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Research Article

Optimum Performance-Based Seismic Design Using a Hybrid Optimization Algorithm

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A hybrid optimization method is presented to optimum seismic design of steel frames considering four performance levels. These performance levels are considered to determine the optimum design of structures to reduce the structural cost. A pushover analysis of steel building frameworks subject to equivalent-static earthquake loading is utilized. The algorithm is based on the concepts of the charged system search in which each agent is affected by local and global best positions stored in the charged memory considering the governing laws of electrical physics. Comparison of the results of the hybrid algorithm with those of other metaheuristic algorithms shows the efficiency of the hybrid algorithm.

1. Introduction

Many of engineering problems can be modeled into optimization problems. Therefore, developing new optimization techniques to solve these types of problems becomes highly significant. For this case, a large number of optimization algorithms as optimization techniques have already been proposed and applied in solving engineering problems such as ant colony optimization (ACO) [1], ABC (artificial bee colony) [2, 3], cuckoo search (CS) [4–6], bat algorithm (BA) [7, 8], genetic programming (GP) [9], ES (evolutionary strategy) [10], GA (genetic algorithm) [11], HS (harmony search) [12, 13], biogeography-based optimization (BBO) [14–16], differential evolution (DE) [17–19], particle swarm optimization (PSO) [20, 21], electromagnetism-like mechanism (EM) [22], and the charged system search algorithm (CSS) [23–25].

In 2010, Kaveh and Talatahari have firstly proposed a robust metaheuristic search technique, namely, CSS algorithm [23], for possibly nonlinear functions. The governing laws from the physics initiate the base of the CSS algorithm. CSS is a multiagent algorithm in which each agent is considered as a charged sphere. Since these agents are treated as charged particles that can affect each other according to the Coulomb and Gauss laws from electrostatics, they are called charged particles (CPs). After determining the resultant force affected on each CP, the Newtonian motion law is utilized to determine the movement of the agents. The successive moving of CPs considering the resultant forces directs the agents toward optimum solutions.

The contribution of this paper is to present a hybrid CSS-based algorithm to find a seismic optimum design of steel frames considering four performance levels. The nonlinear analysis is required to reach the structural response at various performance levels. Therefore, the refined plastic hinge analysis method is developed to estimate the nonlinear behavior of the entire structural system and members effectively.

The organization of this paper is as follows. Section 2 and Section 3 describe the statement of the problem and the utilized analyses method, respectively. Our proposed CSS-based hybrid method is described in detail in Sections 4 and 5. Subsequently, the merits of our method are verified by numerical examples in Section 6. At last, Section 7 summarizes our work.

2. Statement of Seismic Design of Frames

The mathematical formulation of the structural optimization problems can be expressed as minimizing the weight of structures as the cost function without taking into consideration other influencing tributary parameters:

$$\text{Minimize}: \quad W(X) = \sum_{j=1}^{ne} \rho \cdot L_j \cdot A_j, \tag{1}$$

where $W(X)$ is the weight of the structure; X is the vector of design variables taken from W-shaped sections found in the AISC design manual [26]; ne is the number of members; ρ is the material mass density; and L_j and A_j are the length and the cross-sectional area of the member j, respectively.

Lateral deflections of a building may cause human discomfort and minor damage of nonstructural components. Extreme inelastic lateral deflections due to a severe earthquake can cause the failure of mechanical, electrical and plumbing systems or suspended ceilings and equipment to fall, thereby posing threats to the human life. This matter is considered as the constraint functions in this paper as [27]

$$\begin{aligned} \text{OP Level} \quad & \Delta^{\text{OP}}(X) \le \overline{\Delta}^{\text{OP}}, \\ \text{IO Level} \quad & \Delta^{\text{IO}}(X) \le \overline{\Delta}^{\text{IO}}, \\ \text{LS Level} \quad & \Delta^{\text{LS}}(X) \le \overline{\Delta}^{\text{LS}}, \\ \text{CP Level} \quad & \Delta^{\text{CP}}(X) \le \overline{\Delta}^{\text{CP}}, \end{aligned} \tag{2}$$

