



HYBRID CHARGED SYSTEM SEARCH - PARTICLE SWARM OPTIMIZATION FOR DESIGN OF SINGLE-LAYER BARREL VAULT STRUCTURES

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ABSTRACT

The barrel vaults are composed of member elements arranged on a cylindrical surface. This kind of structure is utilized to cover the long spans. In this paper, the hybrid charge system search and particle swarm optimization algorithm is improved and utilized to optimal design of single-layer barrel vault frames. Some modifications on parameter values are performed to enhance the performance of the hybrid algorithm. Comparison of the results with other meta-heuristic algorithms illustrates the efficiency of the hybrid CSS and PSO algorithm. Also some discussion on the loading conditions and group selecting are presented.

Keywords: Charged system search, particle swarm optimization, hybrid algorithms, optimal design, single layer barrel vault frame

1. INTRODUCTION

Space frames are usually arranged in an array of single, double, or multiple layers of intersecting members. A single-layer space frame that has the form of a curved surface is termed as braced vault, braced dome, or latticed shell. The barrel vaults, having the diagonal or hexagonal types of bracing, must have rigid joints to be stable and the influence of bending moments in their stress distribution is much more pronounced than the other types.

In the field of structural optimization, many meta-heuristic algorithms have been proposed in the last three decades. Although, there are many studies on optimization of structures using the current meta-heuristic algorithms; however, there are not many studies on optimization of space structures, and further studies on optimization of these spatial structures seems necessary. Kaveh et al. [1-3] are the first researchers who formulated the problem of optimum design of barrel vault structures. In Ref. [1], they optimized two single barrel vaults utilizing different Charged System Search (CSS)-based methods containing the standard CSS [4], improved CSS [5], a magnetic CSS (MCSS) [6], and its improved version

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(IMCSS). Also, Kaveh and Eftekhari [2] have performed optimal design of barrel vault frames using an improved Big Bang-Big Crunch algorithm, in which a single layer barrel vault is optimized under both symmetrical and unsymmetrical loading cases. In the other study by Kaveh et al. [3], some single and multiple layer barrel vaults are optimized via the CSS algorithms.

In the present study, optimal design of single layer barrel vault frames structures is performed and the aim is to optimize this kind of structures with a hybrid CSS and particle swarm optimization (PSO) method. This method utilizes some benefits of the PSO into the CSS. An improved variant of the hybrid method is presented and a comparing to the other CSS-based method as well as some aspects regarding to the problem statement are discussed.

2. OPTIMUM DESIGN OF BARREL VAULT STRUCTURES

The purpose of size optimization of barrel vault structures is to minimize the weight of the structure, W , through finding the optimal cross-sectional areas A_i of members, in which all constraints exerted on the problem must be satisfied, simultaneously. Thus, the optimal design of barrel vault frame structures can be formulated as:

$$\text{Find } X = [x_1, x_2, x_3, \dots, x_n] \quad (1)$$

$$\text{to minimize } Mer(X) = f_{penalty}(X) \times W(X) \quad (2)$$

The cost function is

$$W(X) = \sum_{i=1}^{nm} \gamma_i x_i L_i \quad (3)$$

where x_i , γ_i and L_i are the area, material density and length of the steel section selected for member group i , respectively. X is the vector containing the design variables; For the discrete optimum design problem, the variables x_i are selected from an allowable set of discrete values; n is the number of member groups. Here, the objective of finding the minimum weight structure is subjected to several design constraints, including strength and serviceability requirements.

The penalty function is

$$f_{penalty}(X) = \left(1 + \varepsilon_1 \cdot \sum_{j=1}^{np} v_j^k \right)^{\varepsilon_2} \quad (4)$$

where np is the number of multiple loading conditions. In this paper \mathcal{E}_1 is taken as unity and \mathcal{E}_2 is set to 1.5 in the first iterations of the search process, but gradually it is increased to 3, [7]. v^k is the summation of penalties for all imposed constraints for k th charged particle which is mathematically expressed as:

$$v = \sum_{i=1}^{nn} \max(v_i^d, 0) + \sum_{i=1}^{nm} \left(\max(v_i^l, 0) + \max(v_i^s, 0) \right) \quad (5)$$

where v_i^d, v_i^l, v_i^s are the summation of displacement, shear and interaction formula penalties, calculated by Eqs. (6) through (8), respectively.

Displacement constraint:

$$v_i^d = \left| \frac{\delta_i}{\bar{\delta}_i} \right| - 1 \leq 0 \quad i=1,2,\dots,nn \quad (6)$$

Shear constraint, for both major and minor axis, [8]:

$$v_i^s = \frac{V_u}{\phi_v V_n} - 1 \leq 0 \quad i=1,2,\dots,nn \quad (7)$$

Constraints corresponding to interaction of flexure and axial force [8]:

$$v_i^l = \left\{ \begin{array}{l} \frac{P_u}{\phi_c P_n} + \frac{8}{9} \left(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}} \right) - 1 \leq 0 \quad \text{for } \frac{P_{uJ}}{\phi_c P_n} \geq 0.2 \\ \frac{P_u}{2\phi_c P_n} + \left(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}} \right) - 1 \leq 0 \quad \text{for } \frac{P_{uJ}}{\phi_c P_n} < 0.2 \end{array} \right\} \quad i=1,2,\dots,nn \quad (8)$$

where nn is the number of nodes; $\delta_i, \bar{\delta}_i$ are the displacement of the joints and the allowable displacement, respectively; nm is the number of members; V_u is the required shear strength; V_n is the nominal shear strength which is defined by the LRFD Specification, [8]; ϕ_v is the shear resistance factor ($\phi_v=0.9$); P_u is the required strength (tension or compression); P_n is the nominal axial strength; ϕ_c is the resistance factor ($\phi_c=0.9$ for tension, $\phi_c=0.85$ for compression); M_u is the required flexural strength; i.e., the moment due to the total factored load (Subscript x or y denotes the axis about which bending occurs.); M_n is the nominal

flexural strength determined in accordance with the appropriate equations in Chapter F of the LRFD Specification, [8] and ϕ_b is the flexural resistance reduction factor ($\phi_b = 0.9$).

