

## Optimum Design of Scallop Domes for Dynamic Time History Loading by Harmony Search-Firefly Algorithm

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### ABSTRACT

This paper presents an efficient meta-heuristic algorithm for optimization of double-layer scallop domes subjected to earthquake loading. The optimization is performed by a combination of harmony search (HS) and firefly algorithm (FA). This new algorithm is called harmony search firefly algorithm (HSFA). The optimization task is achieved by taking into account geometrical and material nonlinearities. Operation of HSFA includes three phases. In the first phase, a preliminary optimization is accomplished using HS. In the second phase, an optimal initial population is produced using the first phase results. In the last phase, FA is employed to find optimum design using the produced optimal initial population. The optimum design obtained by HSFA is compared with those of HS and FA. It is demonstrated that the HSFA converges to better solution compared to the other algorithms.

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**KEY WORDS:** optimization; earthquake; scallop dome; nonlinear behavior; harmony search; firefly algorithm.

### 1. INTRODUCTION

Optimum design of structures is usually achieved by selecting the design variables such that an objective function is minimized while all of the design constraints are satisfied. Structural optimization requires the structural analysis to be performed many times for the specified external loads. This makes the optimal design process inefficient, especially when a time history analysis is considered. This difficulty will be compounded when the optimization

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method possesses a stochastic nature such as meta-heuristics [1].

This paper deals with optimum design of double layer scallop domes subject to earthquake loading considering structural nonlinear behaviour. In the recent years, much progress has been made in optimum design of space structures by considering linear behavior [2-4]. It is observed that some structures appear nonlinear behavior even in usual range of loading [5-6]. Therefore, neglecting of nonlinear effects in design optimization of these structures may be led to uneconomic designs. It is demonstrated in [6] that considering nonlinear behaviour in optimization process of scallop domes subject to static loading results in more efficient structures compared with the optimization process considering linear behaviour.

The main aim of the present study is to design double-layer scallop domes [7] subject to earthquake loading [8] for optimal weight considering nonlinear behavior. In the case of nonlinear optimization geometrical and material nonlinearities are taken into account. All of the structural optimization problems have two main phases: analysis and optimization. In the analysis phase, OPENSEES [9] is employed and in the optimization phase, a combination of harmony search (HS) [10] and firefly algorithm (FA) [11] is utilized. This combined algorithm is termed as harmony search firefly algorithm (HSFA). In order to implement HSFA, at first, a preliminary optimization is accomplished using HS. Then, an optimal initial population is produced using the preliminary optimization results. Finally, FA is employed to find optimum design using the optimal initial population. All of the required programs in the optimization phase are coded in MATLAB [12]. In this paper, the design variables are cross sectional areas of the structural elements. In order to illustrate the efficiency of the proposed methodology two numerical examples including optimization of a 1200-bar, 8-segment and a 1500-bar, 10-segment double layer scallop domes subject to earthquake loading are presented. As the main contribution of the present paper is to propose an efficient meta-heuristic algorithm for optimization of scallop domes, full practical considerations such as earthquake records scaling and simultaneous application of horizontal and vertical records are not included in the numerical examples.

## 2. SCALLOP DOMES

One of the most challenging tasks in the field of structural engineering is to cover large spans, such as exhibition halls, stadium and concert halls, without intermediate columns. Space structures, especially domes, offer economical solutions to this problem. The latticed domes are given special names depending on the form in which steel elements are connected to each other. Scallop dome is a specific type of space dome structures and was introduced by Nooshin et al [7]. Scallop domes are a particularly magnificent family of domes that could be constructed as latticed dome or continuous shell domes. Configuration of scallop domes depends on a various number of variable features such as the frequency of undulating segments as well as the shape of the segment. In general, a scallop dome may have any number of arched segments. If the number of arched segments is  $n$ , then the dome is referred to as ' $n$ -segment scallop dome'. The maximum rise for a circumferential ring which occurs at the middle of each segment is referred to as 'amplitude of the ring'. The furthest ring from the crown, namely, the 'base ring' has the largest amplitude. This one is referred as

'amplitude of dome' [7]. The amount of amplitude considering the architectural or structural requirements could be different. In Fig 1 a 5-segment scallop dome with the ratio of the amplitude to the span of 0.2 is shown.

