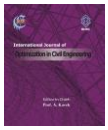
INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2019; 9(3):483-498



PERFORMANCE-BASED OPTIMIZATION AND SEISMIC COLLAPSE SAFETY ASSESSMENT OF STEEL MOMENT FRAMES

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ABSTRACT

The main aim of the present study is to optimize steel moment frames in the framework of performance-based design and to assess the seismic collapse capacity of the optimal structures. In the first phase of this study, four well-known metaheuristic algorithms are employed to achieve the optimization task. In the second phase, the seismic collapse safety of the obtained optimal designs is evaluated by conducting incremental dynamic analysis and generating fragility curves. Three illustrative examples including 3-, 6-, and 12-story steel moment frames are presented. The numerical results demonstrate that all the performance-based optimal designs obtained by the metahuristic algorithms are of acceptable collapse margin ratio.

Keywords: structural optimization; performance-based design; incremental dynamic analysis; collapse margin ratio; steel moment frame.

Received: 2 December 2018; Accepted: 4 March 2019

1. INTRODUCTION

One of the modern seismic design procedures for the rehabilitation of existing structural systems and the seismic design of new structures is performance-based design (PBD) [1] which its main objective is to decrease vulnerability of structures subject to earthquake. In the PBD approach, nonlinear analysis procedures are employed to evaluate the seismic response of structures. Pushover analysis is a simplified static nonlinear procedure in which a predefined pattern of earthquake loads is applied incrementally to structures until a plastic collapse mechanism is reached. One of the major concerns of structural engineers and designers is to find cost-efficient structures having acceptable performance subject to

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earthquake. To this end, structural optimization methodologies were developed in the last decades. Structural performance-based optimal design is a topic of growing interest [2-12].

In general, there are two types of optimization techniques: gradient-based methods and metaheuristics. Many of gradient-based methods have difficulties when dealing with complex and discrete optimization problems, and they converge to local optima. In order to overcome these difficulties, it is necessary to use global search algorithms such as metaheuristics. Metaheuristics are designated based on stochastic natural phenomena and they have attracted a great deal of attention during the last two decades. As the metaheuristic optimization techniques require no gradient computations, they are simple for computer implementation. During the recent years, researchers have designed many metaheuristic algorithms and many successful applications of them have been reported in optimization literature. In the present work, four swarm intelligence and Physics-based algorithms including particle swarm optimization [13] (PSO), firefly algorithm (FA) [14] bat algorithm (BA) [15] and enhanced colliding bodies optimization (ECBO) [16] are employed due to their efficiency and simplicity.

Seismic assessment of structures is one of the most attractive research fields in structural engineering. In order to determine the seismic safety factor of structures, collapse fragility curves can be generated using the results of incremental dynamic analysis (IDA) [17] and the collapse margin ratio (CMR) [18] can be subsequently computed. The work of Fattahi and Gholizadeh [19] is the first study in the field of seismic fragility assessment of optimal steel moment frame (SMF) structures and further studies need to be conducted in this area. In the present work, 3-, 6-, and 12-story SMFs are optimized in the framework of PBD by using PSO, FA, BA, and ECBO metaheuristics and then the seismic collapse safety of the optimal designs are assessed.

2. PERFORMANCE-BASED DESIGN OPTIMIZATION

Based on the modern approach of PBD, the structures should meet performance objectives for a number of different hazard levels ranging from earthquakes with a small intensity and with a small return period to a more destructive event with large return period. According to FEMA-350 [20], performance ratings are divided into two levels: Immediate Occupancy (IO), and Collapse Prevention (CP). The IO level implies very light damage with minor local yielding and negligible residual drifts, while the CP level is associated with extensive inelastic distortion of structural members with little residual strength and stiffness. According to FEMA-350 [20], two hazard levels are defined as earthquakes with 50% and 2% probability of exceedance in 50 years.

In the framework of PBD, geometric constraints should be checked at each structural joint to ensure that the dimensions of beams and columns are consistent. As the strength constraints, the strength of structural members need to be checked for gravity loads based on AISC 360-16 [21] design code. Based on FEMA-350 [20], the constraints of confidence level (CL) at IO and CP performance levels can be written as follows:

$$CL_{\mathrm{IO}} - \overline{CL}_{\mathrm{IO}} \geq 0 \qquad (1)$$

$$CL_{\mathrm{CP}} - \overline{CL}_{\mathrm{CP}} \geq 0 \qquad (2)$$

where $\overline{CL}_{IO}$ = 50% and $\overline{CL}_{CP}$ = 90% are minimum confidence levels for IO and CP performance levels, respectively.

The confidence level for hazard levels can be computed using the following equation:.

$$CL = \Phi\left(\frac{k\,\beta_{UT}}{2} - \frac{\ln(\gamma\,\gamma_a\,D/\phi\,C)}{b\beta_{UT}}\right) \tag{3}$$

in which Φ is the normal cumulative distribution function; k is the slope of the hazard curve; γ is a demand variability factor; β_{UT} is an uncertainty measure equal to the vector sum of the logarithmic standard deviation of the variations in demand and capacity resulting from uncertainty; γ_a is an analysis uncertainty factor; D is the calculated demand; C is the capacity of the structure; and ϕ is a resistance factor; and b=1.0 [20].

In this work, pushover analysis is conducted to evaluate the structural nonlinear responses. In this method, the structure is pushed with a specific distribution of lateral loads, until the displacement of a specific point of the structure reaches the target displacement and it can be obtained as follows:

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

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; and g is ground acceleration.

