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ANT COLONY SEARCH METHOD IN PRACTICAL STRUCTURAL OPTIMIZATION

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ABSTRACT

This paper is concerned with application and evaluation of ant colony optimization (ACO) method to practical structural optimization problems. In particular, a size optimum design of pin-jointed truss structures is considered with ACO such that the members are chosen from ready sections for minimum weight design. The application of the algorithm is demonstrated using two design examples with practical design considerations. Both examples are formulated according to provisions of ASD-AISC (Allowable Stress Design Code of American Institute of Steel Institution) specification. The results obtained are used to discuss the computational characteristics of ACO for optimum design of truss type structures.

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KEY WORDS: ant colony optimization, stochastic search techniques, discrete optimum, steel truss structures, minimum weight design.

1. INTRODUCTION

Structural optimization is a highly attractive research field positioned in the intersection of continuous and discrete (combinatorial) optimizations. A group of receptive techniques referred to as stochastic search methods have been contemplated to deal with these kinds of optimization problems borrowing their characteristics from biological methodologies and other natural phenomena. It is generally accepted that stochastic approaches can handle

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structural optimization problems more efficiently and easily than the deterministic algorithms. In addition to robustness with respect to the growth of problem size, other significant advantages of these methods are related to their relative simplicity and suitability for problems where the implementation of the optimization process is complicated by complexity and differentiability of design domain [1]. These heuristic algorithms are now becoming very popular in many disciplines of science and engineering. The fundamental of these algorithms are based on analogies with natural processes [2-7]. A detailed review of these algorithms as well as their applications in optimum structural design is carried out by Saka [8] and Hasançebi et al. [9,10].

The ant colony optimization (ACO) was originated by Dorigo et al [11-13] and the initial algorithm for this method was developed by Dorigo and Gambardella [12, 13]. In their study, the travelling salesman benchmark problem is used for a numerical implementation and verification of the technique. Camp and Bichon [14] first developed a design algorithm with ACO to size steel space trusses for minimum weight subject to stress and deflection limitations. Later, they extended this work to optimize rigid steel frames in Camp *et al.* [15]. Kaveh and Shojaee [16] also presented an ACO integrated solution algorithm for discrete optimum design of steel frames with design constraints consisting of combined bending and compression, combined bending and tension and deflection limitations. In some studies in the literature, the attempts are made to accelerate performance of ACO by hybridizing it with another meta-heuristic technique, namely particle swarm method, Refs. [17-19]. In Aydoğdu and Saka [20], ACO is employed to seek optimum design of the three dimensional irregular steel frames, taking into account warping deformations of thin walled sections.

This study is concerned with the application and evaluation of ACO for structural optimization problems. The minimum weight design of pin-jointed steel trusses with practical design considerations is particularly dealt with using two variants of ACO algorithm. These two variants are identical to each other in terms of algorithmic outline and computational steps except for implementation of global pheromone update scheme. In the first variant, global pheromone update is implemented in accordance with original development of the technique as proposed by Dorigo *et al*. [11-13]. The second variant, on the other hand, corresponds to the enhancement of the method by Camp *et al*. [14-15], where a selected number of ants ranked in terms of objective function values are used to update the pheromone levels on the paths and thus to bias the search towards favourable regions. The applications of the ACO algorithms are demonstrated using two design examples. These examples are a 160-bar pyramid and a 693-bar braced barrel vault as space steel truss. In both examples the trusses are sized for minimum weight considering stress, stability and displacement limitations according to the provisions of ASD-AISC [21] specification. The results obtained in these examples are used to compare numerical performances of the ACO algorithms.

2. MATHEMATICAL FORMULATION OF STRUCTURAL OPTIMIZATION PROBLEM

The design of steel truss structures requires the selection of members from a standard steel pipe section table such that the structure satisfies the strength and serviceability requirements specified by a chosen code of practice, while the economy is observed in the overall or material cost of the structure. For a pin-jointed space steel truss which consists of N_m members grouped into N_d design variables, this problem can be formulated as follows.

2.1. Objective Function

Find a vector of integer values **I** (Eq. (1)) representing the sequence numbers of standard sections in a given section table

$$\mathbf{I}^T = [I_1, I_2, ..., I_{N_d}] \quad (1)$$

to generate a vector of cross-sectional areas **A** for N_m members of the truss

$$\mathbf{A}^T = [A_1, A_2, ..., A_{N_m}] \quad (2)$$

such that **A** minimizes the objective function

$$W = \sum_{m=1}^{N_m} \rho_m L_m A_m \quad (3)$$

where W refers to the weight of the dome; ρ_m, A_m, L_m are cross-sectional area, length and unit weight of the *m-th* truss member, respectively.