3. NOMINAL STRENGTHS

Based on AISC-LRFD [8] specification, the nominal tensile strength of a member is equal to:

$$P_n = F_y A_g \quad (9)$$

where A_g is the gross section of the member.

The nominal compressive strength of a member is the smallest value obtained from the limit states of flexural buckling, torsional buckling, and flexural-torsional buckling. For members with compact and/or non-compact elements, the nominal compressive strength of the member for the limit state of flexural buckling is as follows:

$$P_n = F_{cr} A_g \quad (10)$$

where F_{cr} is the critical stress based on flexural buckling of the member, calculated as:

$$\text{For } \lambda_c = \frac{Kl}{r\pi} \sqrt{\frac{F_y}{E}} \leq 1.5 \quad F_{cr} = \left(0.658^{\lambda_c^2}\right) F_y \quad (11)$$

$$\text{For } \lambda_c = \frac{Kl}{r\pi} \sqrt{\frac{F_y}{E}} > 1.5 \quad F_{cr} = \left[\frac{0.877}{\lambda_c^2}\right] F_y \quad (12)$$

In the above equations, l is the laterally unbraced length of the member; K is the effective length factor; r is the governing radius of gyration about the axis of buckling and E is the modulus of elasticity.

4. DESIGN LOADS

According to ANSI-A58.1 and ASCE/SEI 7-10 codes [9,10], there are some specific considerations for loading conditions of arched roofs such as barrel vault structures. In this study, the load conditions are taken from Ref. [1].

4.1 Dead Load

The design dead load is established on the basis of the actual loads that may be expected to act on the structure of constant magnitude. The weight of various accessories, cladding,

supported lighting, heat and ventilation equipment, and the weight of space frame comprise the total dead load. In this study, a uniform dead load of 100 kg/m^2 is considered for estimated weight of sheeting, space frame, and nodes of barrel vault structures.

4.2 Snow Load

The snow load for arched roofs is calculated according to mentioned codes. Snow loads acting on a sloping surface shall be assumed to act on the horizontal projection of that surface. The sloped roof (balanced) snow load, P_s , shall be obtained by multiplying the flat roof snow load, P_f , by the roof slope factor, C_s , as follows:

$$P_s = C_s \cdot P_f \quad (13)$$

where C_s is

$$C_s = \begin{cases} 1.0 & \alpha < 15^\circ \\ 1.0 - \frac{\alpha - 15^\circ}{60^\circ} & 15^\circ < \alpha < 60^\circ \\ 0.25 & \alpha > 60^\circ \end{cases} \quad (14)$$

The distribution in arched roofs is shown in Fig. 1. In this paper, the flat roof snow load (P_f) is set to 150 kg/m^2 .

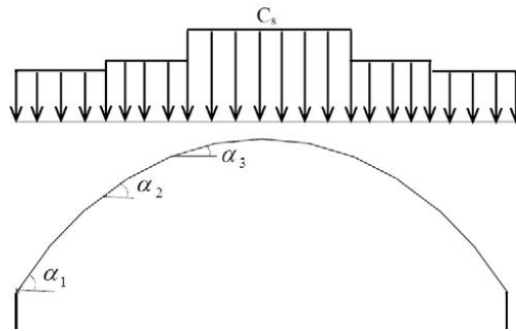


Figure 1. C_s distribution in arched roofs, [1]

4.3 Wind Load

For the wind load in arched roofs, different loads are applied in the windward quarter, center half and leeward quarter of the roof (Fig. 2) which are calculated based on ANSI and ASCE codes [9,10] as:

$$P = qG_hC_p \quad (15)$$

where q is the wind velocity pressure, G_h is the gust-effect factor and C_p is the external

pressure coefficient.

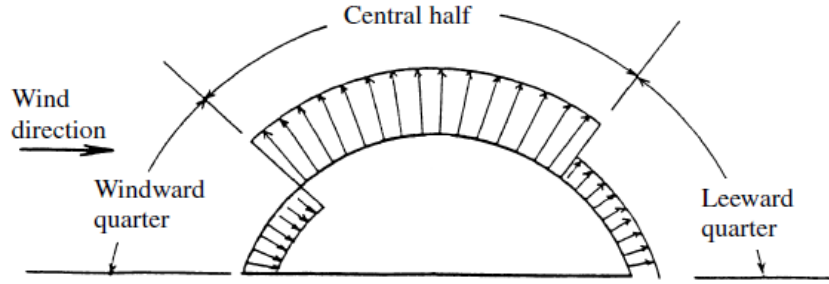


Figure 2. Wind pressure on an arched roof, [1]

5. A REVIEW ON CHARGED SYSTEM SEARCH AND PARTICLE SWARM OPTIMIZATION

Since the hybrid algorithm is based on the CSS and PSO, here a brief review on these algorithms is described in the following subsections and then the hybrid algorithm will be developed in the next section.

5.1 Charged system search

The CSS algorithm contains a number of CPs where each one is treated as a charged sphere and can insert an electric force to the others, [4]. The pseudo-code for the CSS algorithm is summarized as follows:

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

$$q_i = \frac{W_i - W_{worst}}{W_{best} - W_{worst}}, \quad i=1,2,\dots,N \quad (16)$$

where W_{best} and W_{worst} are the best and the worst objective function values among all of the particles; W_i represents the fitness of the agent i ; and N is the total number of CPs. The separation distance r_{ij} between any two CP is defined as follows:

$$r_{ij} = \frac{\|X_i - X_j\|}{\|(X_i + X_j)/2 - X_{best}\| + \varepsilon} \quad (17)$$

Where X_i and X_j are the positions of the i th and j th CPs, respectively; X_{best} is the position of the best current CP; and ε is a small positive number. The initial positions of CPs are determined randomly and the initial velocities of CPs are assumed to be zero.

Step 2: CM creation. A number of the best CPs 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 is determined using the following function:

$$p_{ij} = \begin{cases} 1 & \frac{W_i - W_{best}}{W_j - W_i} > rand \text{ or } W_j > W_i \\ 0 & \text{otherwise} \end{cases} \quad (18)$$

Then, the resultant force vector for each CP is calculated as:

$$F_j = q_j \sum_{i, i \neq j} \left(\frac{q_i}{a^3} r_{ij} \cdot i_1 + \frac{q_i}{r_{ij}^2} \cdot i_2 \right) p_{ij} (X_i - X_j), \left\langle \begin{array}{l} j = 1, 2, \dots, N \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < a \\ i_1 = 0, i_2 = 1 \Leftrightarrow r_{ij} \geq a \end{array} \right\rangle \quad (19)$$

where F_j is resultant force acting on the j th CP; X_i and X_j are the positions of the i th and j th CPs, respectively.

