorithms. Two types of design constraints are checked during the optimization process. At first, each structural element is checked to satisfy the AISD-LRFD constraints for the non-seismic load combinations. While the second type includes the check of inter-story drifts and axial deformation of braces at IO, LS and CP performance levels according to the FEMA-356 provided constraints. Two numerical examples including a three story and a nine-story steel braced frames are presented. The numerical results imply that the computational performance of FA is better than that of the PSO metaheuristic.

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