2.2. Design Constraints

The structural behavioral and performance limitations of pin-jointed space steel truss can be formulated as follows:

$$g_m = \frac{\sigma_m}{(\sigma_m)_{all}} - 1 \leq 0 \quad ; \quad m = 1, ..., N_m \quad (4)$$

$$s_m = \frac{\lambda_m}{(\lambda_m)_{all}} - 1 \leq 0 \quad ; \quad m = 1, ..., N_m \quad (5)$$

$$\delta_{jk} = \frac{d_{j,k}}{(d_{j,k})_{all}} - 1 \leq 0 \quad ; \quad \mathrm{j} = 1, ..., N_j \quad (6)$$

In Eqs. (4-6), the functions g_m , s_m and $\delta_{j,k}$ are referred to as constraints being bounds on stresses, slenderness ratios and displacements, respectively; σ_m and $(\sigma_m)_{all}$ are the computed and allowable axial stresses for the *m*-the member, respectively; λ_m and $(\lambda_m)_{all}$ are the slenderness ratio and its upper limit for *m-th* member, respectively; N_j is the total number of joints; and finally $d_{j,k}$, and $(d_{j,k})_{all}$, are the displacements computed in the *k-th* direction of the *j-th* joint and its permissible value, respectively. In the present study, these limitations are implemented according to ASD-AISC [21] code provisions.

Accordingly, the maximum slenderness ratio is limited to 300 for tension members, and it is taken as 200 for compression members. Hence, the slenderness related design constraints are formulated as follows:

$$\lambda_m = \frac{K_m L_m}{r_m} \leq 300 \text{ (for tension members)}$$
$$\lambda_m = \frac{K_m L_m}{r_m} \leq 200 \text{ (for compression members)} \tag{7}$$

where, K_m is the effective length factor of *m-th* member (K_m=1 for all members), and r_m is its minimum radii of gyration.

The allowable tensile stresses for tension members are calculated as in Eq. (8):

$$(\sigma_t)_{all}=0.60F_y$$
$$(\sigma_t)_{all}=0.50F_u \tag{8}$$

where F_y and F_u stand for the yield and ultimate tensile strengths, and the smaller of the two formulas is considered to be the upper level of axial stress for a tension member.

The allowable stress limits for compression members are calculated depending on two possible failure modes of the members known as elastic and inelastic buckling, Eqs. (9-11).

$$C_c = \sqrt{\frac{2\pi^2 E}{F_y}} \tag{9}$$

$$(\sigma_c)_{all} = \frac{\left[1 - \frac{(K_m L_m / r_m)^2}{2C_c^{\ 2}}\right] F_y}{\frac{5}{3} + \frac{3(K_m L_m / r_m)}{8C_c} - \frac{(K_m L_m / r_m)^3}{8C_c^{\ 3}}} \quad ; \quad \lambda_m < C_c \text{ (inelastic buckling)} \tag{10}$$

$$(\sigma_c)_{all} = \frac{12\pi^2 E}{23(K_m L_m / r_m)^2} \quad ; \quad \lambda_m \geq C_c \text{ (elastic buckling)} \tag{11}$$

In Eqs. (9-11), E is the modulus of elasticity, and C_c is referred to as the critical slenderness ratio parameter. For a member with $\lambda_m< C_c$, it is assumed that the member buckles inelastically, and its allowable compression stress is computed according to Eq. (10). Otherwise ($\lambda_m >C_c$), elastic buckling of the member takes place, in which case the allowable compression stress is computed as to Eq. (11).

3. ANT COLONY OPTIMIZATION

Ant colony optimization technique is inspired from the way that ant colonies find the shortest route between the food source and their nest. The biologists studied extensively for a long time the way in which ants manage collectively to solve difficult problems in a natural way which is too complex for a single individual. Ants being completely blind individuals can successfully discover as a colony the shortest path between their nest and the food source. They manage this through their typical characteristic of employing a volatile substance called pheromones. They perceive these substances through very sensitive receivers located in their antennae. The ants deposit pheromones on the ground when they travel which is used as a trail by other ants in the colony. When there is choice of selection for an ant between two paths it selects the one where the concentration of pheromone is greater. Since the shorter trail will be reinforced more than the long one after a while a great majority of ants in the colony will travel on this route. The computational steps of the technique are outlined as follows:

Step 1. Initialization of pheromones (Trails):

Given that a profile list with N_s steel sections is used, each design variable can assume N_s number of different values (paths). The term ‘‘path” is used synonymously with standard steel section for a variable in ACO to implicate the choice of an ant. Each path is characterized by a pheromone level, indicating the suitability of the path (discrete section) for the variable. If there are a total of N_d design variables, the pheromone levels deposited in all paths for these variables are stored in a matrix called a trail matrix **T**, Eq. (12). It is a N_s x N_d matrix with a typical element T_{ji} indicating pheromone level in the *j-th* path for the *i-th* design variable. Consequently, each column vector in **T** represents the entire set of pheromones accumulated in all N_s paths for a design variable.

