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PERFORMANCE-BASED OPTIMAL DESIGN OF RC SHEAR-WALLS UTILIZING PSO AND PSOHS METAHEURISCTIC ALGORITHMS

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ABSTRACT

The main objective of this paper is to present a new approach for seismic design of RC shear-walls. In order to achieve the desired performance with the minimum possible cost, a formulation is presented which fulfills the constraints of FEMA 365. The robust meta-heuristic algorithm PSO and its recently enhanced version, PSOHS, are employed and the results compared. This approach is applied to some practical structural examples to certify the proposed formulation, and to examine whether the PSOHS performs better than PSO in this class of problems. The results illustrate the effectiveness of the PSOHS and its suitability for design of shear-walls.

Keywords: Performance-based design; RC shear-wall; PSO; PSOHS

1. INTRODUCTION

Since most of engineering projects are cost-dependent significantly, in recent decades, meta-heuristic algorithms have drawn the attention of many researchers in the field of engineering as an efficient tool to reduce the costs of the projects. In the field of structural design, numerous studies have been accomplished; for instance, Perez and Behdinan [1] employed the PSO in design of truss structures. Some researchers devise new algorithms or improve the performance of the existing algorithms by making hybrid algorithms. A good example of the latter is the work of Kaveh and Talatahari [2] in hybridizing PSO, ACO, and HS to provide a robust algorithm for optimal design of truss structures. Lee and Geem [3] utilized the HS algorithm for this purpose. Charged system search is also proposed for structural optimization by Kaveh and Talatahari [4]. Lepš [5] performed a discrete optimization of reinforced concrete (RC) frames. Kaveh and Shakouri Mahmud Abadi [6] used a harmony

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search algorithm for design optimization of composite floor systems. Kaveh and Zakian [7] performed seismic design optimisation of RC moment frames and dual shear wall-frame structures via CSS algorithm.

Particle swarm Optimization (PSO) algorithm is presented by Kennedy and Eberhat [8], and extensively employed in optimal design of structures [9-12]. This algorithm is inspired from the social behavior of swarms and flocks, and can easily be implemented. The ability of searching the continuous feasible space and robustness are the main characteristics of the PSO. However, the lack of balance between exploration and exploitation is the main drawback of the PSO. Furthermore, dependency on the one of algorithm constants, inertia weight, is another deficiency attributed to the PSO.

In order to remove the drawbacks of the PSO, several modifications have been performed. She and Eberhart [13] proposed a dynamic varying inertia weight to provide balanced global and local searches. Kaveh and Nasrollahi [14] also hybridized the PSO algorithm with HS, called PSOHS, in order to deal with the particles violating the feasibility boundaries. The main objective of this paper is to contemplate a new formulation and approach for performance-based optimal design of RC shear-walls. The constraints of this problem are suggested based on FEMA 365 [15], and both PSO and PSOHS algorithm are linked to the OPENSEES analysis package software to perform a Push-Over Analysis. The results illustrates two main point: (a) the proposed cost function and constraint formulating and method for optimal design is properly adjusted; (b) the PSOHS is more robust than original PSO in providing a design with less cost in this type of problems.

2. PSO, HS AND PSOHS OPTIMIZATION ALGORITHMS

2.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a multi-agent meta-heuristic optimization algorithm which has been introduced by Eberhart and Kennedy [1]. It makes use of velocity vector to update the current position of each particle in the swarm. The velocity vector is updated using a memory in which the best position of each particle and the best position among all particles are stored. This can be considered as an autobiographical memory. Therefore, the position of each particle in the swarm which adapts to its environment by flying in the direction of best position of the whole particles and the best position of particle itself provides the search of PSO. The position of the ith particle at iteration k+1 can be calculated using Eq. (1)

$$x_{k+1}^{i} = x_{k}^{i} + v_{k+1}^{i}.\Delta t \tag{1}$$

where, x_{k+1}^{i} is the new position; x_{k}^{i} is the position at iteration k; v_{k+1}^{i} is the updated velocity vector of the ith particle; and Δt is the time step which is considered as unity. The velocity vector of each particle is determined using Eq. (2)

$$v_{k+1}^{i} = w.v_{k}^{i} + c_{1}.r_{1}.\frac{\left(p_{k}^{i} - x_{k}^{i}\right)}{\Delta t} + c_{2}.r_{2}\,\frac{\left(p_{k}^{g} - x_{k}^{i}\right)}{\Delta t} \tag{2}$$

where, v_k^i is the velocity vector at iteration k; r_1 and r_2 are two random numbers between 0 and 1; p_k^i represents the best ever position of ith particle, local best; p_g^k is the global best position in the swarm up to iteration k; c_1 is the cognitive parameter; c_2 is the social parameter; and w is a constant named inertia weight.

With the above description of PSO, the algorithm can be summarized as follow:

1. Initialization

Initial position, x_0^i, and velocities, v_0^i, of particles are distributed randomly in feasible search space.

$$x_0^i = x_{\min} + r.(x_{\max} - x_{\min}) \tag{3}$$

$$v_0^i = \frac{x_{\min} + r.(x_{\max} - x_{\min})}{\Delta t} \tag{4}$$

where r is a random number uniformly distributed between 0 and 1; $x_{\min}$ and $x_{\max}$ are minimum and maximum possible variables for the ith particle, respectively.

2. Solution Evaluation

Evaluate the objective function values for each particle, $f(x_k^i)$, using the design variables correspond to iteration k.

3. Updating Memory

Update the local best of each particle, p_k^i, and the global best, p_g^k, at iteration k.

4. Updating Positions

Update the position of each particle utilizing its previous position and updated velocity vector as specified by Eqs. (1 and 2).

5. Stopping Criteria

Repeat steps 2~4 until the stopping criteria is met.

For further information on recent meta-heuristic algorithms the reader may refer to [16].

2.2 Harmony Search

Harmony Search (HS) algorithm is a meta-heuristic algorithm based on natural musical performance that occurs when a musician searches for a better state harmony, such as jazz improvisation. This algorithm has been presented by Geem et al. [3] and works as: the engineers seek for a global optimum of an objective function, just like the musicians seek to find a musical pleasing harmony as determined by aesthetics, Fig. 1.