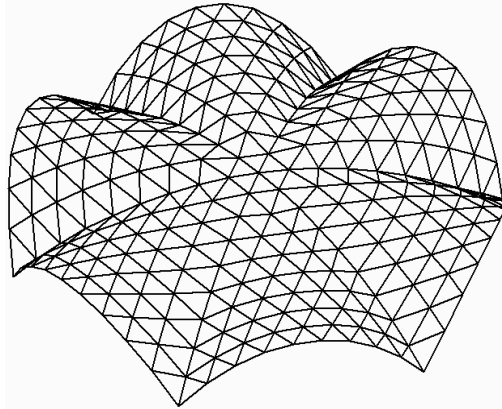


Figure 1. A 5-segment scallop dome with the ratio of the amplitude to the span of 0.2

The style of the variation of the height along with the circumferential ring can be accomplished in different ways. These height variations can be parabolic or sinusoidal. More details about scallop domes may be found in [6].

The present paper tackles the sizing optimization problem of double layer scallop domes subject to time history earthquake loading. Formulation of the optimization problem is presented in the next section.

### 3. FORMULATION OF OPTIMIZATION PROBLEM

In sizing optimization problems the aim is usually to minimize the weight of the structure, under some behavioural constraints. Due to the practical demands the cross-sections are selected from the sections available in the manufacture catalogues. Optimal design of structures subjected to time history earthquake loading is the solution procedure to find the design variables in the following optimization formulation:

$$\text{Minimize: } f(X) \quad (1)$$

$$\text{Subject to: } g_j(X, Z(t), \dot{Z}(t), \ddot{Z}(t), t) \leq 0; \quad j=1, \dots, m \quad (2)$$

$$M\ddot{Z}(t) + C\dot{Z}(t) + KZ(t) - M\mathbf{I} \ddot{u}_g(t) = 0 \quad (3)$$

$$X_i \in R^d; \quad i=1, \dots, n \quad (4)$$

where  $f$ ,  $g$ ,  $I$ ,  $X$ ,  $\ddot{z}(t)$ ,  $\dot{z}(t)$ ,  $z(t)$ ,  $M$ ,  $C$ ,  $K$ ,  $\ddot{u}_g(t)$ ,  $m$ ,  $n$ , and  $t$  are objective function, behavioural constraint, unit vector, design variables vector, acceleration vector, velocity vector, displacement vector, mass matrix, damping matrix, stiffness matrix, ground acceleration, the number of constraints, the number of design variables, and time, respectively.  $R^d$  is a given set of discrete values.

As all the constraints are time-dependent the consideration of all the constraints requires

an enormous amount of computational effort [13-14]. In [15] some methods for dynamic constraint treatment have been proposed. In the present paper, limitation on the maximum deflection and the overall stability of the structure during the earthquake are considered as the design constraints.

In this study, penalty function method (PFM) is employed to handle the constraints of the structural optimization problem. PFM transforms the basic constrained optimization problem into alternative unconstrained one. The above constrained optimization problem can be converted into an unconstrained problem by constructing a function of the following form:

$$f(X) = \begin{cases} f(X) & \text{if } X \in \tilde{\Delta} \\ f(X) + f_p(X) & \text{otherwise} \end{cases} \quad (5)$$

$$f_p(X) = r_p \sum_{j=1}^m (\max(g_j(X), 0))^2 \quad (6)$$

where  $f_p(X)$ ,  $\tilde{\Delta}$ , and  $r_p$  are the penalty function, the feasible search space, and an adjusting factor, respectively.

In order to perform dynamic analysis considering nonlinear behaviour, OPENSEES is employed.