$$\mathbf{T}=\begin{bmatrix} T_{11} & T_{12} & \cdots & \cdots & T_{1N_d} \\ T_{21} & T_{22} & \cdots & \cdots & T_{2N_d} \\ \cdots & \cdots & T_{ji} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ T_{N_s1} & T_{N_s2} & \cdots & \cdots & T_{N_sN_d} \end{bmatrix} \tag{12}$$

The pheromones collected in all N_s paths for the *i-th* design variables

The trail matrix is initialized such that all the elements of the matrix are assigned an initial value of $T_{ji}^{(0)}=1/W_{min}$, where W_{min} is the minimum weight of the structure resulting from assigning the smallest steel section (indicated by sequence number I_{min}) to all members of the structure.

Step 2. Selection probabilities:

Once the trail matrix is constructed, the selection probabilities of the paths are calculated next using Eq. (13).

$$p_{ji} = \frac{[T_{ji}].[\upsilon_j]^{\beta}}{\sum_{k=1}^{N_s}[T_{ki}].[\upsilon_k]^{\beta}} \tag{13}$$

In Eq. (13), p_{ji} indicates the selection probability of *j-th* path for the *i-th* design variable. This probability is a function of the ratio of the path's pheromone level (T_{ji}) to the sum of all others' for the *i-th* design variable. It follows that those paths with higher pheromone levels probabilistically have a greater chance for being selected. The visibility coefficient for the jth section (υ_j) in this Eq. is defined as follows:

$$\upsilon_j = \frac{1}{A_j} \tag{14}$$

where A_j represents cross-sectional area of the *j-th* section. As seen from Eq. (14), the visibility is inversely proportional to the cross-sectional area, increasing selection probabilities of paths with small sections to some extent in order to bias the search towards these paths. Finally, β is a constant parameter used to adjust the relative importance between the visibility and the trail.

Step 3. Constructing a colony of ants:

An ant colony consists of a predefined number of ants (μ, colony size), each of which represents a potential solution to a problem of interest. Each ant within the colony is constructed probabilistically based on paths' selection probabilities for each design variable. Selection process is carried out such that each design variable is selected by all ants before proceeding to the other. Whenever a choice is performed by an ant for a design variable, the intensity of pheromone on the selected path (T_{ji}) is somewhat lowered using the following local update equation:

$$T_{ji}^{\,new} = \xi . T_{ji}^{\,old} \tag{15}$$

where ξ is the local update parameter assigned to a suitable value between 0 and 1. The path probabilities are recalculated (updated) accordingly, and the forthcoming ant makes its choice under updated values. As anticipated, the rationale behind local update is to encourage the subsequent ants to choose different sections, and thus to produce dissimilar solutions for a more exhaustive search. Since pheromone levels and probabilities at any time depend on earlier selections made, when an ant makes its own choice becomes important. An order of selection is determined anew for all μ ants at random prior to selection of each variable. The construction of colony is completed when all design variables are selected for all the ants in the colony.

Step 4. Evaluation of colony:

The structure is analyzed for the designs characterized by μ ants, and an objective function value is assigned to each ant. The ants evaluated are ranked by their objective function values, and the elitist ant is updated. Elitist ant is the best feasible ant located so far since the beginning of the process.

Step 5. Global pheromone update:

A global pheromone update scheme is implemented next to add pheromones to the paths selected by the ants. In the original ACO algorithm developed by Dorigo [22], this scheme is formulated in Eq. (16).

$$T_{ji}^{new} = (1 - e_r).T_{ji}^{old} + \sum_{k=1}^{\mu} (\Delta T_{ji})_k \tag{16}$$

In Eq. (16), e_r is a constant referred to as evaporation rate, and $(\Delta T_{ji})_{\mathrm{k}}$ defined in Eq. (17) is the amount of pheromone added to path *ji* by the *k-th* ant in the colony, where φ_k represents the objective function value of this ant.

$$(\Delta T_{ji})_{\mathrm{k}} = \begin{cases} 1/\varphi_k, & \text{if the } ij \text{ selected by } k\text{-}th \text{ ant} \\ 0, & \text{otherwise} \end{cases} \tag{17}$$

In fact, Eq. (16) consists of two terms; an evaporation term and an accumulation term. The evaporation term is applied to all the paths T_{ji} to simulate the nature such that in nature the pheromone is subject to evaporation over time. This term helps prevent an early convergence of the algorithm by implementing a positive form of forgetting. The second term accounts for the accumulation of pheromones on selected paths. Paths that are not selected by an ant receive no pheromone update.