The problem of performance-based optimization of SMFs can be formulated as follows:

$$\text{Minimize: } W(X) = \sum_{i=1}^{ne} \rho_i A_i l_i \tag{5}$$

$$\text{Subject to: } g_j(X) \le 0 \text{ , } j = 1, 2, \ldots, nc \tag{6}$$

where X is a vector of design variables; W is the weight of structural elements; ρ_i, A_i, and l_i are weight density, cross-sectional area and length of the ith element, respectively; and g_j is the jth design constraint.

3. METAHEURISTIC ALGORITHMS

The main idea behind designing the metaheuristic algorithms is to tackle complex optimization problems where other optimization methods have failed to be effective. Metaheuristics are applied to a very wide range of problems and they mimic natural metaphors to solve complex optimization problems. In this study, PSO, FA, BA and ECBO metaheuristics are applied to solve the PBD optimization problem of SMFs.

3.1 Particle swarm optimization

Eberhart and Kennedy [13] proposed PSO to simulate the motion of bird swarms. The position of each particle is updated based on the social behavior of the swarm, which adapts to its environment by returning to promising regions of design 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:

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (7)$$

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 \left(P_i^t - X_i^t\right) + c_2 r_2 \left(G_{best}^t - X_i^t\right) \quad (8)$$

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} . t \quad (9)$$

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 represents the best ever particle position of particle i; G_{best}^t corresponds to the global best position in the swarm up to iteration t; c_1, and c_2 are social parameters; $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of ω, respectively; and $t_{\max}$ is the number of maximum iterations.

3.2 Firefly algorithm

The FA inspired by the flashing behavior of fireflies. Fireflies communicate, search for pray and find mates using bioluminescence with varied flashing patterns [14]. 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.

The attractiveness β, which is related to the judgment of the beholder, can be defined as:

$$\beta = \beta_0 \mathrm{e}^{-\gamma . r^2} \quad (10)$$

where r is the distance of two fireflies, β_0 is the attractiveness at r = 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:

$$r_{ij} = \left\| X_i - X_j \right\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \quad (11)$$

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

The movement of a firefly i towards a more attractive firefly j is determined as follows:

$$X_i = X_i + \beta_0 \mathrm{e}^{-\gamma . r_{ij}^2} (X_j - X_i) + \alpha (r_1 - 0.5) \quad (12)$$

where the second term is related to the attraction, while the third term is randomization with α being the randomization parameter. In addition, r_1 is a random number generator uniformly distributed in [0, 1].

3.3 Bat algorithm

The BA meta-heuristic is inspired from the echolocation behavior of microbats [15]. Echolocation is an advanced hearing based navigation system used by bats to detect objects in their surroundings by emitting a sound to the environment. The position and velocity of bats can be updated in design space as follows:

$$f_i = f_{\min} + (f_{\max} - f_{\min})u_i \tag{13}$$

$$V_i^{t+1} = V_i^t + (X_i^t - G_{best}^t)\, f_i \tag{14}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{15}$$

where $f_{\min}$ and $f_{\max}$ are the lower and upper bounds imposed for the frequency range of bats. In this study, $f_{\min} = 0.0$ and $f_{\max} = 1.0$ are used; u_i from [0,1] is a vector containing uniformly distribution random numbers.

A local search is implemented on a randomly selected bat from the current population using the following equation:

$$X^{t+1} = X^t + \varepsilon_j\, A^{t+1} \tag{16}$$

where ε_j is a uniform random number in the range of [-1, 1] selected for each design variable of the selected bat; A^{t+1} is the average loudness of all the bats at the current iteration.

The loudness A_i and the rate r_i of pulse emission have to be updated accordingly as the iterations proceed. In this work, A_0 =1 and $A_{\min}$ = 0 also, r_0 = 0 and $r_{\max}$ = 1.

$$A_i^{t+1} = 0.9\, A_i^t \tag{17}$$

$$r_i^{t+1} = r_i^0\,(1 - \mathrm{e}^{-0.01t}) \tag{18}$$

3.4 Enhanced colliding bodies optimization

Kaveh and Ilchi Ghazaan [16] proposed enhanced colliding bodies optimization (ECBO) to improve convergence rate and reliability of colliding bodies optimization (CBO) [22] by adding a memory to save some of the best solutions during the optimization process and also utilizing a mutation operator to decrease the probability of trapping into local optima. The basic steps of ECBO are as follows [16]:

1. The initial positions of all colliding bodies (CBs) are determined randomly in an m-dimensional search space as follows:

$$X_i^0 = X_{\min} + R \circ (X_{\max} - X_{\min})\,,\; i = 1,2,...,n \tag{19}$$

in which X_i^0 is the initial solution vector of the *i*th CB. Here, $X_{\min}$ and $X_{\max}$ are respectively the lower and upper bounds of design variables; *r* is a random vector in the interval [0, 1]; *n* is the number of CBs.

2. The value of mass for each CB is evaluated as follows:

$$m_i = \frac{1}{F(X_i)} \tag{20}$$

where $F(X_i)$ is the objective function value of the *i*th CB.

3. Colliding memory (CM) is utilized to save a number of historically best CBs and their related masses. Solution vectors in CM, are added to the population and the same number of current worst CBs are deleted. Finally, CBs are sorted according to their masses.
4. CBs are divided into two equal groups:

(a) Stationary group; $i_S = 1,2,...,\frac{n}{2}$ and (b) Moving group; $i_M = \frac{n}{2}+1, \frac{n}{2}+2,...,n$

5. The velocities of stationary and moving bodies before collision are evaluated as follows:

$$V_{i_S} = 0 \tag{21}$$

$$V_{i_M} = X_{i_S} - X_{i_M} \tag{22}$$

6. The velocities of stationary and moving bodies after collision are evaluated as follows:

$$V'_{i_S} = \left(\frac{(1+\varepsilon)\, m_{i_M}}{m_{i_S} + m_{i_M}}\right) V_{i_M} \tag{23}$$

$$V'_{i_M} = \left(\frac{(m_{i_M} - \varepsilon\, m_{i_S})}{m_{i_S} + m_{i_M}}\right) V_{i_M} \tag{24}$$

$$\varepsilon = 1 - \frac{t}{t_{\max}} \tag{25}$$

where ε is the coefficient of restitution.