This seeking for a new improvised harmony is a search which if can be regulated in optimization; it can find the global minimum of the objective function.

HS algorithm includes a number of optimization operators, such as the harmony memory HM which is a memory that some best so far results are saved in it, and if in a stage better solution is obtained, it is saved in HM and the worst one is excluded from it; Harmony memory size HMS, which is the number of solution vectors saved in HM; Harmony memory considering rate HMCR varying between 0 and 1 sets the rate of choosing a value in the new vector from the historic values stored in the HM; and the pitch adjusting rate PAR. The pitch adjusting process is performed only after a value is chosen from HM and sets the rate of choosing a value from neighboring of the best vector. Steps of the HS are as follows:

A new harmony vector is improvised from the HM based on HMCR and PAR. With the probability of HMCR the new vector is generated from HM and with the probability of (1−HMCR) the new vector is generated randomly from possible ranges of values. The pitch adjusting process is performed only after a value is selected from HM. The value (1−PAR) sets the rate of doing nothing. A PAR of 0.25 indicates that the algorithm will select a neighboring value with $0.25\times$HMCR. It is recommended not to set HMCR as 1.0 because it is probable that the global minimum does not exist in HM. With the aforementioned the search of HM is summarized in Eq. (5). In which the term “w.p.” represents “with the probability”.

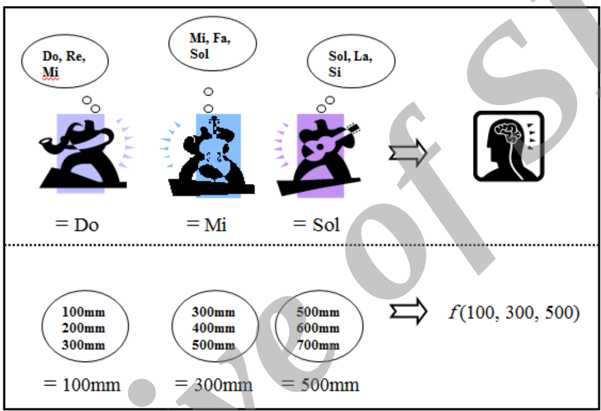

Figure 1. The resemblance between music improvisation and optimization [3]

If the generated harmony vector is better than a harmony vector in HM, judged in terms of the objective function value, the new harmony is included in HM and the worst one is excluded from it.

$$x_{i,j} = \begin{cases} \text{w.p. HMCR} \\ \qquad \Rightarrow \text{ select a value for a variable from HM} \\ \qquad \Rightarrow \text{ w.p. (1–PAR) do nothing} \\ \qquad \Rightarrow \text{ w.p. PAR choose a neighboring value} \\ \text{w.p. (1–HMCR)} \\ \qquad \Rightarrow \text{ select a new variable randomly} \end{cases} \tag{5}$$

2.3 PSOHS

The hybrid PSO and HS is proposed by Kaveh and Nasrollahi [14]. Previous to that, it is necessary to explain why this modification is performed. There are two main problems in PSO: first, the lack of balance between exploration and exploitation; second, there is no good idea to control the violating variables from feasible search space. For definition of the first problem it should be mentioned that in meta-heuristic optimization algorithms, there should be a balance between exploration and exploitation in a way that at initial iteration, the algorithm should have a global search and this search should cover the whole search space in a logical manner. In this stage, some points which are expected to be near the global minimum of the cost function are found. Then at the latest iterations, the algorithm should perform a local search using the solution vectors found so far. As seen in Eq. (2), velocity vector definition of PSO which is the search engine of the algorithm has not this specification and at initial iteration is the same to latest iterations and this issue causes a lack of balance between exploration and exploitation of PSO.

This problem has been solved using dynamic variation of inertia weight by linearly decreasing w with each algorithm iteration presented by Shi and Eberhart [13] as shown in Eq. (6)

$$w_{k+1} = rand \times \left(w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} k \right) \tag{6}$$

where, $rand$ represents a random number in the [0,1]; $w_{\max}$ is the maximum considered inertia weight; $w_{\min}$ is the minimum considered inertia weight; $k_{\max}$ is the number of iterations.

Utilizing Eq. (6), at initial iterations there will be a large value of inertia weight providing a global search and by progression of algorithm this value reduces until at the latest iterations there only local search will be performed based on position of the best particle and the best ever position of particles as seen in Eq. (2). The random multiplier provides a random search which prevents the particles to move far from their best position during global search process.

The second problem that is involved in PSO like many other optimization algorithms, is the violation of variables that should be controlled. There are many methods to control the violating variables. One of the simplest approaches is utilizing the nearest limit values for the violating variable. Alternatively, one can force the violating particle to return to its previous position, or reduce the maximum value of the velocity to allow fewer particles to violate the variable boundaries. Although these approaches are simple, they are not sufficiently efficient and may lead to reduction of the exploration of the search space. This problem has previously been addressed and solved using the harmony search based handling approach [2]. According to this mechanism, any component of the solution vector violating the variable boundaries can be regenerated from the HM by use of Eq. (11). This approach is an efficient one which improves convergence rate of algorithm because of simultaneous action of two algorithms. If a particle is in the feasible search space, PSO will work and if violates from boundaries, HS will be activated. However, in PSOHS it is necessary that the memory in which the global best is stored be extended and some of best designed vectors stored. This memory can be used as HM when a particle violates and HS becomes active.

With the above mentioned explanation, the steps of PSOHS are shown in flowchart of Fig. 2.