A number of extensions of the original global pheromone update scheme have been proposed in the literature. One of such extensions, called the *ranked ant system*, was formulated by Camp et al. [15], where the elitist ant and a selected number of λ_r top ranked ants in an iteration are used for pheromone update to bias the search towards favorable regions, Eq. (18).

$$T_{ji}^{new} = (1 - e_r).T_{ji}^{old} + e_r.\left[\lambda_r \Delta T_{ji}^{+} + \sum_{k=1}^{\lambda_r} (\lambda_r - r_k)(\Delta T_{ji})_k\right] \tag{18}$$

In Eq. (18), ΔT_{ji}^{+} refers to the pheromone accumulation due to the elitist ant, and r_k is the rank of the ant (between 1 and λ_r).

Step 6. Termination:

The steps 2 through 5 define a single iteration of the algorithm. The process is repeated for a predefined number of iterations N_{ite}.

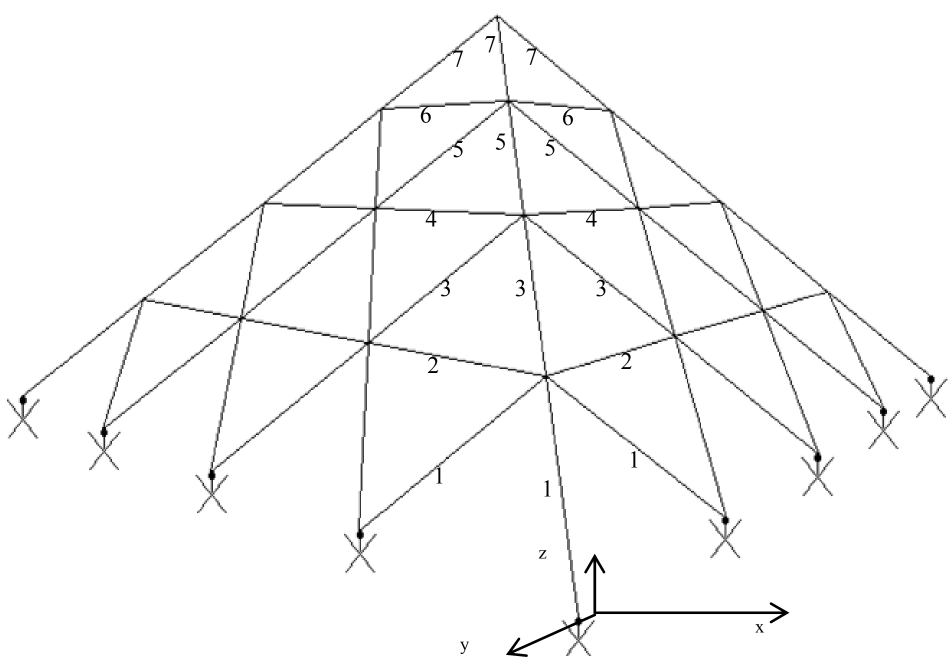
4. DESIGN EXAMPLES

Two design examples are considered for numerical applications. The first example is a 160-

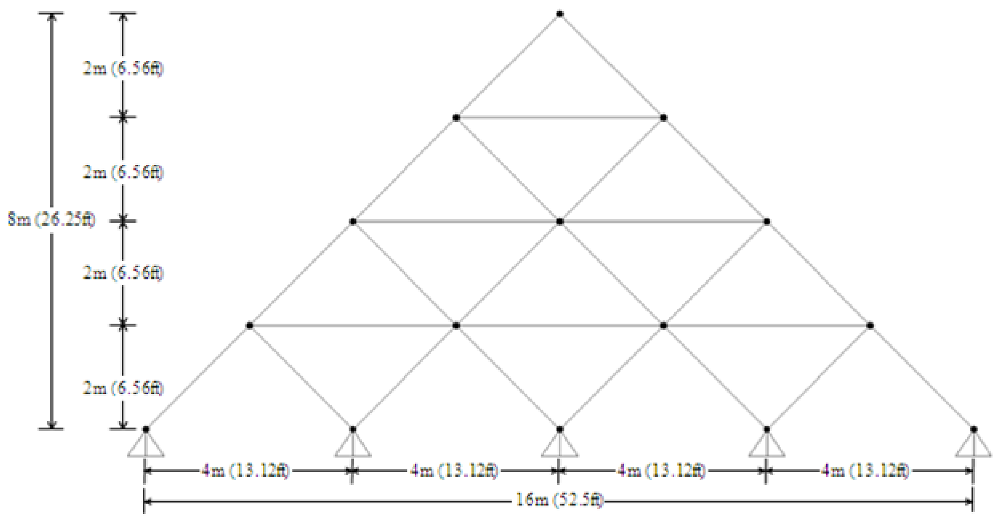
bar space steel pyramid and the second one is 693-bar braced barrel vault. They are designed for minimum weight with cross-sectional areas of the members being the design variables using two algorithmic variants of ACO technique. In the first variant referred to as ACO1, global pheromone update is implemented in accordance with original development of the technique as proposed by Dorigo [22]. The second variant, on the other hand, corresponds to the enhancement of the method by Camp *et al*. [14-15]. In both design examples, the following material properties of the steel are used: modulus of elasticity E = 29,000 ksi (203,893.6 MPa) and yield stress F_y =36 ksi (253.1 MPa).