where Δ^{level} is the lateral drift and $\overline{\Delta}^{\text{level}}$ is the allowable lateral drift (0.4%, 0.7%, 2.5% and 5% of the height of the building are taken as the allowable roof drifts for the OP, IO, LS, and CP performance levels, resp.). Here, OP, IO, LS, and CP are the different performance levels. Operational (OP), Immediate Occupancy (IO), life safety (LS), and collapse Prevention (CP) (FEMA-273, 1997), [28] are building performance levels. The operational level is that at which a building has sustained minimal or no damage to its structural and nonstructural components, and the building is suitable for normal occupancy or use; a building at the immediate occupancy level has sustained minimal or no damage to its structural elements and only minor damage to its nonstructural components, and is safe to be reoccupied immediately; a building at the life safety level has experienced extensive damage to its structural and nonstructural components and, while the risk to life is low, repairs may be required before reoccupancy can occur; the collapse prevention level is when a building has reached a state of impending partial or total collapse, where the building may have suffered a significant loss of lateral strength and stiffness with some permanent lateral deformation, but the major components of the gravity load carrying system should still continue to carry gravity load demands.

3. Pushover Analysis for Performance-Based Design

There are various methods of static pushover analyses to predict the seismic demands on building frameworks under equivalent static earthquake loading [29–35]; however, here a developed computer-based pushover analysis procedure is utilized [27] which was originally conceived for the elastic analysis of steel frameworks with semirigid connections [36, 37]. The analysis process is inspired from second-order inelastic analysis of semi-rigid framed structures that rigidity factor is replaced with plasticity factor in stiffness matrix. Fictitious plastic-hinge connections are necessary at the two ends of beam-column elements and semi-rigid analysis techniques were modified for the nonlinear load-deformation analysis of building frameworks under increasing seismic loads. The value of plasticity factor p is conceived from rigidity factor used in semi-rigid analysis. This factor r_i defines the rotational stiffness of the connection and can be interpreted as the ratio of the end-rotation α_i of the member to the combined rotation θ_i of the member as

$$r_i = \frac{\alpha_i}{\theta_i} = \frac{1}{1 + (3\text{EI}/RL)} \quad (i = 1, 2), \tag{3}$$

where R is the rotational stiffness of connection i and EI and L are the bending stiffness and length of the connected member, respectively. In fact, upon replacing connection rotational stiffness R with section postelastic flexural stiffness in (3), the degradation of the flexural stiffness of a member section experiencing postelastic behavior can be characterized by the plasticity factor:

$$p = \frac{1}{1 + (3\text{EI}/R^p L)}, \tag{4}$$

where $R^p = dM/d\phi$ is the section postelastic flexural stiffness and p is the plasticity factor:

$$\%\text{plasticity} = 100(1 - p). \tag{5}$$

Here, the elastic stiffness matrix is comprised of both the first-order and the second-order geometric properties:

$$K = S_e C_e + S_g C_g. \tag{6}$$

The matrix K consists of two parts; the first part is conceived from Monfortoon and Wu's method [38] that employs the rigidity factor concept to develop a first-order elastic analysis technique for semi-rigid frames (i.e., $S_e \times C_e$) and the second part is conceived from Xu's method [36] that considers the rigidity-factor concept to develop a second-order elastic analysis technique for semi-rigid frames (i.e., $S_g \times C_g$). Here S_e and S_g are the standard first-order elastic and the second-order geometric stiffness matrices, respectively, when the member has rigid moment-connections; C_e and C_g are the corresponding correction matrices which account for the reduced rotational stiffness of the semi-rigid moment-connections. The flowchart of pushover analysis for performance-based design is shown in Figure 1.