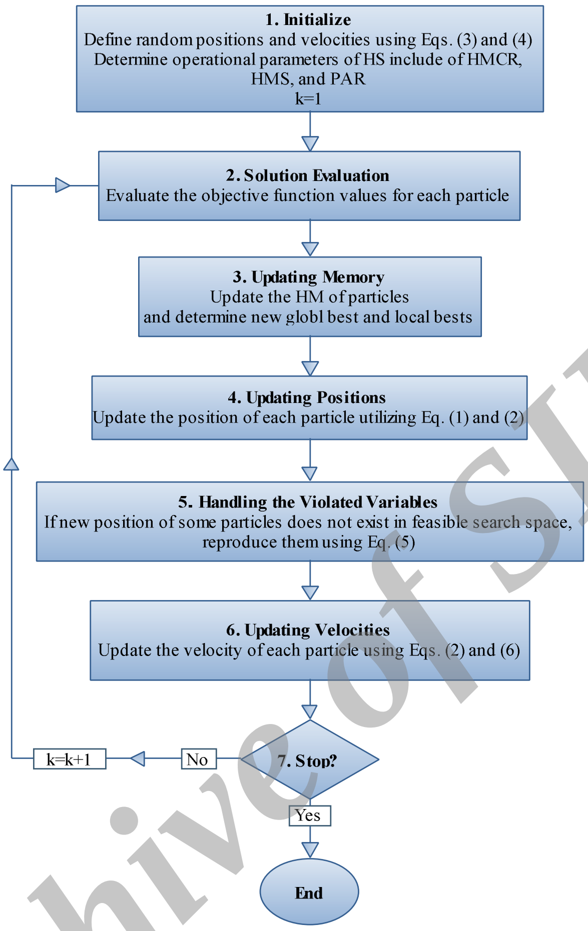

Figure 2. Flowchart of PSOHS

3. DEFINITION OF THE PROBLEM

3.1 Variables

For the purpose of optimal design of RC shear-walls, a set of predefined elements are considered as the feasible search space; therefore, in this paper this set is built on chapter 14 of ACI 318-08 requirements for shear-wall design. In what follows, these requirements are presented:

Minimum portion of vertical reinforcement is 0.0012 for bars with diameter equal or less than 16mm.

Minimum portion of vertical reinforcement is 0.0015 for the rest of bars.

Minimum portion of horizontal reinforcement is 0.002 for bars with diameter equal or less than 16mm.

Minimum portion of vertical reinforcement is 0.0025 for the remaining bars.

For the RC shear-walls with the thickness more than 250mm there should be two layers reinforcement.

The space between reinforcement should be less than 450mm or less than threefold of wall thickness.

If the portion of vertical reinforcement is more than 0.01, there is no need to place any closed loop.

Considering all these constraints, the initial set of shear-walls is built characterized as follows:

The length of shear-wall is constant and equal to 6.7m, and the following constraint is considered to be true:

$$l_w = h_w + 2 \times t_f \tag{7}$$

In this correlation, l_w is the length of the shear-wall; h_w represents the height of the shear-wall; t_f is the length of the wall flange.

In Fig. 3 different variables are delineated, and combining these variables in the range presented in Table 1, leads to a set of shear-walls containing 7,653 elements which are presented in Table 2, and values in this table are calculated using the following correlations:

$$A_{sf\,\max} = 0.04 \times (t_f \times b_f) \tag{8}$$

$$A_{sf\,\min} = 0.01 \times (t_f \times b_f) \tag{9}$$

$$nw_1 = 2Int\left(\frac{b_f - 2(t_c + d_t) + s_c}{d_b + s_c} - 0.5\right) \tag{10}$$

$$nw_2 = 2Int\left(\frac{b_f - 2(t_c + d_t) + s_c}{d_b + s_c} + \frac{t_f - 2(t_c + d_t) + s_c}{d_b + s_c} - 0.5\right) \tag{11}$$

$$nrl_{\min} = \max\left(Int\left(\frac{b_f}{t_f + b_f} \times \frac{A_{sf\,\min}}{a_s} + 0.5\right), 4\right) \tag{12}$$

$$nrl_{\max} = \min\left(Int\left(\frac{b_f}{t_f + b_f} \times \frac{A_{sf\,\max}}{a_s} - 0.5\right), nw_1\right) \tag{13}$$

$$nud_{\min} = \max\left(Int\left(\frac{A_{sf\,\min}}{a_s} + 0.5\right), 4\right) - nrl_{\min} \tag{14}$$

$$nud_{\min} = \max\left(Int\left(\frac{A_{sf\,\max}}{a_s} - 0.5\right), nw_2\right) - nrl_{\max} \tag{15}$$

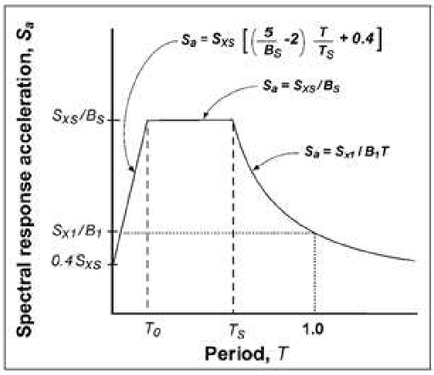

Figure 3. Spectral response acceleration of FEMA 356 [15]

Table 1: Range of variables

Variable	range	Variable values
Shear-wall thickness	200mm-400mm	continuous between the range
The length of shear-wall flange	600mm-1200mm	continuous between the range
The thickness of shear-wall flange	200mm-1200mm	continuous between the range
Vertical reinforcement space	300mm-450mm	continuous between the range
Reinforcement diameter	12mm-36mm	12mm-14mm-16mm-18mm-20mm-22mm-25mm-32mm-36mm

Table 2: set of RC shear wall elements used for design

Section	t_w (mm)	t_f (mm)	b_f (mm)	S_{sh} (mm)	ϕ_w (mm)	ϕ_f (mm)	S_f (mm)	nw	nud	nrl
1	200	600	300	300	16	32	130	38	4	4
2	200	600	300	300	16	32	140	38	4	4
3	200	600	300	300	16	32	150	38	4	4
4	200	600	300	350	16	32	130	34	4	4
5	200	600	300	350	16	32	140	34	4	4
…	…	…	…	…	…	…	…	…	…	…
3826	300	900	1000	400	16	32	110	26	12	18
3827	300	900	1000	400	16	32	120	26	10	16
3828	300	900	1000	400	16	32	130	26	10	14
3829	300	900	1000	400	16	32	140	26	8	14
3830	300	900	1000	400	16	32	150	26	8	14
…	…	…	…	…	…	…	…	…	…	…
7652	400	1200	1200	450	16	36	110	22	18	22
7653	400	1200	1200	450	16	36	120	22	16	20