4.1. Example 1; 160-Bar Space Steel Pyramid

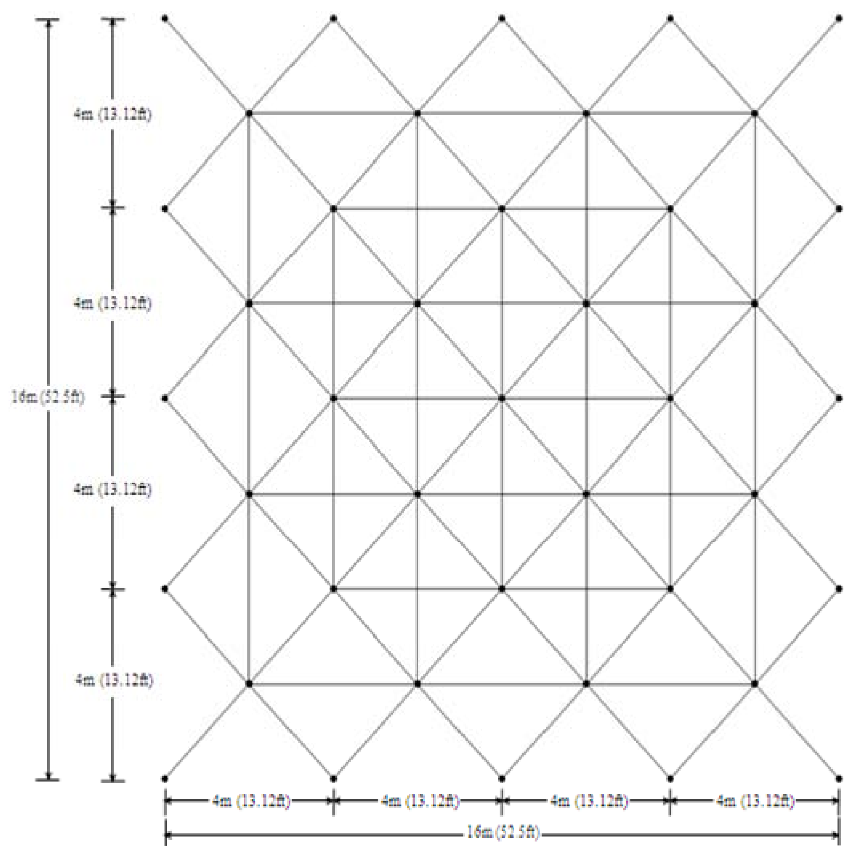
Figure 1 shows 3-D, front, and plan views of a 160-bar space steel pyramid with a square base diameter of 16m (52.5ft) along both x and y axis and a total height of 8m (26.25ft). The structure consists of 55 joints and 160 members that are grouped into 7 independent size design variables. The grouping of members is shown in Figure 1-a. The size variables are to be selected from a database of 37 pipe (circular hollow) sections issued in ASD-AISC [21] standard section tables. The stress and stability limitations of the members are calculated according to the provisions of ASD-AISC [21], as explained in Section 2. The displacements of all nodes are limited to 4.45cm (1.75in) in any direction. For design purpose, a single load case is considered such that it consists of a vertical load of -8.53kN (-1.92kips) applied in the z-direction at all nodes of the pyramid.



a) 3-D view



b) Front view



c) Plan view

Figure 1. **A** 160-bar pyramid; a) 3-D view, b) Front view, c) Plan view

The pyramid is optimized for minimum weight using the standard (ACO1) and ranked (ACO2) ant colony optimization algorithms. In these runs, the algorithm control parameters are chosen based on extensive numerical experimentation as well as recommendations of the former studies [9, 10, 14, 15], as follows: μ=50, β=0.2 , e_r=0.5, λ_r =25, ξ_{min} =0.90, and N_{ite} =1000. Depending on probabilistic nature of the technique, the space steel pyramid is separately designed a number of times with each ACO algorithm, and the best performance is considered. The ACO1 algorithm relatively performed poorly and located a final design weight of 6338.31 lb (2875.01 kg). The ACO2 algorithm yielded a better design that weighs 6211.65 lb (2817.56 kg) only. These designs are tabulated in Table 1 with section designations attained for each member group. In all the cases a total of approximately 50,000 function evaluations (structural analyses) were performed to reach the final designs reported above. In Figure 2, the variation of feasible best design obtained so far during the search is plotted against the number of function evaluations for the two algorithms mentioned above.