7. The new position of each CB is calculated as follows:

$$X_{i_S}^{\text{new}} = X_{i_S} + \overline{R}_{i_S} \circ V'_{i_S} \tag{26}$$

$$X_{i_M}^{\text{new}} = X_{i_M} + \overline{R}_{i_M} \circ V'_{i_M} \tag{27}$$

where $\overline{R}_{i_S}$ and $\overline{R}_{i_M}$ are random vectors uniformly distributed in the range of [-1,1].

8. A random parameter pro is introduced and it is specified whether a component of each CB must be changed or not. For each CB, pro is compared with rni (i=1,…,n) which is a random number uniformly distributed within (0, 1). If rni < pro, one dimension of the ith CB is selected randomly.
9. When a stopping criterion is satisfied, the optimization process is terminated.

4. SEISMIC COLLAPSE SAFETY ASSESSMENT

The methodology proposed by FEMA-P695 [18] is an efficient IDA-based approach to assess the collapse capacity of structures. In this methodology, many nonlinear time-history analyses should be implemented for a suit of 22 ground motions listed in Table 1.

Table 1: Ground motion records set

Name	M	Year	Record Station
Northridge	6.7	1994	Beverly Hills - Mulhol
Northridge	6.7	1994	Canyon Country-WLC
Duzce, Turkey	7.1	1999	Bolu
Hector Mine	7.1	1999	Hector
Imperial Valley	6.5	1979	Delta
Imperial Valley	6.5	1979	El Centro Array #11
Kobe, Japan	6.9	1995	Nishi-Akashi
Kobe, Japan	6.9	1995	Shin-Osaka
Kocaeli, Turkey	7.5	1999	Duzce
Kocaeli, Turkey	7.5	1999	Arcelik
Landers	7.3	1992	Yermo Fire Station
Landers	7.3	1992	Coolwater
Loma Prieta	6.9	1989	Capitola
Loma Prieta	6.9	1989	Gilroy Array #3
Manjil, Iran	7.4	1990	Abbar
Superstition Hills	6.5	1987	El Centro Imp. Co.
Superstition Hills	6.5	1987	Poe Road (temp)
Cape Mendocino	7.0	1992	Rio Dell Overpass
Chi-Chi, Taiwan	7.6	1999	CHY101
Chi-Chi, Taiwan	7.6	1999	TCU045
San Fernando	6.6	1971	LA - Hollywood Stor
Friuli, Italy	6.5	1976	Tolmezzo

To implement IDA, engineering demand parameter (EDP) and the intensity measure (IM) are usually taken as maximum inter-story drift ratio, $d_{\max}$, and 5% damped spectral acceleration at structural fundamental period, $S_a(T_1, 5\%)$, respectively. In this way, nonlinear time-history analyses of structures for increasingly scaled records are performed and IDA curves are generated and this process is continued until one of the collapse conditions is satisfied. The results of IDA curves are then used to generate collapse fragility curves. Collapse margin ration (CMR) [18] is defined as the ratio of the spectral acceleration for which half of the pre-defined earthquake records cause collapse ($S_a^{50\%}$) to the spectral acceleration of the maximum considered earthquake (MCE) ground motion (S_a^{MCE}) as follows:

$$CMR = \frac{S_a^{50\%}}{S_a^{\text{MCE}}} \tag{28}$$

5. NUMERICAL EXAMPLES

Three numerical examples of 3-, 6-, and 12-story SMFs, shown in Fig. 1, are illustrated. The sections of all members are selected from the W-shaped sections listed in Table 2. The modulus of elasticity and yield stress are 210 GPa and 235 MPa, respectively. The constitutive law is bilinear with pure strain hardening slope of 3% of the elastic modulus. The dead and live loads of 2500 and 1000 kg/m are applied to the all beams, respectively.