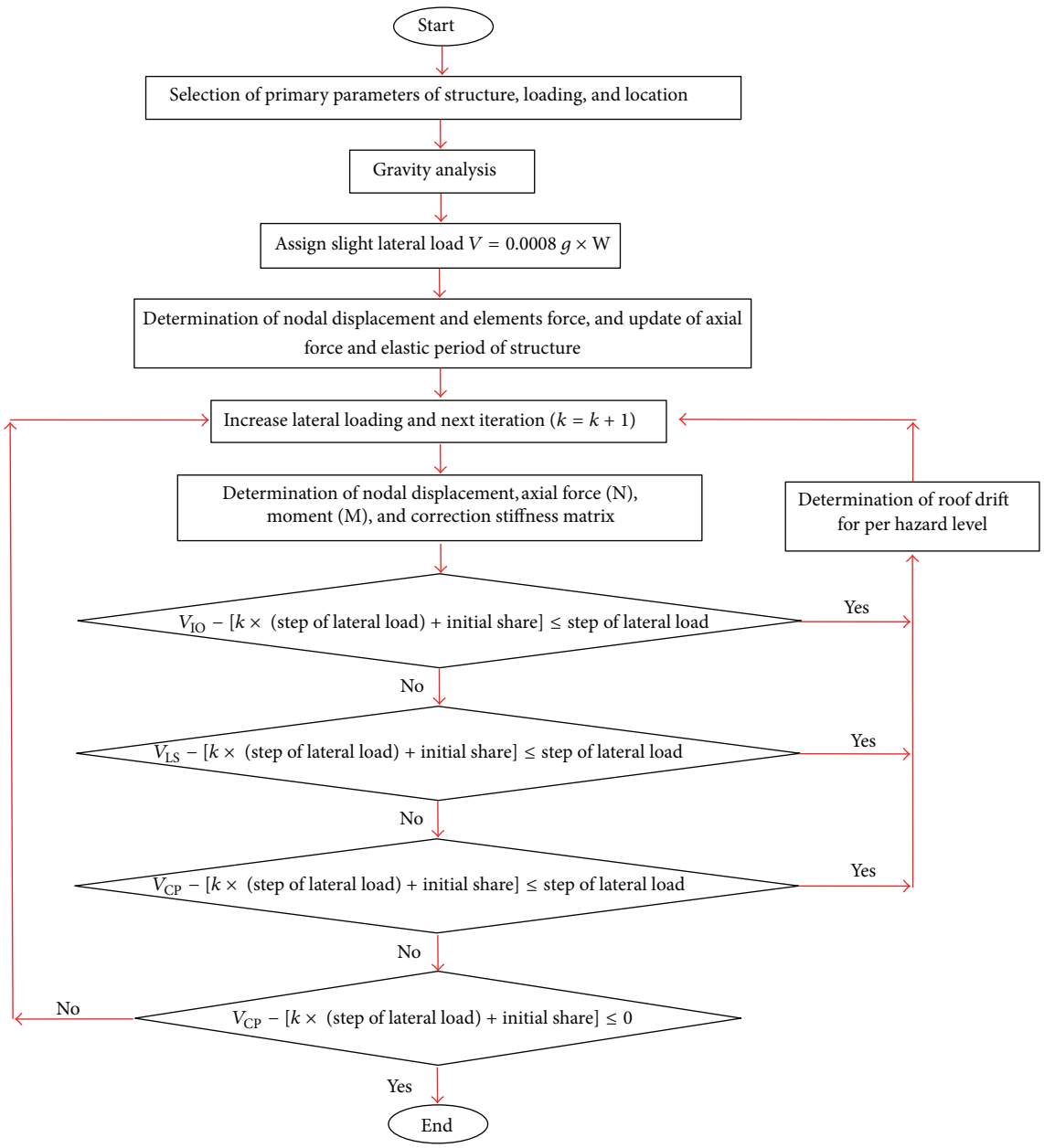

Figure 1: Flowchart of pushover analysis for performance-based design.

4. Utilized Algorithms

A review of utilized metaheuristic algorithms is presented in the following subsections.