Step 4: Solution construction. Each CP moves to the new position as:

$$X_{j,new} = rand_{j1} \cdot k_a \cdot F_j + rand_{j2} \cdot k_v \cdot V_{j,old} + X_{j,old} \quad (20)$$

$$V_{j,new} = \frac{X_{j,new} - X_{j,old}}{\Delta t} \quad (21)$$

where k_a and k_v are the acceleration and the velocity coefficients, respectively; and $rand_{j1}$, $rand_{j2}$ are two random numbers.

Step 5: CM updating. The better new vectors are included to the CM and the worst ones are excluded from the CM.

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

5.2. Particle swarm optimization

The PSO is based on a metaphor of social interaction such as bird flocking and fish schooling, and is developed by Eberhart and Kennedy, [11]. The PSO simulates a commonly observed social behavior, where particles of a group (swarm) tend to follow the lead of the best of the group. In other words, the particles fly through the search space and their positions are updated based on the best positions of individual particles denoted by P_i^k and the best position among all particles in the search space represented by P_g^k .

The procedure of the PSO is reviewed as follows:

Step 1: Initialization. An array of particles and their associated velocities are initialized with random positions.

Step 2: Local and global best creation. The initial particles are considered as the first local best and the best of them corresponding to the minimum fitness function will be the first global best.

Step 3: Solution construction. The velocity and location of each particle are changed to the new position using the following equations:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (22)$$

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 \circ (P_i^k - X_i^k) + c_2 r_2 \circ (P_g^k - X_i^k) \quad (23)$$

where X_i^k and V_i^k are the position and velocity for the i th particle at iteration k ; ω is an inertia weight to control the influence of the previous velocity; r_1 , and r_2 are two random numbers; c_1 and c_2 are two constants; P_i^k is the best position of the i th particle up to the current iteration; P_g^k is the so-far best position among all particles in the swarm and the sign “ \circ ” denotes element-by-element multiplication.

Step 4: Local best updating. The objective function of the particles is evaluated and P_i^k is updated according to the best current value of the fitness function.

Step 5: Global best updating. The current global minimum objective function value among the current positions is determined and thus P_g^k is updated if the new position is better than the previous one.

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

It should be noted that for improving the performance of the PSO algorithm, equation (23) can be modified as

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 \circ (P_i^k - X_i^k) + c_2 r_2 \circ (P_g^k - X_i^k) + \sum_{j=1}^{ne} c_j r_j \circ (R_j^k - X_i^k) \quad (24)$$

where c_j is a constant and r_j is a random vector. ne denotes the number of extra terms considered in the algorithm, and R_j^k is a position of an agent defined based on the type of the algorithm being used.

6. A HYBRID CHARGED SYSTEM SEARCH - PARTICLE SWARM OPTIMIZATION

The hybrid CSS-PSO algorithm was presented by Kaveh and Talatahari [12] in which the location of the global and local best CPs are utilized to improve the searching process. In other words in the CSS-PSO, the advantage of the PSO consisting of utilizing the local best and the global best is added to the CSS algorithm.

6.1. Hybrid CSS-PSO Method

The CM for the hybrid algorithm is treated as the local best in the PSO, and the CM updating process is defined as follows, [12]:

$$CM_{i,new} = \begin{cases} CM_{i,old} & W(X_{i,new}) \geq W(CM_{i,old}) \\ X_{i,new} & W(X_{i,new}) < W(CM_{i,old}) \end{cases} \quad (25)$$

If the coefficient k_i is defined as:

$$k_i = \left(\frac{q_i}{a^3} r_{ij} \cdot i_1 + \frac{q_i}{r_{ij}^2} \cdot i_2 \right) ar_{ij} p_{ij} \quad (26)$$

Then the equation (13) can be simplified as

$$F_j = \sum_{i \in S_1} k_i (CM_{i,old} - X_j) + \sum_{i \in S_2} k_i (X_i - X_j) \quad (27)$$

Here, ar_{ij} determines the kind of force and is defined as

$$ar_{ij} = \begin{cases} +1 & \text{rand} < 0.8 \\ -1 & \text{otherwise} \end{cases} \quad (28)$$

where *rand* represents a random number.

In Ref. [12], four variant hybrid methods were proposed as the CSS-PSO algorithms. Here, the best one is selected and utilized. In the selected method, not only the global and local best agents from the CM but some other stored points are utilized. In addition, some of the locations of the current agents are also utilized to determine the resultant force. The corresponding equation can be expressed as:

$$F_j = k_1 (CM_{g,old} - X_j) + k_2 (CM_{j,old} - X_j) + \sum_{i \in S_1} k_i (CM_{i,old} - X_j) + \sum_{i \in S_2} k_i (X_i - X_j) \quad (29)$$

Where S_1 and S_2 are defined as follows:

$$S_1 = \{t_1, t_2, \dots, t_n \mid q(t) > q(j), \quad j=1,2,\dots,N, \quad j \neq i, g\} \quad (30)$$

$$S_2 = S - S_1 \quad (31)$$

in which S_1 determines the set of agents from CM utilized in equation (29). N denotes the number of agents in the CM. 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 . These equations clarify that for each agent one of its locations, namely its local best or its current location, are certainly utilized. For this formulation, in the primary iterations n is set to zero then it is increased linearly to N in the last iterations.