3.2 Cost function and constraints

The cost function of this problem is defined by Eq. (16), containing the cost of the concrete, reinforcement, and forming.

$$\begin{aligned} f(X) &= C_c \times (2\times b_f \times t_f \times H_w + l_w \times t_w \times H_w - 2\times m_l \times A_{sf} - m_2 \times A_{sw}) \\ &+ C_s \times \gamma_s \times ((2\times m_l \times A_{sf} + m_2 \times A_{sw}) \times H_w + 2\times l_w \times Int(H_w / S_{sh}) \times A_{sw}) \\ &+ C_f \times (4\times (b_f + t_f - 0.5\times t_w) \times H_w + 2\times h_w \times H_w) \end{aligned} \tag{16}$$

In this equation different parameters are as follows:

C_c, C_s, and C_f : cost of concrete per cubic meter, cost of steel per kilogram, and cost of forming per square meter respectively; H_w: total height of shear-wall; A_{sf} and A_{sw}: applied reinforcement in the flange and web of shear-wall respectively; h_w: length of shear-wall web; m_1 and m_2: the number of longitudinal reinforcement of the flange and the web of shear-wall, respectively.

The applied constraints are as follows:

The plastic rotation of elements as a performance constraint: The moment-curvature of the elements are obtained after implementing a pushover analysis and then the plastic rotation of each element are calculated using as:

$$\theta_p = (\phi_u - \phi_y).L_p \tag{17}$$

where θ_p is the plastic rotation of the element; ϕ_u represents the ultimate curvature of the element; ϕ_y is the yielding curvature and is defined as:

$$\phi_y = \frac{0.003}{l_w} \tag{18}$$

Finally, L_p is the probable length of plastic hinge and is determined by

$$g_i = \frac{\theta_p}{\theta_{p_{all}}^{PL}} - 1 \leq 0 \tag{19}$$

In this equation, i=1, 2, 3 are for the performance levels of IO, LS, and CP respectively, and $\theta_{p_{all}}^{PL}$ is the allowable plastic rotation for each performance level according to the FEMA-356 [15]. The allowable plastic rotations of the RC shear wall are 0.005, 0.010, and 0.015 for these performances.

Shear Stress constraint: The shear stress constraint is defined as follows:

$$g_4 = \frac{V_u}{\phi_v V_n} - 1 \le 0 \tag{20}$$

In which, V_u is the induced shear force in the wall. ϕ_v is the shear resistance reduction factor, and its value is equal to 0.75; V_n is the nominal shear resistance of a shear wall, and it is defined as:

$$V_n = A_{cv}\left(\frac{1}{6}\sqrt{f_c'} + \rho_t . f_y\right) \tag{21}$$

where α_c is equal to 1/6 when f'_c is in MPa; ρ_t is the shear reinforcement ratio; A_{cv} is the total area of the shear wall and can be stated as follows:

$$A_{cv} = t_w \times l_w \tag{22}$$

Since in this research the value of shear force is more than $\frac{1}{6}\sqrt{f'_c}A_{cv}$, based on ACI-318-08, two shear reinforcement plain is required for the wall.

Minimum Shear Reinforcement constraint: The constraint for ρ_t is defined as follows:

$$g_3 = \frac{\rho_t}{\rho_{t\min}} - 1 \ge 0 \tag{23}$$

This is a constraint which forces the shear reinforcement fulfills its minimum requirement.

3.3 Pushover analysis

In this study, FEMA 356 [15] requirements are considered for the static nonlinear analysis (pushover analysis). According to this code, the steps of implementing pushover analysis are as follows:

The target displacement is determined using:

$$\delta_t = C_0 C_1 C_2 C_3 S_a \frac{T_e^2}{4\pi^2} g \tag{24}$$

where,

C_0 is a modification factor to relate the spectral displacement of an equivalent SDOF system to the roof displacement of the MDOF system, and here C_0 is equal to 1.3.

C_1 is a modification factor to relate the expected maximum inelastic displacements to the calculated linear elastic response displacements; C_1 is equal to 1.0 for this structure.

C_2 is the modification factor to represent the effect of pinched hysteretic shape, stiffness degradation and strength deterioration on maximum displacement response for IO level and for this structure it is considered as 1.0.

C_3 is the modification factor to represent the increased displacements due to dynamic P-Δ effects; for buildings with positive post-yield stiffness, this is equal to 1.0. S_a is the spectral acceleration which in this paper are calculated for a type D soil according to FEMA 356 and it is calculated by:

$$\begin{cases} S_a = S_{XS}\left[\left(\dfrac{5}{B_s}-2\right)\dfrac{T}{T_S}+0.4\right] & 0<T<T_0 \\ S_a = \dfrac{S_{XS}}{B_S} & T<T_S \\ S_a = \left(\dfrac{S_{X1}}{B_1 T}\right) & T>T_S \end{cases} \tag{25}$$

where S_{XS} and S_{X1} are determined by:

$$S_{XS} = F_a S_S \tag{26}$$

$$S_{X1} = F_v S_1 \tag{27}$$

where for soil type D, the value of F_a, F_v, S_S, and S_1 are 1.0, 1.5, 1.5, and 0.6, respectively.

Also, T_S and T_0 are determined using Eqs. (28) and (29), and B_s and B_1 are 1.0 based of FEMA 356. Determining the spectral acceleration using the abovementioned parameters is depicted in Fig. 3.

$$T_S = \frac{S_{X1} B_s}{S_{XS} B_1} \tag{28}$$

$$T_0 = 0.2 T_S \tag{29}$$

where g is the gravity acceleration; and T_e represents the effective period of the structure and is determined using the following equation:

$$T_e = T_i \sqrt{\frac{K_i}{K_e}} \tag{30}$$

where, T_i represents period of the structure when the structure has not experienced any nonlinearity; K_i is the lateral stiffness of the structure at the beginning of the pushover curve; and K_e is the elastic stiffness of the structure obtained from bilinear approximating the pushover curve based on FEMA 356 requirements. These parameters along with FEMA 356 requirements are delineated in Fig. 4.