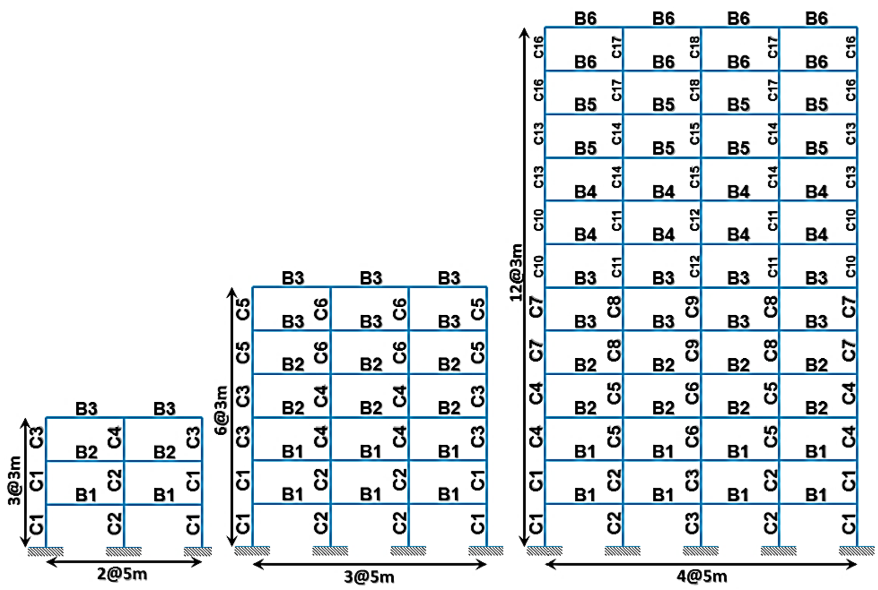


Figure 1. Grouping details of 3-, 6- and 12-story SMFs

Table 2: Available W-sections

Columns				Beams			
No.	Profile	No.	Profile	No.	Profile	No.	Profile
1	W14×48	13	W14×257	1	W12×19	13	W21×50
2	W14×53	14	W14×283	2	W12×22	14	W21×57
3	W14×68	15	W14×311	3	W12×35	15	W24×55
4	W14×74	16	W14×342	4	W12×50	16	W21×68
5	W14×82	17	W14×370	5	W18×35	17	W24×62
6	W14×132	18	W14×398	6	W16×45	18	W24×76
7	W14×145	19	W14×426	7	W18×40	19	W24×84
8	W14×159	20	W14×455	8	W16×50	20	W27×94
9	W14×176	21	W14×500	9	W18×46	21	W27×102
10	W14×193	22	W14×550	10	W16×57	22	W27×114
11	W14×211	23	W14×605	11	W18×50	23	W30×108
12	W14×233	24	W14×665	12	W21×44	24	W30×116

In this study, the 5%- damped acceleration response spectra of frequent earthquake and maximum considered earthquake of the Iranian Seismic Code 2800 [23] with less than respectively 50% and 2% probability of exceedance in 50 years are employed.

5.1 Example 1: 3-story SMF

In 3-story SMF example, PSO, FA, BA, and ECBO metaheuristics are used to conduct 10 independent PBD optimization runs and the best design obtained by each algorithm are compared in Table 3. It can be observed that BA dominates all the other algorithms and the second best algorithm is ECBO. The IDA and fragility curves of the best designs found by different algorithms are depicted in Figs. 2 and 3, respectively.

Table 3: PBD optimization results for 3-story SMF

Design variables	Algorithm			
	PSO	FA	BA	ECBO
C1	W14×53	W14×53	W14×53	W14×48
C2	W14×68	W14×68	W14×68	W14×74
C3	W14×48	W14×48	W14×48	W14×48
C4	W14×53	W14×48	W14×48	W14×48
B1	W12×22	W12×22	W12×22	W12×22
B2	W12×22	W12×22	W12×22	W12×22
B3	W12×19	W12×22	W12×19	W12×22
Weight (kg)	3152.90	3176.15	3130.16	3139.76
CL_{IO} (%)	53.48	52.65	53.35	51.28
CL_{CP} (%)	99.75	99.76	99.75	99.75

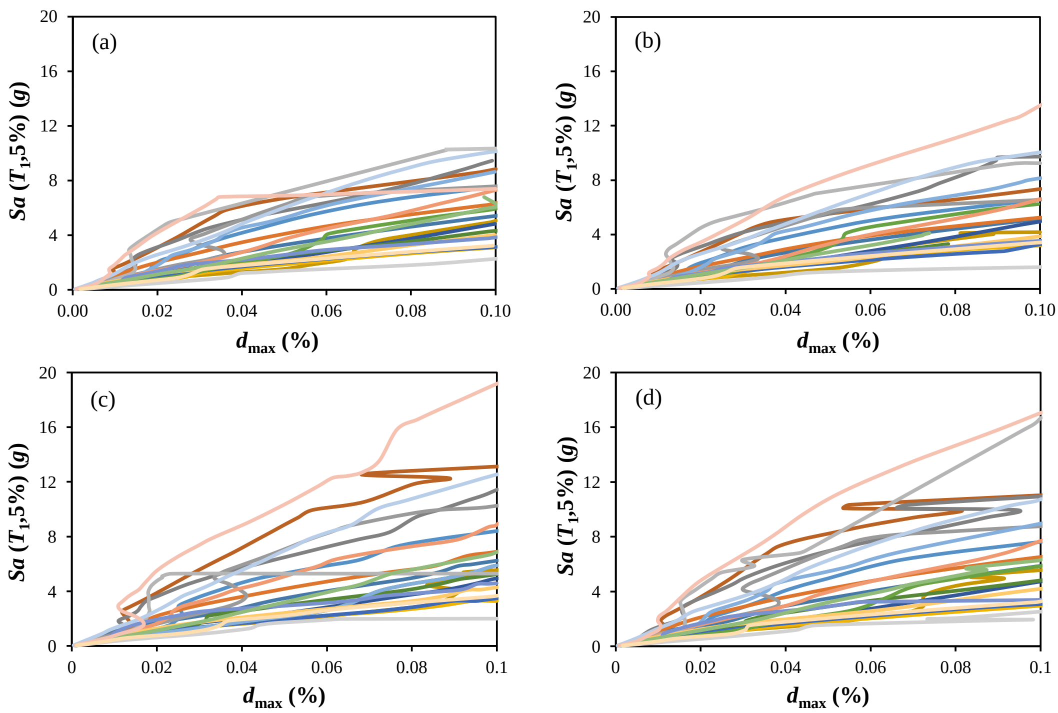


Figure 2. IDA curves for the optimum 3-story SMF structures found by (a) PSO, (b) FA, (c) BA and (d) ECBO