4.1. Charged System Search Algorithm. The charged system search (CSS) algorithm is based on the Coulomb and Gauss laws from electrical physics and the governing laws of motion from the Newtonian mechanics. This algorithm can be considered as a multiagent approach, where each agent is a charged particle (CP). Each CP is considered as a charged sphere with radius a, having a uniform volume charge density, and is equal to [23]

$$q_j = \frac{W_j - W_{\text{worst}}}{W_{\text{best}} - W_{\text{worst}}}, \quad j = 1, 2, \ldots, N, \tag{7}$$

where W_{best} and W_{worst} are the minimum and the maximum weight among all the particles, W_j represents the weight of the agent i, and N is the total number of CPs.

CPs can impose electrical forces on the others. The kind of the forces is attractive and its magnitude for the CP

located in the inside of the sphere is proportional to the separation distance between the CPs and for a CP located outside the sphere is inversely proportional to the square of the separation distance between the particles:

$$\mathbf{F}_j = q_j \sum_{i,i\neq j} \left(\frac{q_i}{a^3} r_{ij} \cdot i_1 + \frac{q_i}{r_{ij}^2} \cdot i_2 \right) p_{ij} \left(\mathbf{X}_i - \mathbf{X}_j \right), \quad j = 1, 2, \ldots, N, \tag{8}$$
$$i_1 = 1, \quad i_2 = 0 \Longleftrightarrow r_{ij} < a,$$
$$i_1 = 0, \quad i_2 = 1 \Longleftrightarrow r_{ij} \geq a,$$

where $\mathbf{F}_j$ is the resultant force acting on the jth CP and r_{ij} is the separation distance between two charged particles which is defined as follows:

$$r_{ij} = \frac{\left\| \mathbf{X}_i - \mathbf{X}_j \right\|}{\left\| \left(\mathbf{X}_i + \mathbf{X}_j \right) / 2 - \mathbf{X}_{\text{best}} \right\| + \varepsilon}, \tag{9}$$

where $\mathbf{X}_i$ and $\mathbf{X}_j$ are the positions of the ith and jth CPs, respectively; $\mathbf{X}_{\text{best}}$ is the position of the best current CP with the minimal weight; and ε is a small positive number. The initial positions of CPs are determined randomly in the search space and the initial velocities of charged particles are assumed to be zero. P_{ij} determines the probability of moving each CP toward the others as

$$p_{ij} = \begin{cases} 1 & \dfrac{W_i - W_{\text{best}}}{W_j - W_i} > \text{rand or } W_j > W_i \\ 0 & \text{otherwise.} \end{cases} \tag{10}$$

The resultant forces and the motion laws determine the new location of the CPs. At this stage, each CP moves toward to its new position considering the resultant forces and its previous velocity as

$$\mathbf{X}_{j,\text{new}} = \text{rand}_{j1} \cdot k_a \cdot \frac{\mathbf{F}_j}{m_j} \cdot \Delta t^2 + \text{rand}_{j2} \cdot k_v \cdot \mathbf{V}_{j,\text{old}} \cdot \Delta t + \mathbf{X}_{j,\text{old}}, \tag{11}$$
$$\mathbf{V}_{j,\text{new}} = \frac{\mathbf{X}_{j,\text{new}} - \mathbf{X}_{j,\text{old}}}{\Delta t},$$

where k_a is the acceleration coefficient; k_v is the velocity coefficient to control the influence of the previous velocity; and rand_{j1} and rand_{j2} are two random numbers uniformly distributed in the range of (0, 1). If each CP exits from the allowable search space, its position is corrected using the harmony search-based handling approach as described by Kaveh and Talatahari [39]. In addition, to save the best design, a memory (charged memory) is considered containing the CMS number of positions for the so far best agents.

Both CSS and EM [22] are based on the governing laws from the electrical physics; however, the movement strategies, the resultant force for each agent, and deification of electrical charges for agents are different. The CSS algorithm utilizes a velocity term while in the EM we have no term of a velocity. The EM just uses the Coulomb law to determine the forces while the CSS approach uses the Coulomb law as well as Gauss's law to explore the search space more efficiently. After evaluating the total force vector in the EM, each agent is moved in the direction of the force by a random step length (being uniformly distributed between 0 and 1) while the movements in the CSS are based on the governing laws of motion from the Newtonian mechanics. The potency of the EM is summarized to find the direction of an agent' movement, while in the CSS not only the directions but also the amount of movements are determined.