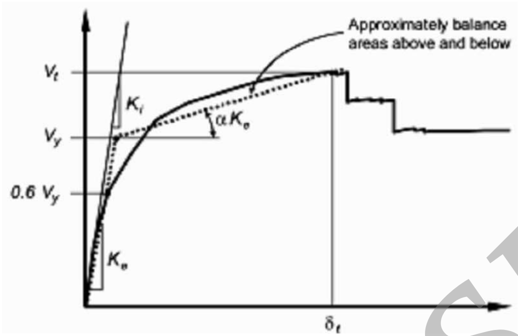

Figure 4 Pushover curve and approximate bilinear behavior of structure based on FEMA 356 requirements [15]

4. NUMERICAL EXAMPLES

To examine the proposed approach and formulation, in this section three RC shear walls are designed using PSO, HS, and PSOHS. Three examples are considered in this section: RC shear wall of a four-story, an eight-story, and a twelve-story frame. In all examples, the value of W_{max} and W_{min} in PSOHS are 1 and 0, respectively. The number of particles is taken as 20, and in HMS it is considered as 5. HMCR and PAR are 0.85 and 0.53 based on the study of Ref. [3]. In order to reduce the effect of random initialization, each problem is run twenty times independently, and statistical analysis is performed to explain the results. For the purpose of pushover analysis of RC shear walls, OPENSEES package is used. The optimization algorithms are coded in MATLAB, and thus the optimization code provides new sections; and then it is analyzed by OPENSEES to check the constraints. For design of RC shear walls, it is considered that the shear wall section can vary in each story; therefore, the number of selections is too large to be determined by try-and-error. Once a shear wall is constructed by the optimization algorithm, its period is determined by performing a modal analysis, and δ_t is calculated using the first mode period which is an acceptable approximate approach for determining δ_t. In all examples, OPENSEES Uniaxial Material Concrete06 and Uniaxial Material Steel02 are utilized to model the shear walls. Mechanical properties of these materials are included in Table 3. The elements are modeled by *dispBeamColumnInt* which not only considers the effects of axial force, but also the effect of shear-bending interactions. In these examples, first, the structure is modeled in ETABS; then the forces on the shear walls are obtained. In the next step, the shear wall along with the forces is modeled in OPENSEES to design it by meta-heuristics. In this study, dead and live loads are taken as 600 kg/m^2 and 200kg/m^2, respectively.

Table 3: Material characteristics used in the analysis of numerical examples

		concrete		
Uniaxial Material Concrete06	f'_c (MPa)	ε_{c0}	f'_{cr} (MPa)	ε_{cr}
	-30	-0.0021	2.78	0.00008
		Reinforcing steel		
Uniaxial Material Steel02	f_y (MPa)		E (MPa)	
	400		200000	

4.1 Four-story RC shear wall

The shear wall of a six-bay, four-story frame shown in Fig. 5 is considered as the first example to examine the proposed approach. Since each story can be constructed from 7653 sections, the number of possible designs is 3^{7653}=2.56×10^{3651}; as a result, reaching to the design with minimum cost by a try and error method is impossible. Thus, in this paper, some meta-heuristics are employed to reach the optimal design. This example is designed by PSO, HS, and PSOHS to prove the efficacy of the improvements.

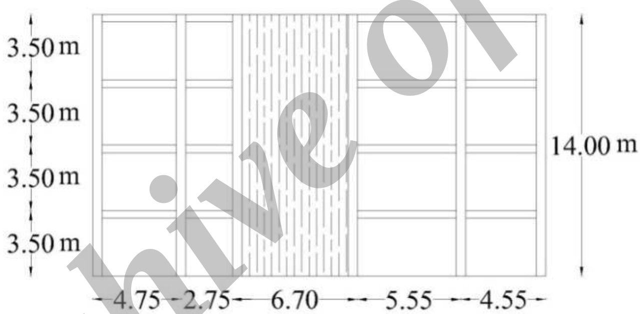

Figure 5. Geometry of the six-bay four-story frame with RC shear wall

Optimal design of four-story shear wall using HS, PSO, and PAOHS is presented in Table 4. It is observed in the table that the best result among these three algorithms is attributed to PSOHS with the value of 6658, while this value for HS and PSO is 7127 and 7862 which are 7% and 18.1% greater than the value for PSOHS, respectively. The values of the constraints are presented in Table 5, and it is observed that all constraints are below 0; therefore, none of the constraints is violated. The convergence history of the best run and average of twenty independent runs are illustrated in Figs. (7) and (8). It can be concluded from these figures that PSOHS has a faster convergence, and optimal result is achievable in fewer iterations; therefore, it is practical when a nonlinear analysis are performed.

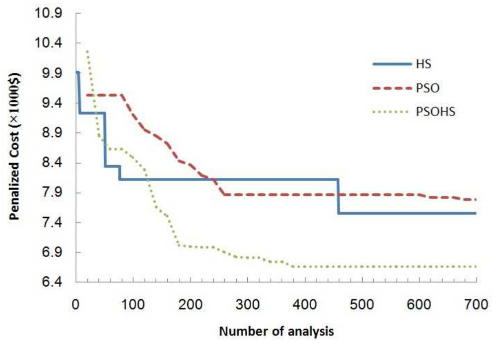

Figure 6. Convergence history of the best run of algorithms

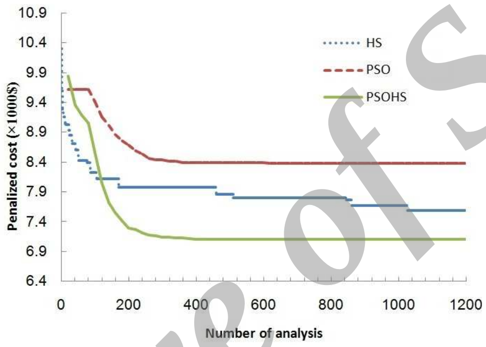

Figure 7. Convergence history of the average of runs

From Table 5, it can be concluded that the active constraint is the minimum ratio of shear reinforcements.