6.2. Parameter improvement for the CSS-PSO method

The CSS-PSO method utilizes harmony search-based approach for position correction of CPs. This method needs some parameters such as *CMCR* (Charge Memory Considering Rate) and *PAR* (Pitch Adjustment Rate) parameters that help the algorithm to find globally and locally improved solutions, respectively [13]. *PAR* and *bw* in this step are very important parameters in fine-tuning of optimized solution vectors, and can be potentially useful in adjusting convergence rate of algorithm to optimal solution [14]. In the standard hybrid algorithm, the fixed values were used for these parameters. Here, to improve the performance of this step of the algorithm and eliminate the drawbacks lies with fixed values of *PAR* and *bw*, they change dynamically with iteration number as follow [14]:

$$PAR_i = PAR_{\min} + \frac{PAR_{\max} - PAR_{\min}}{i_{\max}} \cdot i \quad (32)$$

$$bw_i = bw_{\max} e^{c \cdot i}, \quad c = \frac{\ln(bw_{\max} - bw_{\min})}{i_{\max}} \quad (33)$$

where bw_i is the bandwidth for each iteration, bw_{\min} and bw_{\max} are the minimum and maximum bandwidth, respectively. In this paper PAR_{\min} and PAR_{\max} are set to 0.3 and 0.99, respectively, [13].

7. NUMERICAL EXAMPLES

In this study, two single layer barrel vaults are selected from [1] in which Kaveh et al. used some CSS-based methods to optimize barrel vaults. They used the standard CSS, MCSS, ICSS and IMCSS algorithms and compare the results with each other. Since the proposed algorithm is based on the CSS, we select their examples to compare the results with. In all examples, the material density is 0.2836 lb/in^3 (7850 kg/m^3) and the modulus of elasticity is 30450 ksi ($2.1\text{E}6 \text{ kg/m}^2$). The yield stress F_y of steel is taken as 34135.96 psi (2400 kg/m^2) for both problems. Also, member sections are pipe shape and taken from the AISC-LRFD code [8].

7.1. A 173-member single barrel vault frame

The geometry of this example containing 3D and plan view are shown in Fig. 3. The member groups and support conditions are presented in the figure. Member sections are categorized in 15 groups as shown in Fig. 3b, [1]. The span, length and height of single barrel vaults are 30, 30 and 8 meter, respectively. This example has 173 members and 108 joints.

In this study, similar to Ref. [1], the loading cases contain 3-types of static loads; dead load, snow load and wind load. The uniform dead load equal to 100 kg/m^3 applied to the roof. The snow and wind loads are shown in Fig. 4.

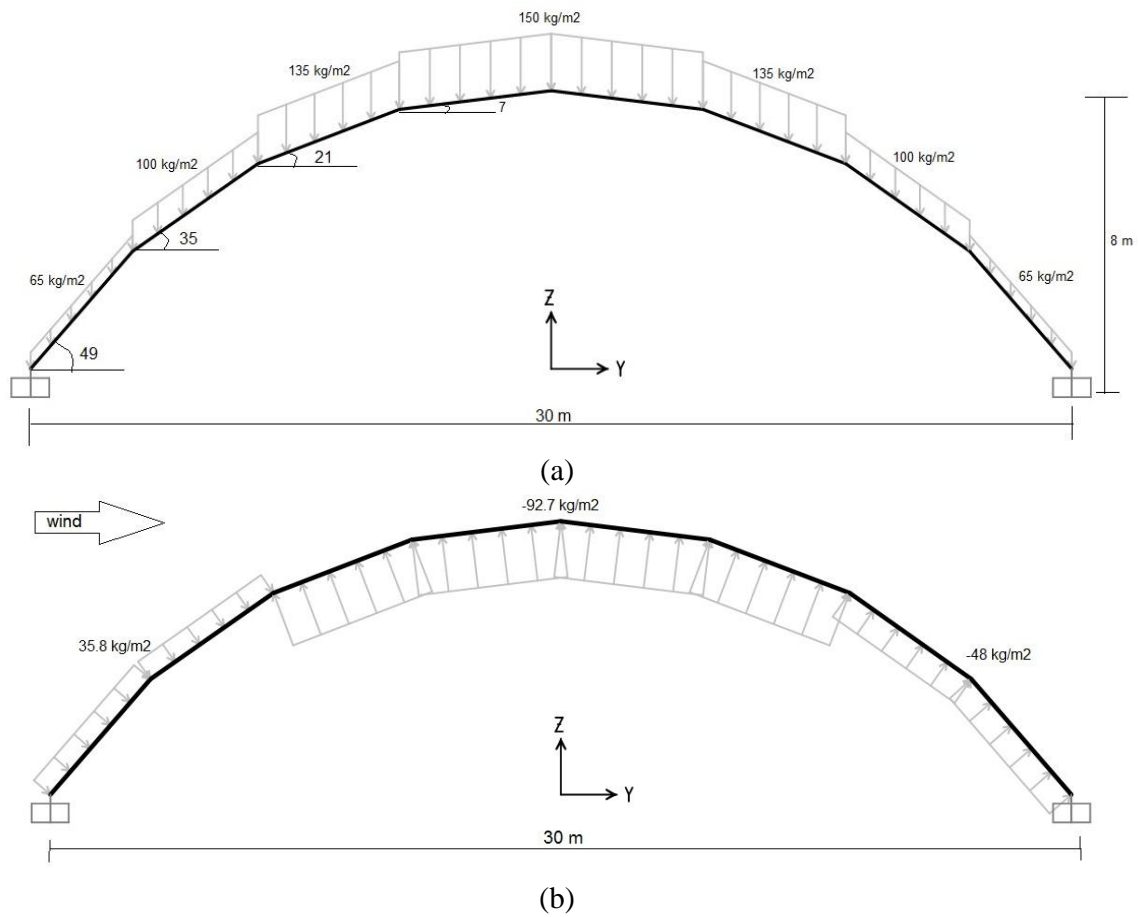


Figure 4. The 173-bar single layer barrel vault frame subjected to: (a) Snow loading, (b) Wind loading