From the above discussion, it can be concluded that the CSS algorithm is a general form of the EM which contains its superiorities and avoids its disadvantages.

4.2. Particle Swarm Optimization. The particle swarm optimization (PSO) is motivated from the social behavior of bird flocking and fish schooling which has a population of individuals, called particles, that adjust their movements depending on both their own experience and the population's experience [20]. In other words, each particle in the PSO algorithm continuously focuses and refocuses on the effort of its search according to both local best and global best. In PSO, the position of each agent, $\mathbf{X}_i^k$, and its velocity, $\mathbf{V}_i^{k+1}$, are calculated as

$$\mathbf{X}_i^{k+1} = \mathbf{X}_i^k + \mathbf{V}_i^{k+1},$$
$$\mathbf{V}_i^{k+1} = \omega \mathbf{V}_i^k + c_1 r_1 \circ \left(\mathbf{P}_i^k - \mathbf{X}_i^k \right) + c_2 r_2 \circ \left(\mathbf{P}_g^k - \mathbf{X}_i^k \right), \tag{12}$$

where ω is an inertia weight to control the influence of the previous velocity, r_1 and r_2 are two random vectors uniformly distributed in the range of (0, 1), and c_1 and c_2 are two acceleration constants, and the sign "$\circ$" denotes element-by-element multiplication. The abovementioned formulations of the PSO algorithm can be combined and rewritten as

$$\mathbf{X}_i^{k+1} = \mathbf{X}_i^k + \omega \mathbf{V}_i^k + c_1 r_1 \circ \left(\mathbf{P}_i^k - \mathbf{X}_i^k \right) + c_2 r_2 \circ \left(\mathbf{P}_g^k - \mathbf{X}_i^k \right). \tag{13}$$

In some previous studies, to improve the performance of the algorithm, another term is added to the above formulae as

$$\mathbf{X}_i^{k+1} = \mathbf{X}_i^k + \omega \mathbf{V}_i^k + c_1 r_1 \circ \left(\mathbf{P}_i^k - \mathbf{X}_i^k \right) + c_2 r_2 \circ \left(\mathbf{P}_g^k - \mathbf{X}_i^k \right) + \sum_{j=1}^{ne} c_j r_j \circ \left(\mathbf{R}_j^k - \mathbf{X}_i^k \right), \tag{14}$$

where c_j, similar to c_1 and c_2, is a constant value and r_j is a random vector. ne denotes the number of extra terms considered in the algorithm and $\mathbf{R}_j^k$ is defined based on the type of the algorithm being used.

5. A Hybrid Optimization Algorithm

In the present hybrid algorithm, the advantage of the PSO containing utilizing the local best and the global best is added

to the CSS algorithm. The charged memory (CM) for the hybrid algorithm is treated as the local best in the PSO, and the CM updating process is defined as

$$\mathrm{CM}_{i,\mathrm{new}} = \begin{cases} \mathrm{CM}_{i,\mathrm{old}}, & W\left(\mathbf{X}_{i,\mathrm{new}}\right) \geq W\left(\mathrm{CM}_{i,\mathrm{old}}\right), \\ \mathbf{X}_{i,\mathrm{new}}, & W\left(\mathbf{X}_{i,\mathrm{new}}\right) < W\left(\mathrm{CM}_{i,\mathrm{old}}\right), \end{cases} \tag{15}$$

in which the first term identifies that when the new position is not better than the previous one the updating does not perform while when the new position is better than the stored so far good position the new solution vector is replaced. In the first iteration, the vector stored in CM and the first positions of the agents will be identical. Considering the abovementioned new charged memory, the electric forces generated by agents are modified as