Table 4: Results of optimal design of four-story RC shear wall by different algorithms

Algorithm	Story	t_w(mm)	t_f(mm)	b_f(mm)	S_{sh}(mm)	ϕ_w(mm)	ϕ_f(mm)	*nud*	*nrl*	Cost ($)
HS	1	200	1100	300	450	16	32	12	4	7127
	2	200	900	300	450	16	32	8	4	
	3	200	600	300	450	16	32	4	4	
	4	200	600	200	450	16	32	4	2	
PSO	1	300	1000	500	450	16	36	10	8	7862
	2	200	900	400	450	16	36	8	6	
	3	200	600	200	450	16	32	4	2	
	4	200	600	200	350	16	32	4	2	
PSOHS	1	200	600	300	450	16	32	4	4	6658
	2	200	600	300	450	16	32	4	4	
	3	200	600	300	450	16	32	4	4	
	4	200	600	300	450	16	32	4	4	

Table 5. The value of constraints of the four-story RC shear wall designed by different algorithms

Algorithm	HS			PSO			PSOHS		
story	constraint 1	constraint 2	constraint 3	constraint 1	constraint 2	constraint 3	constraint 1	constraint 2	constraint 3
1	-1.3	-0.6	-0.5	-1.3	-0.705	-0.327	-1.3	-0.65	-0.41
2	-1.3	-0.64	-0.43	-1.3	-0.603	-0.495	-1.3	-0.69	-0.35
3	-1.3	-0.72	-0.3	-1.3	-0.694	-0.342	-1.3	-0.76	-0.25
4	-1.3	-0.85	-0.15	-1.3	-0.83	-0.165	-1.3	-0.87	-0.12

4.2 Eight-story RC shear wall

The shear wall of a six-bay eight-story frame shown in Fig. 9 is considered as the second example to examine the efficiency of the proposed approach. Since each story can be constructed from 7656 sections, the number of possible designs is 8^{7653}=2.23×10^{6911}; as a result, reaching to the design with minimum cost by a try-error method is impossible. Again, for this example, some meta-heuristics are applied to reach the optimal design. This example is optimized by PSO, HS, and PSOHS to prove the efficiency of the algorithms.

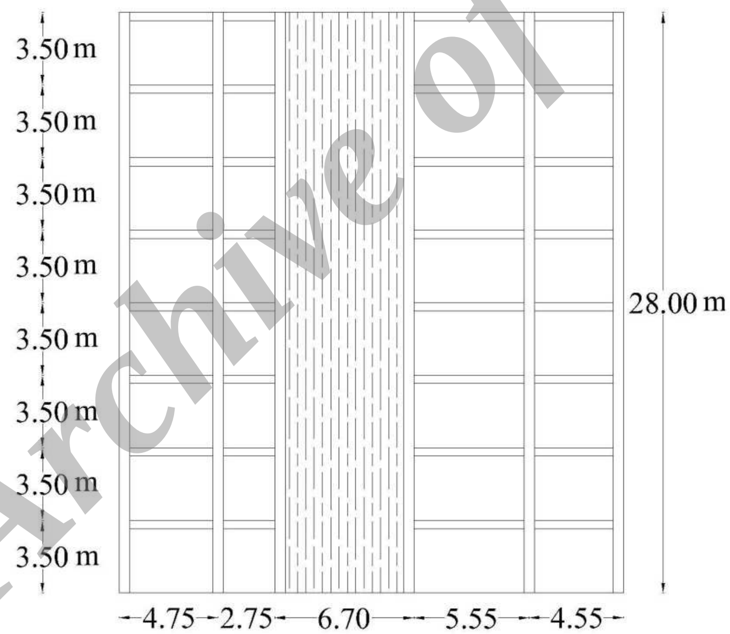

Figure 8. Geometry of the six-bay, eight-story frame with RC shear wall

Optimal design of four-story shear wall using HS, PSO, and PAOHS is presented in Table 6. It can be observed from this table that the best result among these three algorithms is attributed to PSOHS with the value of 14937, while this value for HS and PSO is 15481 and 17032 which are 3.64% and 14.02% greater than the value for PSOHS, respectively. Also, the value of constraints are presented in Table 7, and it can be observed that all constraints are below 0; therefore, none of the constraints is violated. The convergence history of the best run and average of twenty independent runs are illustrated in Figs. 10 and

11. It can be concluded from these figures that PSOHS has a faster convergence, and optimal result is achievable in fewer iterations; therefore, it is practical when nonlinear analyses are performed.

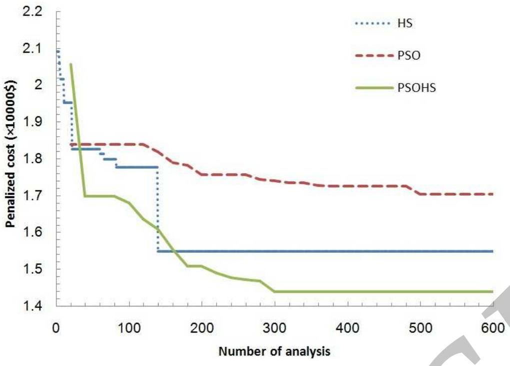

Figure 9. Convergence histories of the best run of algorithms

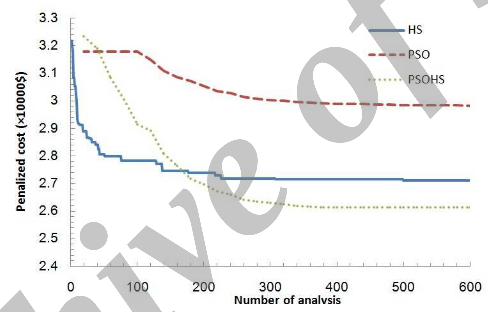

Figure 10. Convergence history of the average of runs

Again, from Table 7, it can be concluded that the active constraint is the minimum ratio of shear reinforcements.