#### 4. NONLINEAR BEHAVIOR OF SCALLOP DOMES

Nonlinear structural behavior arises from a number of causes, which can be grouped into geometrical and material nonlinearity. If a structure experiences large deformations, its changing geometric configuration can cause the structure to respond nonlinearly. Nonlinear stress-strain relationships are a common cause of material nonlinear behavior. One of the main factors that can influence a material's stress-strain properties is load history in elasto-plastic response. In this study, a finite elements model based on geometrical and material nonlinear analysis of scallop domes including plasticity, and large deflection capabilities is presented by OPENSEES. In this model a 3-D uniaxial co-rotational truss element is used. In elasto-plastic analysis the von mises yield function is used as yield criterion. Flow rule in this model is associative and the hardening rule is Bi-linear kinematics hardening in tension. In compression, according to FEMA274 [16], it is assumed that the element buckles at its corresponding buckling stress state and its residual stress is about 20% of the buckling stress. In this case, the stress-strain relation is shown in Fig 2. In this figure,  $\sigma_b$ ,  $\sigma_y$  and  $\sigma_u$  are buckling, yield and ultimate stresses, respectively and  $\varepsilon_b$ ,  $\varepsilon_y$  and  $\varepsilon_u$  are their corresponding strains. Fig 2 implies that for compression if  $\sigma_b < \sigma_y$  the buckling path and if  $\sigma_b > \sigma_y$  the yield path will be traced by the structural elements.

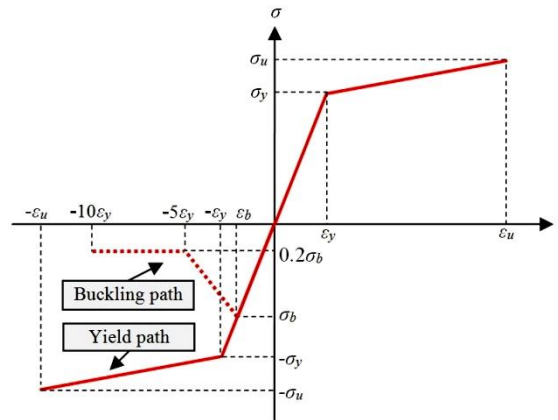


Figure 2. Stress-strain behaviour

The accurate and computationally efficient hysteretic model for space structure members is necessary for simulation of realistic dynamic behaviour of such structures. Hysteretic models that are capable of accurately simulating the behaviour will need to capture the unique nature of the tension and compression backbones, strength degradation, stiffness degradation, and pinching hysteretic shape. In the present study the *Pinching4* uniaxial material model of OPENSEES based on the stress-strain behaviour of Fig 2 is employed to simulate the hysteretic behaviour of structural elements. The *Pinching4* uniaxial material model, developed by Lowes et al. [17], is essentially equivalent to the hysteretic model proposed by Ibarra et al. [18]. In order to determine the parameters related to the *Pinching4* material model an experimental hysteretic response of a 4 in. diameter and 0.357 in. wall thickness steel pipe with  $l/r=80$  reported by Black et al. [19] is selected. This experimental hysteretic response is shown in Fig 3. As this experimental hysteretic response was also employed in [20] for calibrating the computational models more details about it can be found in [20].

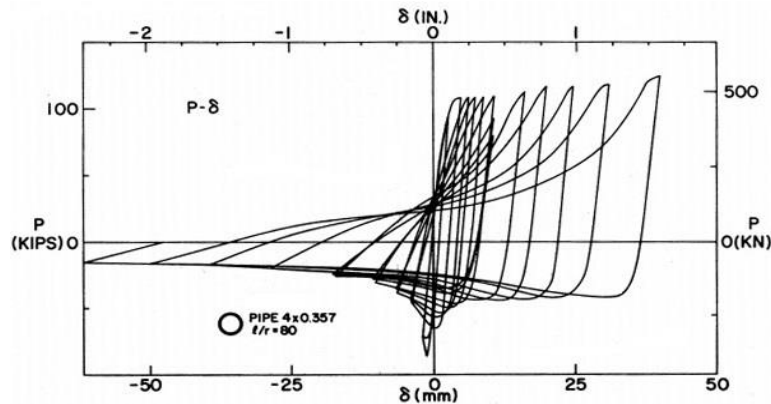


Figure 3. Experimental hysteretic response of 4 in. diameter pipe [18]

*Pinching4*-based simulated hysteretic response of axial behaviour for the 4 in. diameter pipe with  $l/r=80$  of this study is shown in Fig 4.