$$\begin{aligned} \mathbf{F}_j = &\sum_{i\in S_1}\left(\frac{q_i}{a^3}r_{ij}\cdot i_1 + \frac{q_i}{r_{ij}^2}\cdot i_2\right)\left(\mathrm{CM}_{i,\mathrm{old}} - \mathbf{X}_j\right) \\ &+ \sum_{i\in S_2}\left(\frac{q_i}{a^3}r_{ij}\cdot i_1 + \frac{q_i}{r_{ij}^2}\cdot i_2\right) ar_{ij}p_{ij}\left(\mathbf{X}_i - \mathbf{X}_j\right), \end{aligned} \tag{16}$$

where S_1 and S_2 are defined as follows:

$$S_1 = \left\{t_1, t_2, \ldots, t_n \mid q(t) > q(j), j = 1, 2, \ldots, N, j \neq i, g\right\}, \tag{17}$$

$$S_2 = S - S_1, \tag{18}$$

in which S_1 determines the set of agents utilized from CM, n denotes the number of CM agents, S is utilized as a set of all agents' number, and thus S_2 will be the set of current agents used for directing the agent j. Here, in the primary iterations n is set to two continuing the number of the best stored so far agent among all CPs (global best) and jth agent stored in the CM which is treated as local best. Then the number of used agents from CM is increased linearly and finally it reached N in the last iterations. In this hybrid algorithm, $\mathrm{CM}_{i,\mathrm{old}}$ will be treated similar to $\mathbf{P}_i^k$ in the PSO. The other modification is that the forces can be attractive or repulsive, and ar_{ij} is added to fulfill this aim which determines the kind of the force as

$$ar_{ij} = \begin{cases} +1, & \text{w.p. } k_t, \\ -1, & \text{w.p. } 1 - k_t, \end{cases} \tag{19}$$

where "w.p." represents the abbreviation for "with the probability" and k_t is a parameter to control the effect of the kind of forces. Comparing to (10), this new formula (18) considers the best so far location of agents and the best local position of the current agent in addition to the location of other agents. Also, here m_j is assumed to be q_j and therefore (12) is simplified as

$$\mathbf{X}_{j,\mathrm{new}} = k_a \cdot r_1 \cdot \mathbf{F}_j + k_v \cdot r_2 \cdot \mathbf{V}_{j,\mathrm{old}} + \mathbf{X}_{j,\mathrm{old}}. \tag{20}$$

The pseudocode of the hybrid algorithm can be summarized as follows.

Step 1 (initialization). The magnitude of the charge for each CP is defined by (7). The initial positions of the CPs are determined randomly and the initial velocities of charged particles are assumed to be zero.

Step 2 (CM creation). The position of the initial agents and the values of their corresponding objective functions are saved in the charged memory (CM).

Step 3 (the forces determination). The probability of moving each CP towards the others (p_{ij}) and the kind of forces (a_{ij}) are determined using (10) and (19), respectively, and the resultant force vector for each CP is calculated using (18).

Step 4 (solution construction). Each CP moves to the new position according to (20).

Step 5 (CM updating). CM updating is performed according to (15).

Step 6 (terminating criterion control). Steps 3–5 are repeated for a predefined number of iterations.

6. Design Examples

Two building frameworks are selected for seismic optimum design using the metaheuristic algorithm [27]. These frames have previously been used to illustrate the pushover analysis technique by Hasan et al. [42] and Talatahari [40].

The expected yield strength of steel material used for column members is $\sigma_{\mathrm{ye}} = 397$ MPa, while $\sigma_{\mathrm{ye}} = 339$ MPa is considered for beam members. The constant gravity load w is accounted for a tributary-area width of 4.57 m and dead-load and live-load factors of 1.2 and 1.6, respectively. For each example, 30 independent runs are carried out using the new hybrid algorithms and compared with other algorithms. The number of 20 individuals for CPs is used and the values of constants k_v and k_a are set to 0.4.

6.1. Four-Bay Three-Story Steel Frame. The configuration, grouping of the members and applied loads of the four-bay three-story framed structure are shown in Figure 2, [27]. The 27 members, of the structure are categorized into five groups, as indicated in the figure. The modulus of elasticity is taken as $E = 200$ GPa. The constant gravity load of $w_1 = 32$ kN/m is applied to the first and second story beams, while the gravity load of $w_2 = 28.7$ kN/m is applied to the roof beams. The seismic weight is 4,688 kN for each of the first and second stories and 5,071 kN for the roof story.