Table 1. Final best designs of 160-bar space steel pyramid obtained with ACO1 and ACO2

Size variables	**ACO2**		**ACO1**	
	Ready Section	**Area, in^2 (cm^2)**	**Ready section**	**Area, in^2 (cm^2)**
1	P2	1.07 (6.90)	P2	1.07 (6.90)
2	P1.25	0.669 (4.32)	P1.25	0.669 (4.32)
3	P2	1.07 (6.90)	P2	1.07 (6.90)
4	P1.25	0.669 (4.32)	P1.5	0.799 (5.16)
5	P2	1.07 (6.90)	P2	1.07 (6.90)
6	P1.25	0.669 (4.32)	P1.5	0.669 (4.32)
7	PX2	1.48 (9.55)	P2.5	1.70 (10.97)
Weight	6211.65 lb (2817.56 kg)		6338.31 lb (2875.01 kg)	

4.2. Example 2; 693-Bar Braced Barrel Vault

The second example shown in Figure 3 is a three dimensional braced barrel vault [23] consisting of 259 joints and 693 members that are grouped into 23 independent size variables considering the symmetry of the braced barrel vault about centerline. The member grouping scheme is given in Figure 3-a. The dimensions of the barrel vault are shown in the Figure 3-b and c. It is assumed that the barrel vault is subjected to a uniform dead load (DL) pressure of 35 kg/m^2, a positive wind load (WL) pressure of 160 kg/m^2, and a negative wind load (WL) pressure of 240 kg/m^2. For design purposes, these loads are combined under two separate load cases as follows: (i) 1.5DL + 1.5WL = 1.5(35 +160) = + 292.5 kg/m^2 (+2.87 kN/m^2) and (ii) 1.5DL – 1.5WL = 1.5(35 – 240) = –307.5 kg/m^2 (–3.00 kN/m^2), along z-direction. The displacements of all joints in any direction are restricted to a maximum value of 0.254 cm (0.1 in). The strength and stability requirements of steel members are imposed according to ASD-AISC [21]. The structural members are adopted from a list of 37 circular hollow sections issued in ASD-AISC [21] design specification.

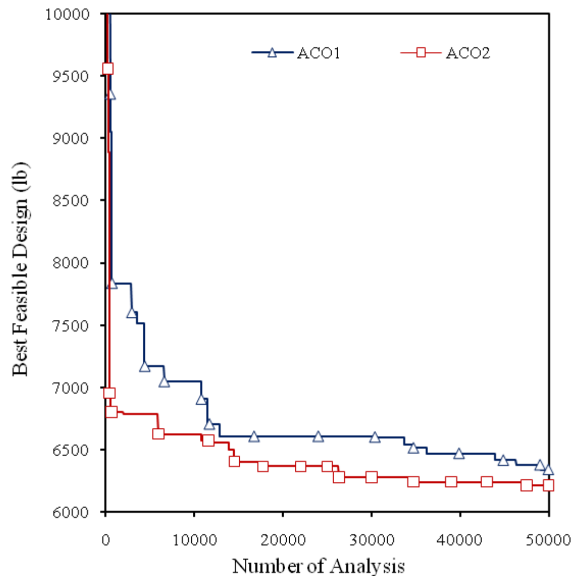
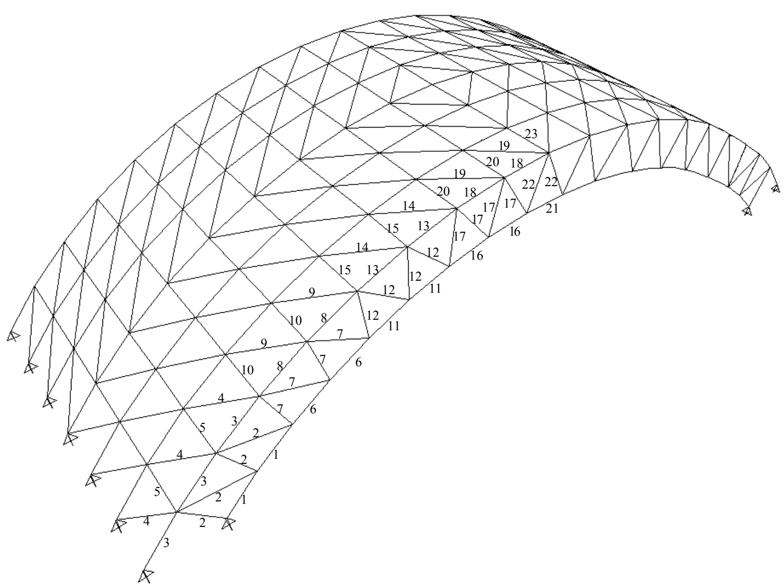
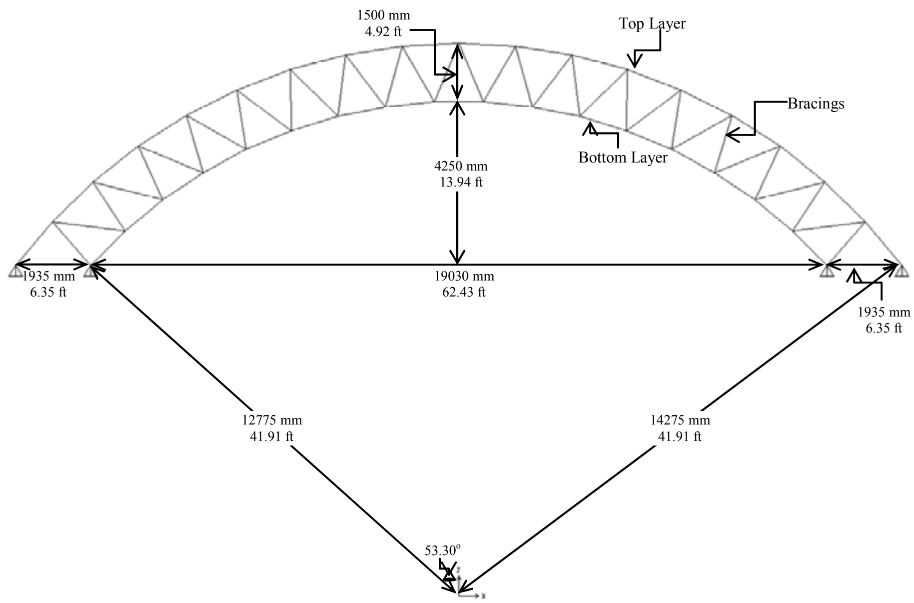