Table 6: Geometry of the six-bay, eight-story frame with RC shear wall

Algorithm	Story	t_w(mm)	t_f(mm)	b_f(mm)	S_{sh}(mm)	ϕ_w(mm)	ϕ_f(mm)	*nud*	*nrl*	Cost ($)
HS	1	200	1200	500	400	16	32	12	6	15481
	2	200	1100	400	450	16	32	12	6	
	3	200	1100	400	450	16	32	10	6	
	4	200	1100	400	450	16	32	10	6	
	5	200	900	300	450	16	32	8	4	
	6	200	900	300	450	16	32	8	4	
	7	200	600	300	450	16	32	4	4	
	8	200	600	300	450	16	32	4	4	
PSO	1	400	1100	700	450	16	36	14	12	17032

	2	400	1100	500	400	16	36	12	6	
	3	300	1000	300	350	16	32	10	4	
	4	300	900	300	350	16	32	8	4	
	5	300	900	300	300	16	32	8	4	
	6	300	700	300	300	16	32	6	4	
	7	200	700	300	300	16	32	6	4	
	8	200	600	300	300	16	32	4	4	
PSOHS	1	400	900	500	450	16	36	8	6	14937
	2	200	600	500	450	16	36	4	6	
	3	200	600	500	450	16	36	4	6	
	4	200	600	500	450	16	36	4	6	
	5	200	600	300	450	16	32	4	4	
	6	200	600	200	450	16	32	4	2	
	7	200	600	200	450	16	32	4	2	
	8	200	600	200	450	16	32	4	2	

Table 7: The value of constraints of the eight-story RC shear wall designed by different algorithms

Algorithm	HS			PSO			PSOHS		
story	constraint 1	constraint 2	constraint 3	constraint 1	constraint 2	constraint 3	constraint 1	constraint 2	constraint 3
1	-1.3	-0.582	-0.535	-1.3	-0.756	-0.255	-1.3	-0.791	-0.211
2	-1.3	-0.594	-0.512	-1.3	-0.763	-0.246	-1.3	-0.593	-0.513
3	-1.3	-0.618	-0.468	-1.3	-0.702	-0.33	-1.3	-0.617	-0.468
4	-1.3	-0.653	-0.406	-1.3	-0.73	-0.29	-1.3	-0.653	-0.407
٥	-1.3	-0.701	-0.332	-1.3	-0.767	-0.241	-1.3	-0.701	-0.333
٦	-1.3	-0.76	-0.25	-1.3	-0.813	-0.184	-1.3	-0.76	-0.25
٧	-1.3	-0.83	-0.165	-1.3	-0.802	-0.198	-1.3	-0.83	-0.165
٨	-1.3	-0.912	-0.079	-1.3	-0.897	-0.094	-1.3	-0.912	-0.08

4.3 Twelve-story RC shear wall

The shear wall of a six-bay twelve-story frame shown in Fig. 12 is considered as the third example to examine the efficiency of the proposed approach. Since each story can be constructed from 7656 sections, the number of possible designs will be 12^{7653}=9.42×10^{8258}; as a result, reaching to the design with minimum cost by a try-error method is impossible. Again, for this example, some meta-heuristics are applied to reach the optimal design. This example is optimized by PSO, HS, and PSOHS to prove the efficacy of the algorithms.

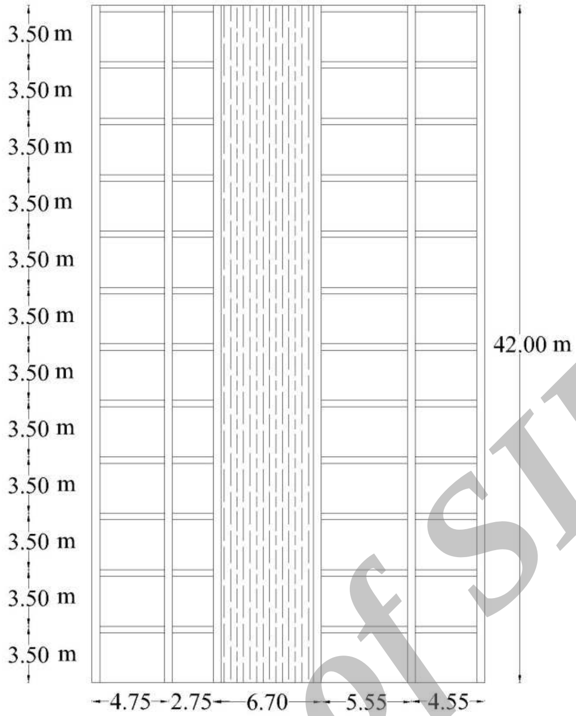

Figure 11. Geometry of the six-bay twelve-story frame with RC shear wall

Optimal design of a four-story shear wall using HS, PSO, and PAOHS is presented in Table 8. Similar to previous examples, it can be observed from the table that the best result among these three algorithms is attributed to PSOHS with the value of 24567, while this value for HS and PSO is 26747 and 28870 which are 8.87% and 17.51% greater than the value for PSOHS, respectively. Also, the value of constraints are presented in Table 9, and it can be seen that all constraints are below 0; therefore, none of the constraints are violated. The convergence history of the best run and average of twenty independent runs are illustrated in Figs. 13 and 14. From these figures it can be concluded that PSOHS has a faster convergence, and optimal result is achievable in fewer iterations; therefore, it is practical when nonlinear analyses are performed.