The performance-based optimum results for the metaheuristic algorithm are summarized in Table 1. The hybrid CSS, HPACO, ACO, and GA need 4500, 4500, 3900 and 6800 analyses to reach a convergence while 8500 analyses required by the PSO. The best hybrid CSS design results in a frame that weighs 273.7 kN, which is lighter than the design of Gall optimization algorithm. The result of conventional design [41] is approximately 50% more than the result of new algorithm. In a series of 30 different design runs, the average weight of the hybrid CSS designs is 286.7 kN, with a standard deviation of 5.651 kN, while the average weight of the PSACO, PSO, and ACO designs is 290.4 kN, 302.4 kN, and 294.3 kN, respectively. The standard deviation values are 6.45 kN, 10.45 kN and 7.56 for the PSACO, PSO, and ACO, respectively.

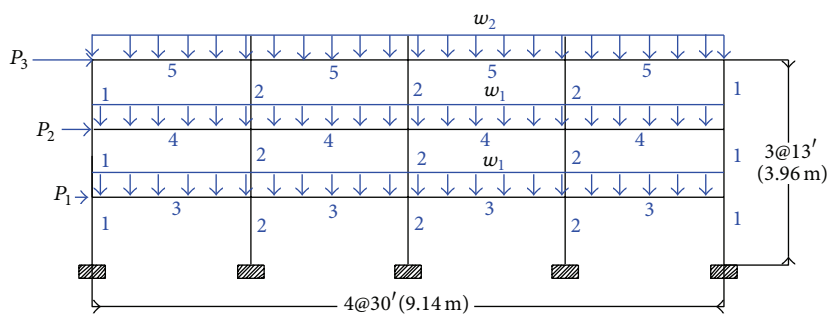

Figure 2: Three-story steel moment-frame.

Table 1: The statistical information of performance-based optimum designs for the 4-bay 3-story frame.

Algorithm	Hybrid CSS	PSACO [40]	PSO [40]	ACO [27]	GA [27]	A conventional design [41]
Best weight (kN)	273.7	279.2	286.3	283.4	303.9	412.9 kN
Average weight (kN)	286.7	290.4	302.4	294.3	321.5	—
Worst weight (kN)	297.8	298.5	310.7	303.2	339.7	—
Std. dev. (kN)	5.651	6.453	10.453	7.566	14.332	
Average number of analyses	4,500	4,500	8,500	3,900	6,800	—

Table 2: The statistical information of performance-based optimum designs for the 4-bay 9-story frame.

Algorithm	Hybrid CSS	PSACO [40]	PSO [40]	ACO [27]	GA [27]
Best weight (kN)	1568.66	1601.32	1682.63	1631.83	1723.1
Average weight (kN)	1626.32	1650.55	1725.36	1696.2	1791.4
Worst weight (kN)	1725.36	1759.65	1813.25	1786.94	1943.2
Std. dev. (kN)	30.35	38.52	66.35	49.33	78.33
Average number of analyses	5,000	6,000	12,500	5,600	9,700

6.2. Five-Bay Nine-Story Steel Frame. A five-bay nine-story steel frame is considered as shown in Figure 3. The material has a modulus of elasticity equal to $E = 200$ GPa. The 108 members of the structure are categorized into fifteen groups, as indicated in the figure. The constant gravity load of $w_1 = 32$ kN/m is applied to the beams in the first to the eighth story, while $w_2 = 28.7$ kN/m is applied to the roof beams. The seismic weights are 4,942 kN for the first story, 4,857 kN for each of the second to eighth stories, and 5,231 kN for the roof story. In this example, each of the five beam element groups is chosen from all 267 W-shapes, while the eight column element groups are limited to W14 sections (37 W-shapes).