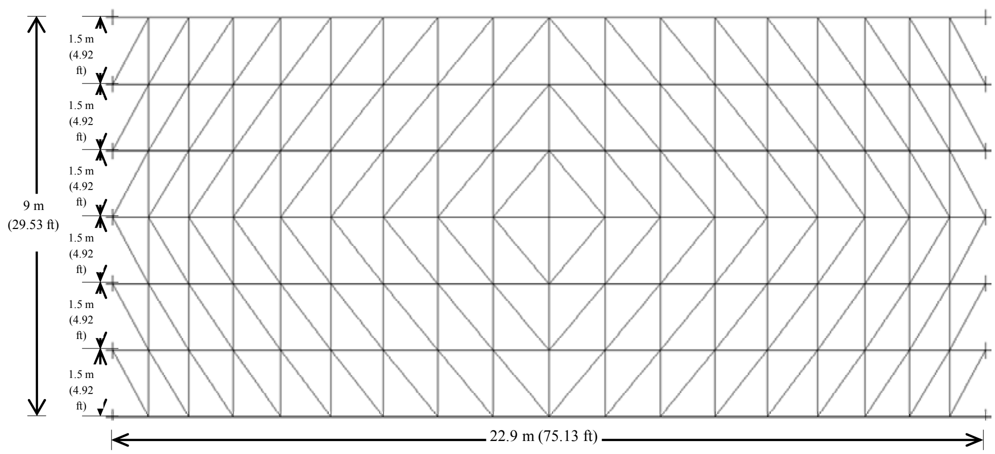
Figure 2. The variation of feasible best design in ACO1 and ACO2 algorithms for 160-bar space steel pyramid



a) 3-D view



b) Front view



c) Plan view

Figure 3. A 693-bar braced barrel vault; a) 3-D view, b) Front view, c) Plan view

Again the ACO1 and ACO2 algorithms are employed to minimize the weight of the braced barrel vault. Each algorithm is run a certain number of times independently, and only the best performances are considered. Once again the ACO1 algorithm exhibited a poor performance. The lack of convergence characteristics of this algorithm has guided the search towards a final design weight of 13379.19 lb (6068.69 kg) that is far from the optimum. A better solution to this problem was obtained with ACO2 with a design weight of 12133.47 lb (5503.65 kg) as tabulated in Table 2. Figure 4 displays the variation of feasible best design in the best runs of both of the ACO algorithms.