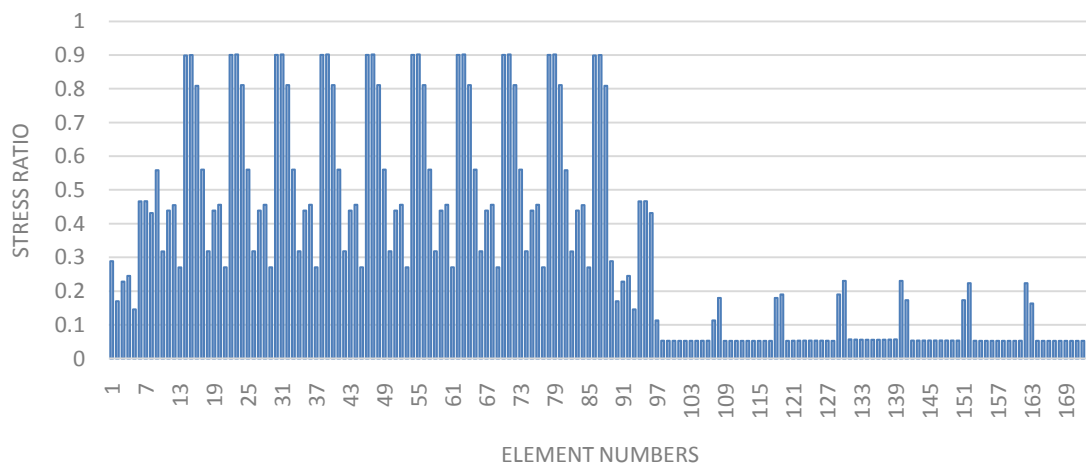


Figure 5. Strength ratios for the elements of the 173-bar single layer barrel vault frame

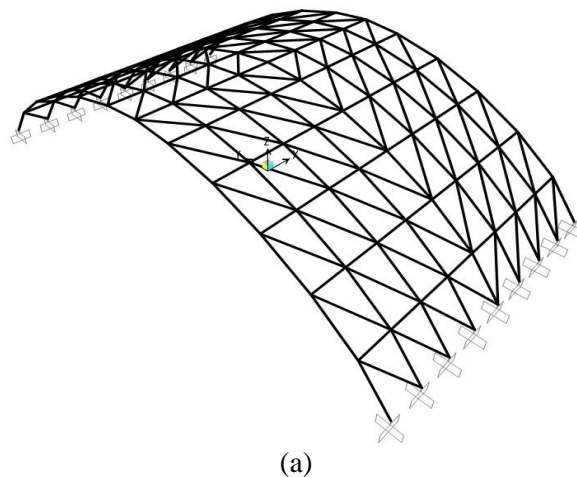
Table 1: Optimal design comparison for the 173-bar single layer barrel vault frame

Element Group	Optimal sections and cross-section Area									
	CSS [1]		MCSS [1]		ICSS [1]		IMCSS [1]		Present study	
	Section Name	Area (in^2)	Section Name	Area (in^2)	Section Name	Area (in^2)	Section Name	Area (in^2)	Section Name	Area (in^2)
1	P1	0.494	XP1	0.639	P0.5	0.25	P0.5	0.25	P0.5	0.25
2	P1	0.494	XP0.75	0.433	P0.5	0.25	P0.5	0.25	P0.5	0.25
3	XP1.5	1.07	P1	0.494	P0.5	0.25	P0.5	0.25	P0.5	0.25
4	P0.75	0.333	P0.75	0.333	P0.5	0.25	P0.5	0.25	P0.5	0.25
5	XP0.5	0.32	XP1	0.639	P0.5	0.25	XP0.5	0.32	P0.5	0.25
6	XP1.25	0.881	XP1.5	1.07	P0.5	0.25	XP0.5	0.32	P0.5	0.25
7	P1.5	0.799	XP1	0.639	P0.5	0.25	P0.5	0.25	P0.5	0.25
8	P10	11.9	P10	11.9	P10	11.9	P12	14.6	P10	11.9
9	P10	11.9	P10	11.9	P10	11.9	XP6	8.6	P10	11.9
10	P10	11.9	P10	11.9	P10	11.9	P10	11.9	P8	8.40
11	P10	11.9	P10	11.9	P10	11.9	P10	11.9	P8	8.40
12	P10	11.9	P10	11.9	P10	11.9	P10	11.9	P10	11.9
13	P6	5.58	P6	5.58	P6	5.58	P6	5.58	P6	5.58
14	P6	5.58	P6	5.58	P6	5.58	P6	5.58	P6	5.58
15	P10	11.9	P10	11.9	P10	11.9	P10	11.9	P10	11.9
Weight. (lb)	50295.90		50247.66		49411.27		48985.05		45297.82	
No. of analysis	20000		20000		20000		19800		14000	

7.2. A 292-member single barrel vault frame

The geometry of a 292-member single barrel vault frame is presented in Fig. 6. The member groups and support conditions are presented as well. Member sections are categorized into 30 groups as shown in Fig. 6b. The span, length and height of single barrel vaults are 36, 20 and 10 meter, respectively. This example has 292 members and 117 joints.

Similar to the previous example, the geometry and load conditions of this example are taken from Ref. [1]. The uniform dead load equal to 100 kg/m^3 applied to roof. The snow and wind loads are shown in Fig. 7.