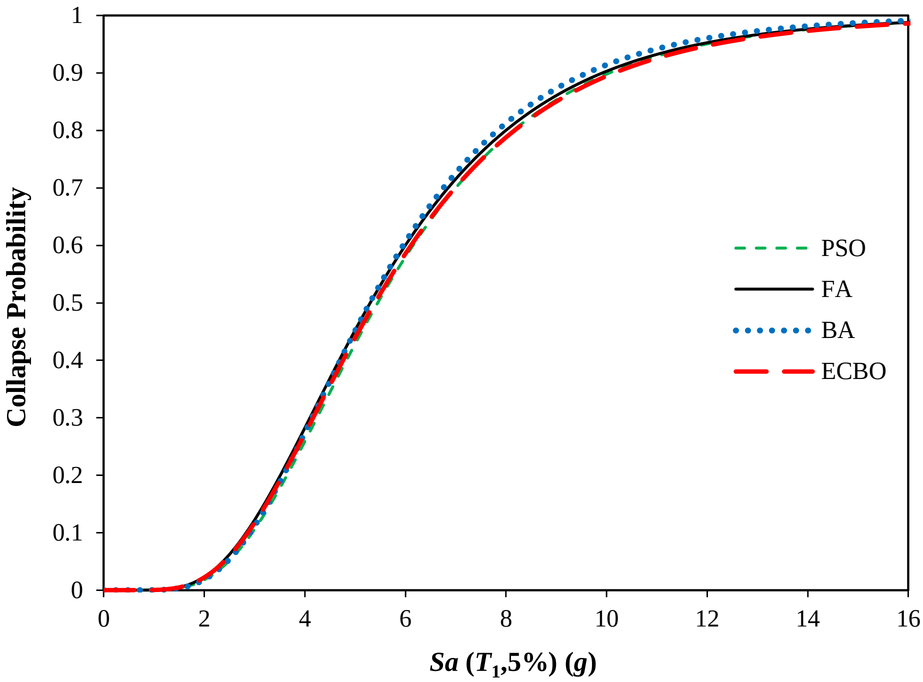


Figure 3. Fragility curves for the optimum 3-story SMF structures found by (a) PSO, (b) FA, (c) BA and (d) ECBO

The results of seismic collapse safety assessment of the optimally designed 3-story SMF structures are summarized in Table 4. It can be observed that *ACMR* values of all the PBD optimal designs are almost the same and these optimal designs are of significant collapse safety.

Table 4: Seismic collapse safety parameters for optimal 3-story SMFs

Seismic parameters	Algorithm			
	PSO	FA	BA	ECBO
$S_a^{50\%}$	5.70	5.35	5.52	5.56
S_a^{MCE}	1.72	1.73	1.72	1.73
CMR	3.31	3.09	3.21	3.21
ACMR	4.01	3.99	4.02	4.00
Acceptable *ACMR*	1.96	1.96	1.96	1.96

5.2 Example 2: 6-story SMF

The best results of 10 independent PBD optimization runs of PSO, FA, BA, and ECBO metaheuristics for 6-story SMF are given in Table 5. The obtained numerical results demonstrate that the structural weight of the best design obtained by BA is lighter than that of the other optimization algorithms. In addition, it is revealed that the second best design is obtained by ECBO.

Table 5: PBD optimization results for 6-story SMF

Design variables	Algorithm			
	PSO	FA	BA	ECBO
C1	W14×74	W14×74	W14×68	W14×74
C2	W14×82	W14×74	W14×68	W14×82
C3	W14×53	W14×53	W14×68	W14×68
C4	W14×68	W14×74	W14×68	W14×68
C5	W14×53	W14×48	W14×48	W14×48
C6	W14×53	W14×53	W14×53	W14×53
B1	W12×50	W18×50	W12×50	W16×45
B2	W18×35	W18×35	W18×35	W18×35
B3	W12×22	W12×22	W12×22	W12×19
Weight (kg)	11585.74	11470.52	11409.88	11426.56
CL_{IO} (%)	56.73	59.98	56.79	51.02
CL_{CP} (%)	99.45	99.49	99.31	99.62

In this example, Figs. 4 and 5 show the IDA and fragility curves of the best designs, respectively.

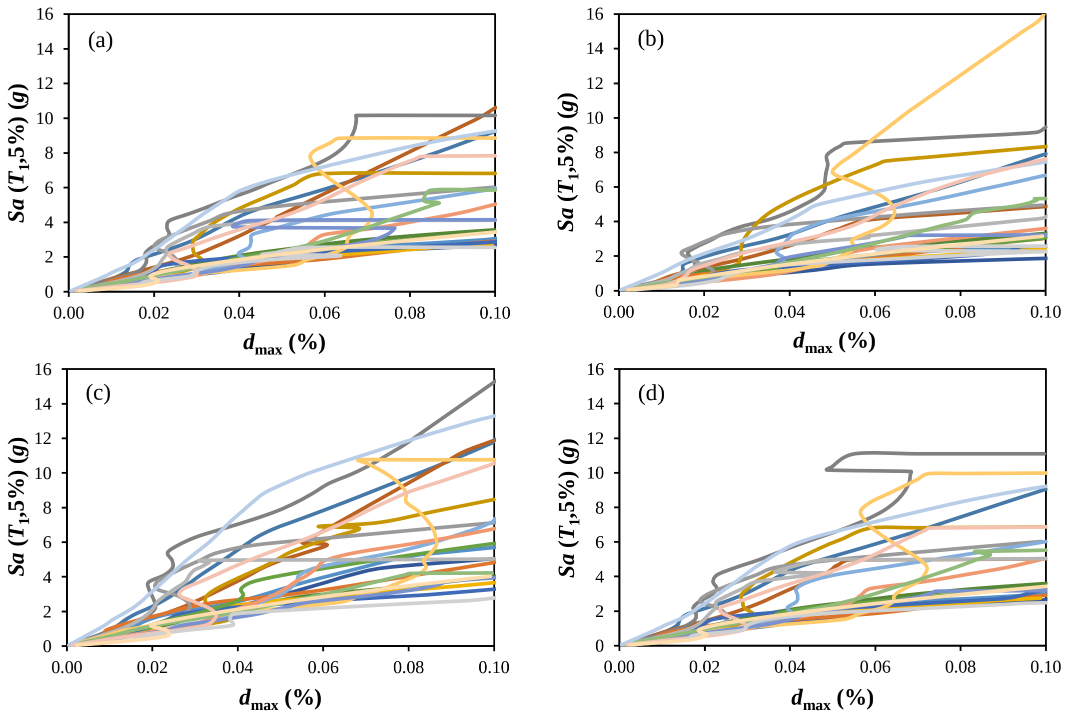


Figure 4. IDA curves for the optimum 6-story SMF structures found by (a) PSO, (b) FA, (c) BA and (d) ECBO