Table 2. Final best designs of the 693-bar braced barrel vault obtained with sACO, cACO, HSO and GAs methods

Size variables	**ACO2**		**ACO1**	
	Ready Section	**Area, in^2 (cm^2)**	**Ready Section**	**Area, in^2 (cm^2)**
1	P4	3.17 (20.45)	P3	3.02 (19.48)
2	P1	0.494 (3.18)	PX1.5	1.07 (6.90)
3	P1.25	0.669 (4.32)	P1	0.494 (3.18)
4	PX1.25	0.881 (5.68)	PX1.25	0.881 (5.68)
5	P.75	0.333 (2.15)	P1.25	0.669 (4.32)
6	P5	4.3 (27.74)	PX4	4.41 (28.45)
7	P1	0.669 (4.32)	P1.25	0.669 (4.32)
8	PX1	0.881 (5.68)	PX1.5	1.07 (6.90)
9	P3	3.68 (23.74)	PXX2	2.66 (17.16)
10	P1	0.669 (4.32)	PX1.25	0.881 (5.68)
11	P1.25	0.433 (2.79)	P1	0.494 (3.18)
12	P1.5	0.799 (5.16)	PX1	0.639 (4.12)
13	P1.5	0.799 (5.16)	PX1.25	0.881 (5.68)
14	P1	0.669 (4.32)	PX2	1.48 (9.55)
15	PX.75	0.433 (2.79)	P.75	0.333 (2.15)
16	P1.5	0.799 (5.16)	P1.5	0.799 (5.16)
17	PX2	1.48 (9.55)	P2.5	1.70 (10.97)
18	P1.25	0.669 (4.32)	P1.25	0.669 (4.32)
19	P1	0.669 (4.32)	P1.5	0.799 (5.16)
20	P.75	0.333 (2.15)	PX1.5	1.07 (6.90)
21	PX2.5	2.25 (14.52)	P4	3.17 (20.45)
22	P1.5	0.799 (5.16)	P1	0.494 (3.18)
23	P.75	0.333 (2.15)	PX.75	0.433 (2.79)
Weight	12133.47 lb (5503.65 kg)		13379.19 lb (6068.69 kg)	

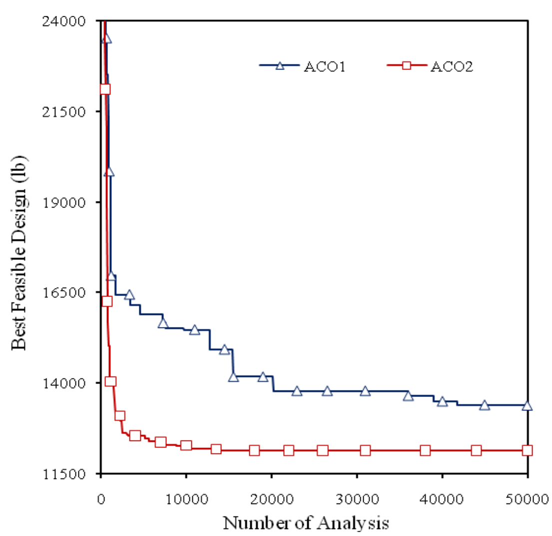


Figure 4. The variation of feasible best design in ACO1 and ACO2 algorithms for 693-bar braced barrel vault

5. CONCLUSIONS

This study is concentrated on application and evaluation of the two variants of ACO algorithm in practical structural optimization problems. The two variants of ACO employed in the study are identical to each other except for global pheromone update scheme. In the so-called standard variant (ACO1), the pheromone levels on paths are updated considering all the ants in the colony. In the second variant (ACO2), only a selected number of promising ants are used to update the pheromone levels so that the search is directed to those paths adopted by successful ants. The two algorithms have been tested and compared on two design examples (Figures 1 and 3) chosen from optimum design of real-life large scale steel trusses. The final designs obtained with ACO2 are lower than those of ACO1 as much as 2 % in the first example and 9.31 % in the second example. A comparison of optimum designs in Tables 1 and 2 reveals that ACO2 is relatively more effective in finding better solutions to large-scale structures as compared to ACO1. A track of pheromone levels on paths in ACO1 indicates that pheromones are concentrated on a group of paths for a design variable soon after the optimization process has started, whereas the other paths tend to go towards zero pheromone levels with no chance of being selected in the following iterations. The problem is that the group of paths on which the pheromone is concentrated may not incorporate the best path that would lead to the optimum design in the end of the process. What is more, the search is confined to a small subset of design space because of restricted mobility in the values of design variables, resulting in solutions far from the true optimum. The problem of pheromone concentration is also observed for ACO2, however this time the paths on which the pheromone levels are concentrated are stronger because of inclusion of distinguished ants for pheromone update. A more efficient search can be conducted with ACO2 using superior paths, yet again in a prematurely limited design space. It is concluded that ACO is a promising technique and offers some computational advantages with respect to more traditional techniques. Yet, the technique entails new enhancements to generate an automated process for online parameter adjustment or any strategy to avoid pheromone concentration.

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