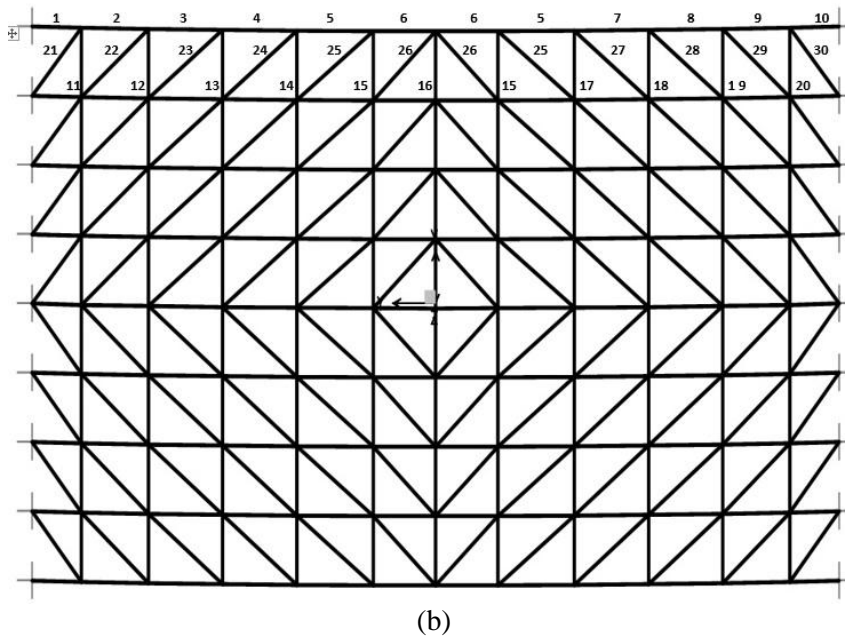
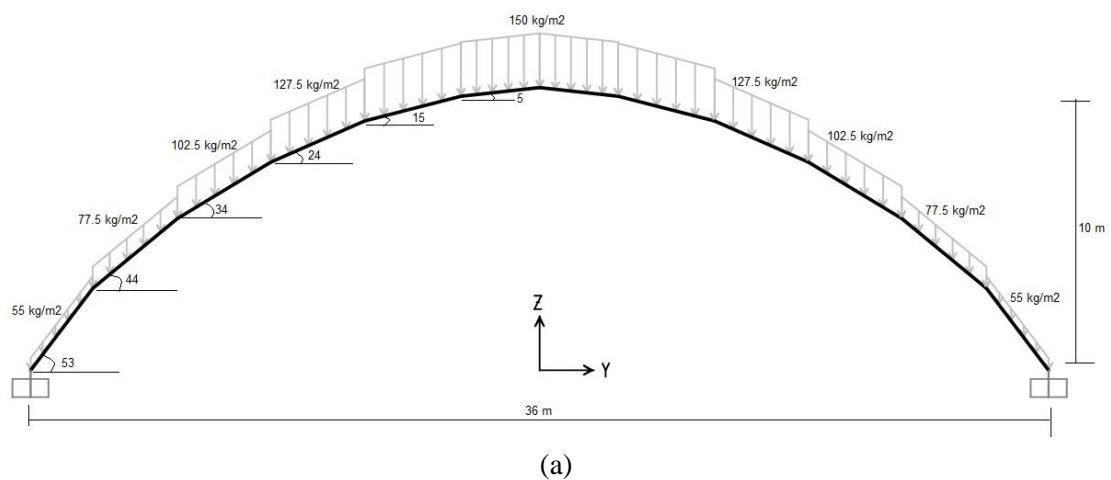


Figure 6. The 292-member single layer barrel vault frame: (a) 3D view, (b) Member groups in top view

Table 2 indicates a comparison between the results of the CSS, MCSS, ICSS, IMCSS and the CSS-PSO algorithms for this example. Table 2 shows that the best weights of present method is 60584.24 lb. while it is 68324.57 lb, 65892.33, 63694.69 lb and 62968.19 lb for the CSS, MCSS, ICSS and IMCSS algorithms. In comparing with the CSS, MCSS, ICSS and IMCSS algorithms, the CSS-PSO algorithm has a good solution. The maximum strength ratio for the design obtained by the new method is 92.50%. This algorithm needs 16000 analyses to find the optimum design as shown in Fig. 8.



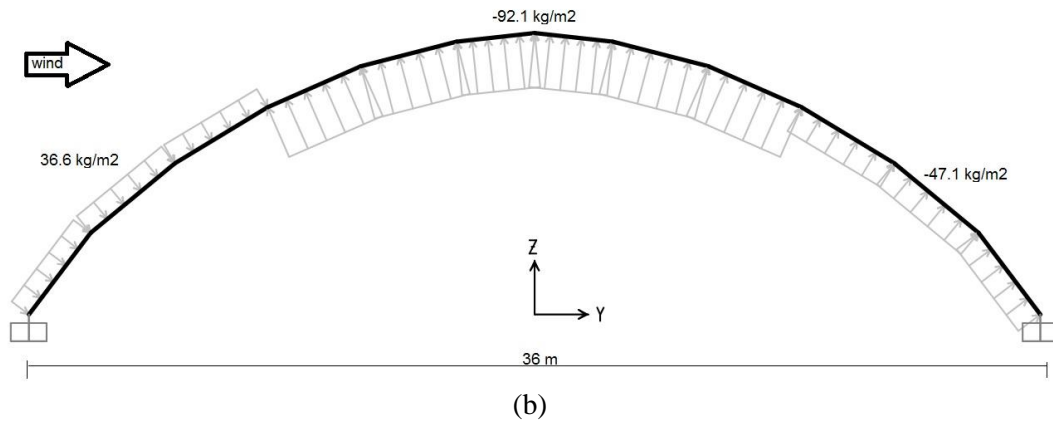


Figure 7. The 292-member single layer barrel vault frame subjected to: (a) Snow loading, (b) Wind loading