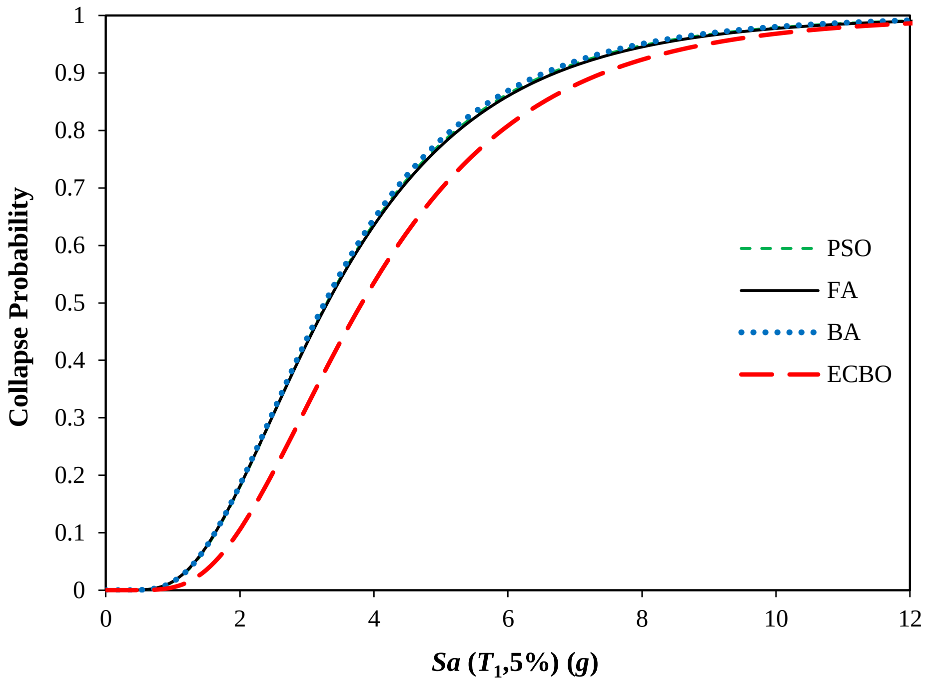


Figure 5. Fragility curves for the optimum 6-story SMF structures found by (a) PSO, (b) FA, (c) BA and (d) ECBO

For the optimal 6-story SMFs, the results of seismic collapse safety assessment are reported in Table 6. It can be observed that *ACMR* values of all the seismic optimal designs are almost the same and the seismic collapse capacity of these optimal designs is significant.

Table 6: Seismic collapse safety parameters for optimal 6-story SMFs

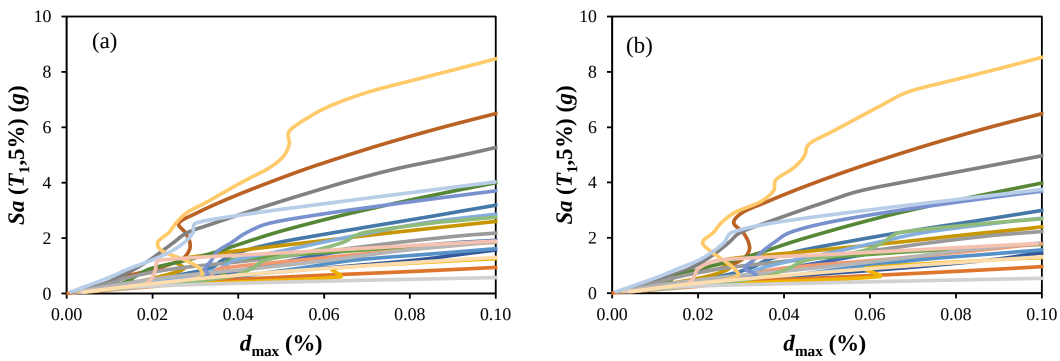
Seismic parameters	Algorithm			
	PSO	FA	BA	ECBO
$S_a^{50\%}$	3.14	3.31	3.14	3.32
S_a^{MCE}	1.22	1.22	1.21	1.28
CMR	2.57	2.71	2.60	2.59
ACMR	3.14	3.31	3.17	3.18
Acceptable *ACMR*	1.96	1.96	1.96	1.96

5.3 Example 3: 12-story SMF

For the 6-story SMF, 10 independent PBD optimization runs are performed by PSO, FA, BA, and ECBO metaheuristics and the best solutions of the algorithms are compared in Table 7. The results indicate that among the obtained solutions, the best design in terms of structural weight is ECBO and the second best design algorithm is BA. In the present example, the IDA and fragility curves for the optimal designs of 12-story SMFs are shown in Figs. 6 and 7, respectively.