Table 2 presents the statistical results obtained by the metaheuristic algorithms. The best hybrid CSS design results in a frame weighing 1568.66 kN which is 1.9%, 7.0%, 3.8%, and 9.5% lighter than the PSACO, PSO, ACO, and GA. In order to converge to a solution for the hybrid CSS algorithm, approximately 5,000 frame analyses are required which are less than the 6,000, 12,500, and 9,700 analyses necessary for the PSACO, PSO, and GA, respectively. The ACO needs only 5,600 analyses to find an optimum result.

7. Conclusion Remarks

The problem of optimum design of frame structures is formulated to minimize the weight of the structure considering the required constraints specified by design codes. For seismic design of structures, two main points should be considered: structural costs and structural damages. As a result, it is essential to control the lateral drift of building frameworks under seismic loading at various performance levels. To fulfill this aim, in this paper a hybrid optimization method is presented. The algorithm is based on the CSS algorithm. CSS is a multiagent algorithm in which each agent is considered as a charged sphere. Since these agents are treated as charged particles that can affect each other according to the Coulomb and Gauss laws from electrostatics, in the present hybrid algorithm, the advantage of the PSO containing utilizing the local best and the global best is added to the CSS algorithm. The charged memory for the hybrid algorithm is treated as the local best in the PSO, and the CM updating process is redefined to adapt the new requirements.

A simple computer-based method for push-over analysis of steel building frameworks subject to equivalent-static earthquake loading is utilized. The method accounts for first-order elastic and second-order geometric stiffness properties and the influence that combined stresses have on plastic behavior and employs a conventional elastic analysis procedure modified by a plasticity-factor to trace elastic-plastic behavior over the range of performance levels for a structure [27]. Two examples are optimized using the new algorithm as

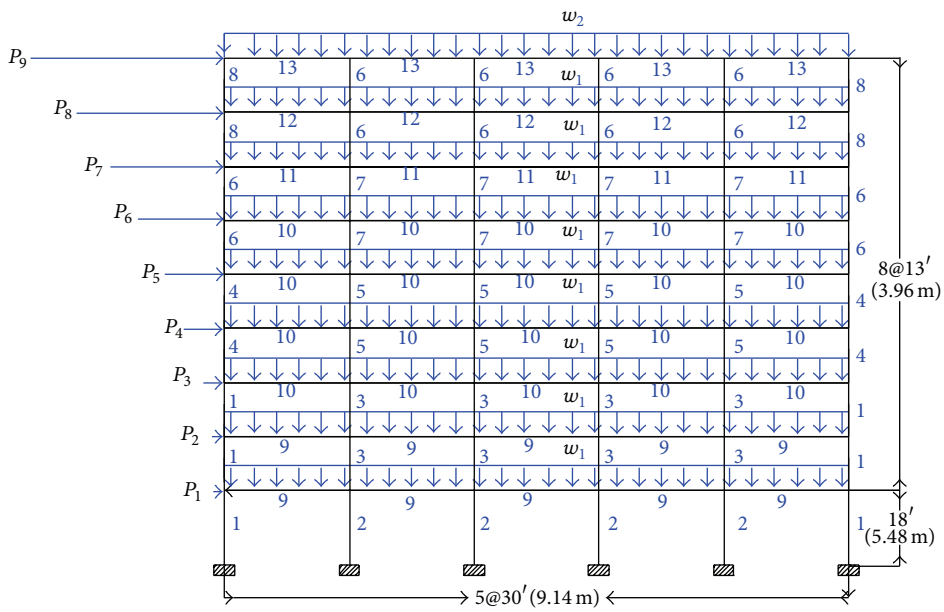

Figure 3: Nine-story steel moment-frame.

well as some advanced metaheuristic algorithms to investigate the capability of the new method. The genetic algorithm, ant colony optimization, particle swarm optimization, and particle swarm ant colony optimization method as well as the new hybrid method are utilized to find optimum seismic design of examples. The obtained results indicate that the new algorithm compared to GA, ACO, PSO, and PSACO can find better optimum seismic design of structures.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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