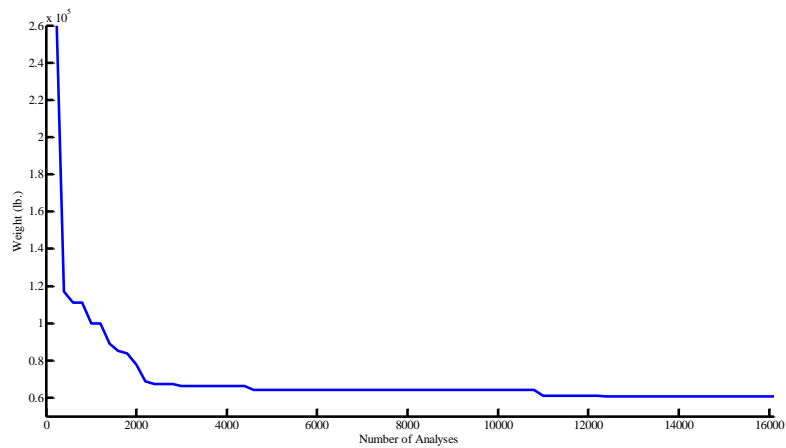


Figure 8. Convergence history for the 292-bar single layer barrel vault frame

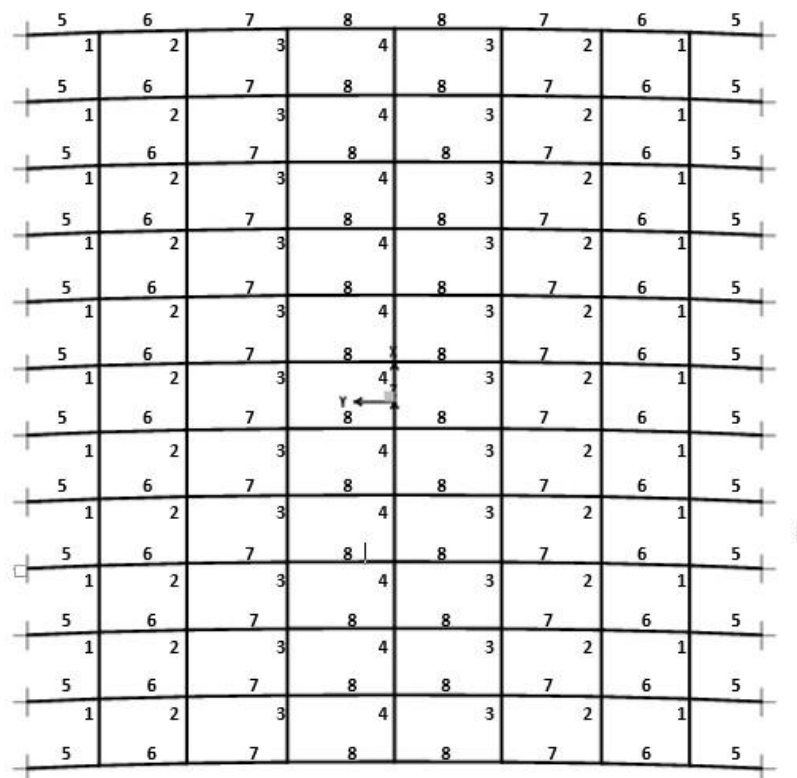
Table 2: Optimal design comparison for the 292-bar single layer barrel vault frame

Element Group	Optimal sections and cross-section Area									
	CSS		MCSS		ICSS		IMCSS		Present study	
	Section Name	Area (in ²)	Section Name	Area (in ²)	Section Name	Area (in ²)	Section Name	Area (in ²)	Section Name	Area (in ²)
1	P12	14.6	P12	14.6	P10	11.9	P12	14.6	P12	14.6
2	P10	11.9	XP6	8.4	P10	11.9	XP6	8.4	P10	11.9
3	XP8	12.8	XP8	12.8	P12	14.6	P10	11.9	P10	11.9
4	P6	5.58	P12	14.6	XP8	12.8	XP6	8.4	P8	8.4
5	XP8	12.8	P10	11.9	P10	11.9	P10	11.9	P10	11.9
6	P10	11.9	P10	11.9	P10	11.9	P10	11.9	P10	11.9
7	P10	11.9	P12	14.6	P10	11.9	P10	11.9	P10	11.9
8	P12	14.6	XP10	16.1	P10	11.9	P12	14.6	P10	11.9
9	P10	11.9	P10	11.9	P10	11.9	P10	11.9	P12	14.6
10	XP12	19.2	XP12	19.2	XP12	19.2	P12	14.6	XP10	16.1

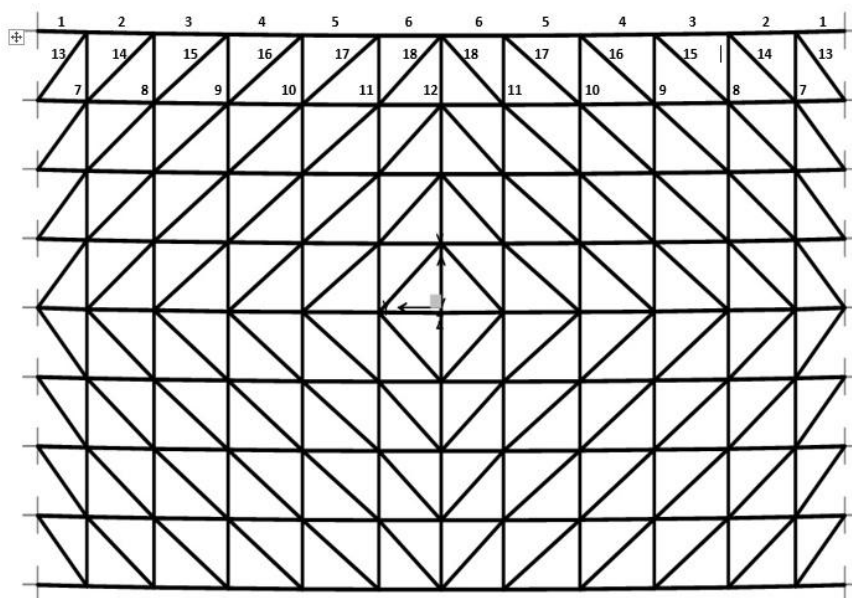
11	XP2.5	2.25	P0.5	0.25	P1.25	0.669	XP2	1.48	P2	1.07
12	P1.25	0.669	XP0.75	0.433	XP2	1.48	P1.5	0.799	P1.5	0.799
13	XP5	6.11	P2.5	1.7	P1	0.494	P1.25	0.669	P1.25	0.669
14	XP3.5	3.68	XP1	0.639	XP2	1.48	P1.5	0.799	P1.5	0.799
15	P2.5	1.7	P1.25	0.669	XP1.5	1.07	P1	0.494	P1	0.494
16	P4	3.17	XP1.5	1.07	XP1.5	1.07	P1.5	0.799	P1.5	0.799
17	XP2	1.48	P3.5	2.68	P1.5	0.799	XP2.5	2.25	P3	2.23
18	XP2	1.48	XP1.5	1.07	XP2	1.48	P1.25	0.669	P1.5	0.779
19	XXP3	5.47	XP1	0.639	XP1	0.639	XP1	0.639	P2	1.07
20	P5	4.3	P3	2.23	XP1.25	0.881	XP2	1.48	P2	1.07
21	XXP2	2.66	XP2	1.48	XP3	3.02	P1.5	0.799	P1.5	0.799
22	XP2.5	2.25	XP1.5	1.07	XP2	1.48	XP1.5	1.07	P1.5	0.779
23	XP1	0.639	P3	2.23	XP0.75	0.433	P1.5	0.799	P1.5	0.779
24	XP2	1.48	P2.5	1.7	XP0.75	0.433	XP1.5	1.07	P2	1.07
25	P1.5	0.799	P1.25	0.669	XP1.25	0.881	P1.25	0.669	P1.25	0.669
26	XP1.5	1.07	P1.25	0.669	XP1.25	0.881	XP1.25	0.881	P1.5	0.779
27	P1.5	0.799	P2.5	1.7	P1.5	0.799	P1.5	0.779	P1.5	0.779
28	XP2	1.48	P3	2.23	XP1.25	0.881	P1.5	0.799	P2.5	1.7
29	XP1.5	1.07	P1.5	0.799	XP2	1.48	XP2	1.48	P2.5	1.7
30	P3.5	2.68	P1.5	0.799	P4	3.17	XP8	12.8	XP2.5	2.25
Weight. (lb)	68324.57		65892.33		63694.69		62968.19		60584.24	
No. of analysis	20000		20000		20000		17500		16000	