Table 7: PBD optimization results for 12-story SMF

Design variables	Algorithm			
	PSO	FA	BA	ECBO
C1	W14×132	W14×132	W14×132	W14×82
C2	W14×145	W14×145	W14×145	W14×145
C3	W14×159	W14×159	W14×159	W14×159
C4	W14×82	W14×82	W14×82	W14×82
C5	W14×132	W14×132	W14×132	W14×132
C6	W14×145	W14×145	W14×145	W14×145
C7	W14×68	W14×74	W14×68	W14×68
C8	W14×132	W14×132	W14×132	W14×132
C9	W14×132	W14×132	W14×132	W14×132
C10	W14×68	W14×68	W14×68	W14×68
C11	W14×82	W14×82	W14×82	W14×82
C12	W14×82	W14×82	W14×82	W14×82
C13	W14×53	W14×53	W14×53	W14×53
C14	W14×68	W14×68	W14×68	W14×68
C15	W14×68	W14×68	W14×68	W14×68
C16	W14×48	W14×48	W14×48	W14×48
C17	W14×48	W14×48	W14×48	W14×48
C18	W14×68	W14×68	W14×53	W14×68
B1	W16×45	W16×45	W16×45	W18×40
B2	W16×50	W16×50	W16×50	W16×50
B3	W16×45	W16×45	W16×45	W16×45
B4	W18×35	W18×35	W18×35	W18×35
B5	W12×35	W12×35	W12×35	W12×35
B6	W12×19	W12×19	W12×19	W12×19
Weight (kg)	38319.97	38429.13	38186.56	37119.25
CL_{IO} (%)	55.0721	55.1957	55.3631	57.4149
CL_{CP} (%)	99.0055	99.0152	99.0048	99.1086



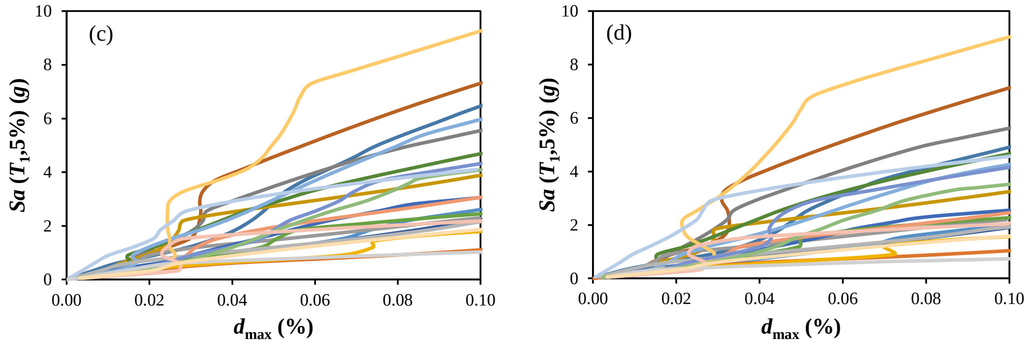


Figure 6. IDA curves for the optimum 12-story SMF structures found by (a) PSO, (b) FA, (c) BA and (d) ECBO

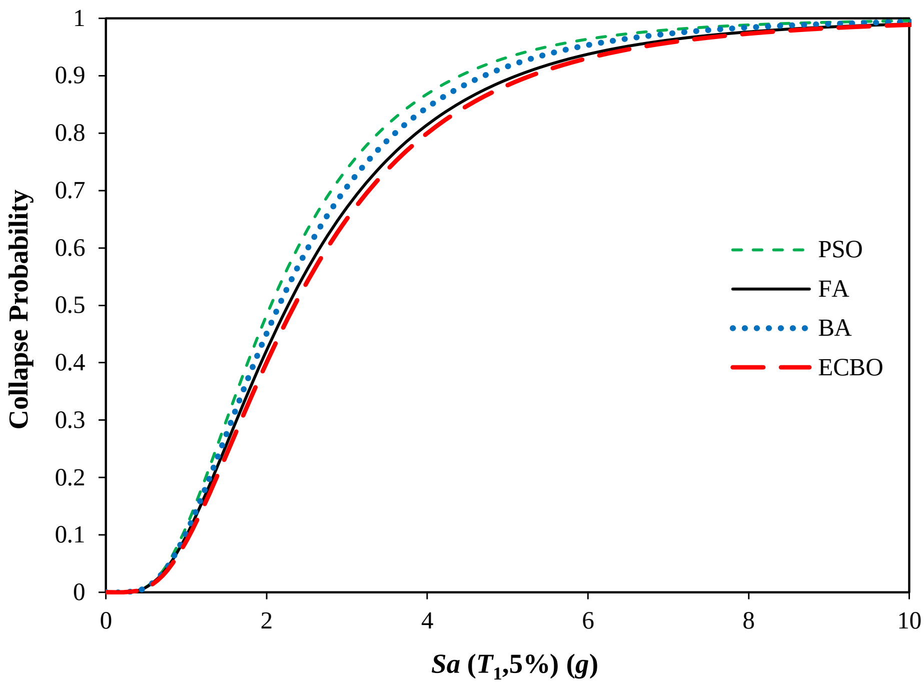


Figure 7. Fragility curves for the optimum 12-story SMF structures found by (a) PSO, (b) FA, (c) BA and (d) ECBO

Table 8: Seismic collapse safety parameters for optimal 12-story SMFs

Seismic parameters	Algorithm			
	PSO	FA	BA	ECBO
$S_a^{50\%}$	1.90	1.90	1.90	1.86
S_a^{MCE}	0.82	0.82	0.82	0.81
CMR	2.32	2.32	2.32	2.29
ACMR	2.84	2.90	2.90	2.84
Acceptable *ACMR*	1.96	1.96	1.96	1.96

For the optimal 12-story SMFs, seismic collapse assessment is achieved and the results are reported in Table 8. The results indicate that the optimal designs have very close *ACMR* values that all of them are acceptable.