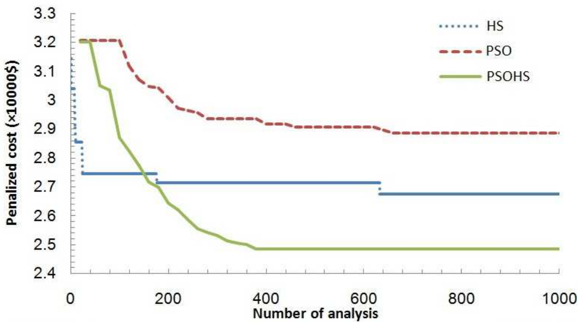

Figure 12. Convergence history of the best run of algorithms

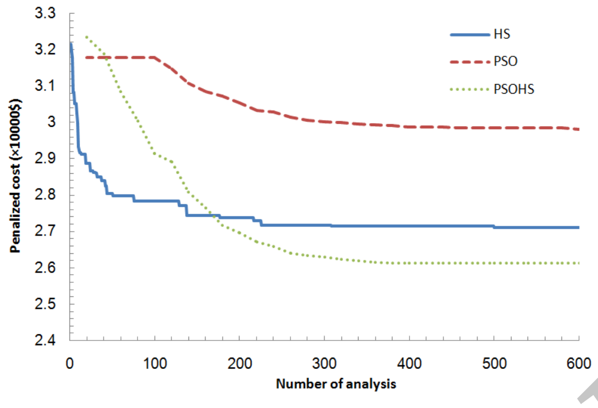

Figure 13. Convergence history of the average of runs

Similar to previous examples, from Table 9 it can be concluded that the active constraint is the minimum ratio of shear reinforcements.

Table 8: Geometry of the six-bay twelve-story frame with RC shear wall

Algorithm	Story	t_w(mm)	t_f(mm)	b_f(mm)	S_{sh}(mm)	ϕ_w(mm)	ϕ_f(mm)	*nud*	*nrl*	*Cost ($)*
HS	1	400	700	1200	450	16	32	10	24	26747
	2	300	700	1000	450	16	32	8	18	
	3	300	700	1000	450	16	32	8	18	
	4	200	700	1000	450	16	32	8	16	
	5	200	700	600	450	16	32	8	10	
	6	200	600	600	450	16	32	4	8	
	7	200	600	500	450	16	32	4	8	
	8	200	600	400	450	16	32	4	6	
	9	200	600	400	450	16	32	4	6	
	10	200	600	400	450	16	32	4	6	
	11	200	600	400	450	16	32	4	6	
	12	200	600	300	450	16	32	4	4	
PSO	1	400	900	1200	450	16	36	8	16	28870
	2	400	900	1100	450	16	36	10	16	
	3	400	800	1100	450	16	36	6	14	
	4	400	600	800	450	16	36	4	12	
	5	300	600	800	450	16	32	4	12	
	6	300	600	800	400	16	32	4	12	
	7	200	600	800	350	16	32	4	10	
	8	200	600	600	350	16	32	4	8	
	9	200	600	600	300	16	32	4	8	
	10	200	600	500	300	16	32	4	6	

	11	200	600	500	300	16	32	4	6	
	12	200	600	500	300	16	32	4	6	
PSOHS	1	200	600	1200	450	16	36	4	16	24567
	2	200	600	1200	450	16	36	4	16	
	3	200	600	900	450	16	36	4	12	
	4	200	600	800	450	16	36	4	10	
	5	200	600	600	450	16	36	4	8	
	6	200	600	500	450	16	36	4	6	
	7	200	600	500	450	16	32	4	6	
	8	200	600	300	450	16	32	4	4	
	9	200	600	300	450	16	32	4	4	
	10	200	600	300	450	16	32	4	4	
	11	200	600	300	450	16	32	4	4	
	12	200	600	300	450	16	32	4	4	

Table 9: The value of constraints of the twelve-story RC shear wall designed by different algorithms

Algorithm	HS			PSO			PSOHS		
Story	constraint 1	constraint 2	constraint 3	constraint 1	constraint 2	constraint 3	constraint 1	constraint 2	constraint 3
1	-1.3	-0.745	-0.27	-1.3	-0.744	-0.271	-1.3	-0.539	-0.624
2	-1.3	-0.664	-0.389	-1.3	-0.748	-0.266	-1.3	-0.545	-0.611
3	-1.3	-0.673	-0.374	-1.3	-0.754	-0.258	-1.3	-0.557	-0.585
4	-1.3	-0.529	-0.645	-1.3	-0.764	-0.245	-1.3	-0.575	-0.549
5	-1.3	-0.556	-0.587	-1.3	-0.703	-0.329	-1.3	-0.599	-0.502
6	-1.3	-0.589	-0.521	-1.3	-0.725	-0.297	-1.3	-0.629	-0.448
7	-1.3	-0.628	-0.449	-1.3	-0.627	-0.451	-1.3	-0.664	-0.389
8	-1.3	-0.673	-0.374	-1.3	-0.672	-0.376	-1.3	-0.705	-0.326
9	-1.3	-0.726	-0.295	-1.3	-0.726	-0.296	-1.3	-0.753	-0.259
10	-1.3	-0.784	-0.219	-1.3	-0.784	-0.22	-1.3	-0.805	-0.194
11	-1.3	-0.851	-0.142	-1.3	-0.851	-0.142	-1.3	-0.865	-0.126
12	-1.3	-0.924	-0.067	-1.3	-0.924	-0.068	-1.3	-0.932	-0.06

5. CONCLUSION

In this paper, performance based optimal design of RC shear walls was investigated using different meta-heuristic algorithms. One of the robust algorithms is PSO which has been utilized in many engineering problems. However, unbalanced exploration and exploitation reduces its robustness; moreover, there is not an appropriate mechanism to deal with violated particles from side boundaries. Therefore, this paper followed two main purposes: first, to reach to performance based optimal design of RC shear walls using pushover analysis; second, examine the recently developed modified version of PSO which is called PSOHS. To show the efficiency of the PSOHS, the design of shear walls were performed by PSO, HS, and PSOHS, and results were compared. Results show that a linear varying inertia weight in PSO provides a balanced exploration and exploitation for the algorithm, and this improvement prevents PSO to be trapped in a local minimum or particles move far from the global minimum due to high velocity. In conclusion, PSOHS seems to be a suitable algorithm for performance based optimal design of shear walls, and it can be utilized in professional applications successfully.

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