8. DISCUSSION

As it can be seen from the obtained results and the related figures for two above mentioned structures, we just considered one direction for the wind load. For example in the first structure, the section for group 10 is P8 (with area equals 8.4 in^2) and it is P10 (11.9 in^2) for elements in group 13 while they are the same locations compared to the peak point of the barrel vault. This means that some elements (that are similar considering the geometry), take completely different optimum sections. Therefore, 15 and 30 different design groups are defined in Ref. [1]. However, according to design codes, both positive and negative direction of the wind load should be taken in account as combination of loads. If one defines such loading combinations, the above structures will be symmetric and the number of group becomes smaller (8 for the first example and 18 for the other one as shown in Fig. 9. Optimization point of view, a small number of design variables creates a small search space and needs a small computational costs. We know that this may cause heavier structures, however structural point of view, the obtained design can be utilized directly because all loading conditions defined by design codes were considered. For the examples prepared in the previous section by using the new design groups and defining all load combinations, the CSS-PSO algorithm is applied and the results are presented in Table 3. As it can be seen, for the first and second examples the obtained weights are 14% and 2.5% more than the designs with the previous loading conditions however the required number of analyses are reduced to 9000 and 12000, respectively.



(a)



(b)

Figure 9. The Member groups in top view for a) the first example, b) the second example.

Table 3: Optimal design obtained for the single layer barrel vault frame considering new loading conditions

Element Group	Optimal sections and cross-section areas			
	First Example		Second Example	
	Section Name	Area (in^2)	Section Name	Area (in^2)
1	P0.5	0.25	P12	14.6
2	P0.5	0.25	P10	11.9
3	P0.5	0.25	P10	11.9
4	P0.5	0.25	P10	11.9
5	P10	11.9	P10	11.9
6	P10	11.9	P10	11.9
7	P8	8.40	P2	1.07
8	P10	11.9	P2	1.07
9			P1.5	0.799
10			P3	2.23
11			P1	0.494
12			P1.5	0.799
13			XP2.5	2.25
14			P2.5	1.7
15			P2.5	1.7
16			P2	1.07
17			P1.25	0.669
18			P1.5	0.779
Weight. (lb)		52784.74	62113.79	
No. of analysis		9000	12000	

9. CONCLUSIONS

Recently, a hybrid charge system search and particle swarm optimization algorithm was developed based on the charge system search (CSS) and positive properties of particle swarm optimization (PSO) are added to it. Here, some parameters of this algorithm are seted in a way that the performance of the algorithm is improved. Then, two single-layer barrel vaults are selected as numerical examples. The geometry and load conditions are taken from Ref. [1]. This examples are optimized with the CSS-PSO algorithm and then compared with other CSS-based algorithms. The results show that the CSS-PSO method can find the good and economical designs of single-layer barrel vaults. Also, the loading conditions are modified according to the recommendations of design codes. This change makes the structures symmetric and therefore, the number of design groups are reduced. Optimization point of view, this change may increase optimum weight more or less, however the computational costs will be reduced.

REFERENCES

1. Kaveh A, Mirzaei B, Jafarvand A. Optimal design of single-layer barrel vault frames using improved magnetic charged system search, *International Journal of Optimization in Civil Engineering*, No. 4, **3**(2013) 575-600.
2. Kaveh A, Eftekhari B. Improved big bang big crunch to optimize barrel vault frames, *Proceeding of the 9th International Congress on Civil Engineering*, Isfahan University of Technology (IUT), Isfahan, Iran, 2012.
3. Kaveh A, Farahani M, Shojaei N. Optimal design of barrel vaults using charged search system, *International Journal of Civil Engineering*, No. 4, **10**(2012) 301-8.
4. Kaveh A, Talatahari S. A novel heuristic optimization method: charged system search, *Acta Mechanica*, Nos. 3-4, **213**(2010) 267-89.
5. Kaveh A, Talatahari S. An enhanced charged system search for configuration optimization using the concept of fields of forces, *Structural and Multidisciplinary Optimization*, No. 3, **43**(2011) 339-51.
6. Kaveh A, Motie Share MA, Moslehi M. Magnetic charged system search: a new meta-heuristic algorithm for optimization, *Acta Mechanica*, **224**(2013) 85-107.
7. Kaveh A, Farahmand Azar B, Talatahari S. Ant colony optimization for design of space trusses, *International Journal of Space Structures*, No. 3, **23**(2008) 167-81.
8. American Institute of Steel Construction (AISC). *Steel Construction Manual*, 13th edition, Chicago, Illinois, USA, 2005.
9. American National Standards Institute (ANSI). *Minimum Design Loads for Buildings and Other Structures* (ANSI A58.1), 1980.
10. American Society of Civil Engineers (ASCE). *Minimum Design Loads for Buildings and Other Structures* (ASCE-SEI 7-10), 2010.
11. Eberhart RC, Kennedy J. A new optimizer using particle swarm theory, *Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, Nagoya, Japan, 1995.
12. Kaveh A, Talatahari S. Hybrid charged system search and particle swarm optimization for engineering design problems, *Engineering Computations*, No. 4, **28**(2011) 423-40.
13. Kaveh A, Mirzaei B, Jafarvand A. An improved magnetic charged system search for optimization of truss structures with continuous and discrete variables, *Applied Soft Computing*, **28**(2015) 400-10.
14. Mahdavi M, Fesanghary M, Damangir E. An improved harmony search algorithm for solving optimization problems, *Applied Mathematics and Computation*, **188**(2007) 1567-79.