6. CONCLUSIONS

This paper is devoted to evaluation of seismic collapse capacity of steel moment frames designed for optimal structural weight by the seismic performance-based design methodology. In order to reduce the dependency of the results to the chosen optimization method, four popular metaheuristics are utilized to tackle the performance-based design optimization problem of steel moment frame structures. The selected algorithms are particle swarm optimization (PSO), firefly algorithm (FA), bat algorithm (BA) and enhanced colliding bodies optimization (ECBO). During the optimization process, the design spectra of the Iranian seismic code 2800 are used and the constraints are checked according to FEMA-350 code. The seismic collapse capacity of the obtained optimal solutions of each algorithm is assessed based on the methodology of FEMA-P695.

Three numerical examples including 3-, 6-, and 12-story steel moment frames are illustrated and the results are compared. In the case of 3-story steel moment frame, it is observed that BA dominates all the other algorithms however, the sesimic collapse safety of all the optimal designs are almost the same and they are of significant collapse capacity. In the example of 6-story steel moment frame, the results reveal that the optimal design found by BA is lighter than the other ones however, all of the optimal designs have almost the same significant collapse safety. For 12-story steel moment frame, ECBO converges to the best design in terms of optimal weight however, the optimal designs of all the algorithms have very close and acceptable seismic collapse capacity.

Finally, it can be concluded that the performance-based optimal designs of regular low-rise and mid-rise steel moment frame structures are of acceptable seismic collapse safety.

REFERENCES

1. FEMA-356. Prestandard and commentary for the seismic rehabilitation of buildings, Federal Emergency Management Agency, Washington, DC, 2000.
2. Fragiadakis M, Lagaros ND, Papadrakakis M. Performance-based multiobjective optimum design of steel structures considering life-cycle cost, *Struct Multidisc Optim* 2006; **32**: 1–11.
3. Pan P, Ohsaki M, Kinoshita T. Constraint approach to performance-based design of steel moment-resisting frames, *Eng Struct* 2007; **29**: 186–94.
4. Kaveh A, Farahmand Azar B, Hadidi A, Rezazadeh Sorochi F, Talatahari S. Performance-based seismic design of steel frames using ant colony optimization, *J Construct Steel Res* 2010; **66**: 566–74.
5. Fragiadakis M, Lagaros ND. An overview to structural seismic design optimisation frameworks, *Comput Struct* 2011; **89**: 1155–65.

6. Kaveh A, Laknejadi K, Alinejad B. Performance-based multi-objective optimization of large steel structures, *Acta Mech* 2012; **232**: 355–69.
7. Kaveh A, Zakian P. Performance based optimal seismic design of RC shear walls incorporating soil–structure interaction using CSS algorithm, *Int J Optim Civil Eng* 2012; **2**: 383-405.
8. Gholizadeh S. Performance-based optimum seismic design of steel structures by a modified firefly algorithm and a new neural network, *Adv Eng Softw* 2015; **81**: 50–65.
9. Liang JC, Li LJ, He JN. Performance-based multi-objective optimum design for steel structures with intelligence algorithms, *Int J Optim Civil Eng* 2015; **5**: 79–101.
10. Rahami H, Mohebian P, Mousavi M. Performance-based connection topology optimization of unbraced and X-braced steel frames, *Int J Optim Civil Eng* 2017; **7**:451–468.
11. Gholizadeh S, Ebadijalal M. Performance based discrete topology optimization of steel braced frames by a new metaheuristic, *Adv Eng Softw* 2018; **123**: 77–92.
12. Ganjavi B, Hajirasouliha I. Optimum performance-based design of concentrically braced steel frames subjected to near-fault ground motion excitations, *Int J Optim Civil Eng* 2019; **9**:177–193.
13. Eberhart RC, Kennedy J. A new optimizer using particle swarm theory, in: *Proceedings of the Sixth International Symposium on Micro Machine and Human Science* 1995, pp. 39-43.
14. Yang XS. *Firefly Algorithms for Multimodal Optimization*, In: Watanabe O, Zeugmann T, editors. Stochastic algorithms: foundations and applications. SAGA 2009, Lecture Notes in Computer Science, 5792. Berlin, Springer, Verlag, 2009, pp. 169–78.
15. Yang XS. *A New Metaheuristic Bat-Inspired Algorithm. Nature Inspired Cooperative Strategies for Optimization, Studies in Computational Intelligence*, J. R. Gonzalez, ed., Springer, Berlin, 2010, 284: pp. 65–74.
16. Kaveh A, Ilchi Ghazaan M. Enhanced colliding bodies optimization for design problems with continuous and discrete variables, *Adv Eng Softw* 2014; **77**: 66–75.
17. Vamvatsikos D, Cornell CA. Incremental dynamic analysis, *Earthq Eng Struct Dynam* 2002; **31**: 491–514.
18. FEMA-P695. Quantification of building seismic performance factors. Washington (DC): Federal Emergency Management Agency, 2009.
19. Fattahi F, Gholizadeh S. Seismic fragility assessment of optimally designed steel moment frames, *Eng Struct* 2019; **179**: 37–51.
20. FEMA-350. Recommended seismic design criteria for new steel moment-frame buildings. Washington (DC): Federal Emergency Management Agency, 2000.
21. AISC 360-16. Specification for structural steel buildings, Chicago: American Institute of Steel Construction, 2016.
22. Kaveh A, Mahdavi VR. Colliding bodies optimization: A novel meta-heuristic method, *Comput Struct* 2014; **139**: 18-27.
23. Standard No. 2800. Iranian Code of Practice for Seismic Resistant Design of Buildings, Building and Housing Research Center, Tehran 2014.