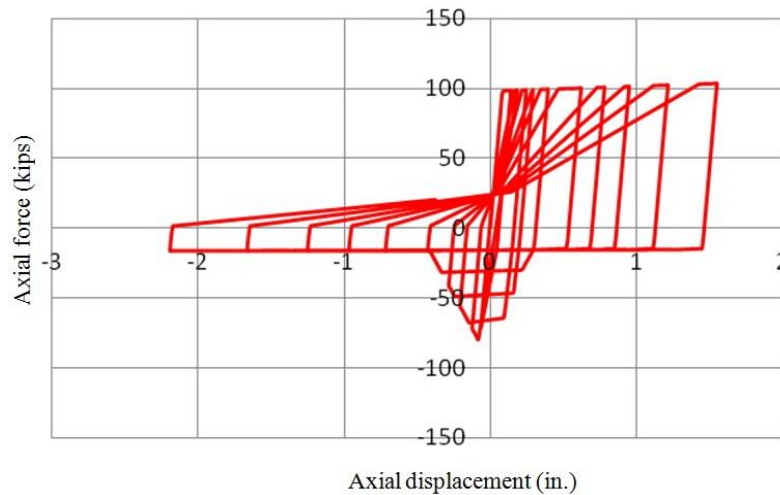


Figure 4. Pinching4-based simulated hysteretic response of 4 in. diameter pipe

The comparison of experimental and *Pinching4*-based simulated hysteretic responses shown in Fig 5 indicates that the calibrated pinching model can capture the cyclic hysteretic behaviour of the element including strength degradation.

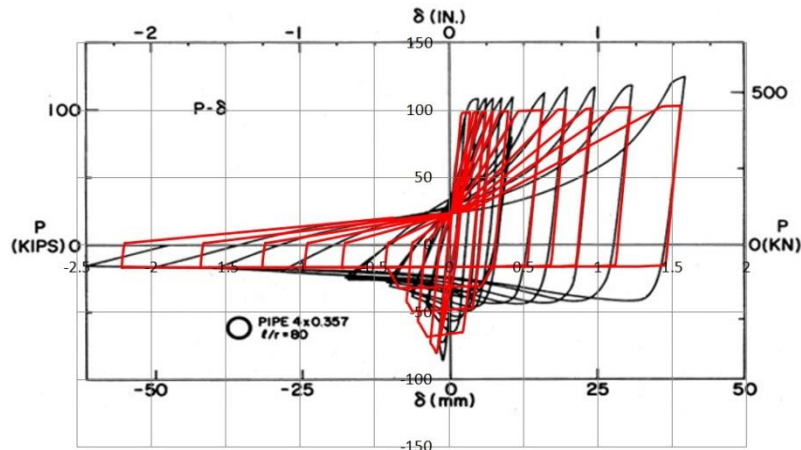


Figure 5. Comparison of experimental and Pinching4-based simulated hysteretic responses

The existing difference between experimental and simulated hysteretic responses in the last cycles is due to this fact that the employed hysteretic model in this study is a simple model based on application of truss elements with low computational demand. As the main aim of this study is optimization of the large-scale scallop domes subject to time history earthquake loading it is obvious that application of simple and computationally efficient models is of high importance for achieving optimization task. Therefore this model is employed in the present study.

In this model, the buckling stress of structural elements is computed based on the AISC-LRFD code [21] as follows:

$$\sigma_b = \begin{cases} (0.658^{\lambda_c^2}) \sigma_y & \lambda_c \leq 1.5 \\ (\frac{0.877}{\lambda_c^2}) \sigma_y & \lambda_c > 1.5 \end{cases} \quad (7)$$

$$\lambda_c = \frac{KL}{r\pi} \sqrt{\frac{\sigma_y}{E}} \quad (8)$$

where  $\lambda_c$  is slenderness parameter; E is modulus of elasticity; and K is effective length factor which for space structure elements is chosen to be 1.

## 5. META-HEURISTIC ALGORITHMS

In structural optimization problems, the computational effort spent in gradient calculations required by the mathematical programming algorithms is usually large. In recent years, it was found that meta-heuristic algorithms are computationally efficient even if greater number of optimization cycles is needed to reach the optimum. Furthermore, meta-heuristic algorithms are more robust in finding the global optima, due to their random search, whereas mathematical programming algorithms may be trapped into local optima. In this work, HS and FA meta-heuristic algorithms are combined to propose an efficient algorithm for tackling the problem of optimization of scallop domes subject to earthquake loading. Before describing the combined algorithm, main concepts of HS and FA are explained as follows.

### 5.1 Harmony Search

The HS is based on the musical performance process that achieves when a musician searches for a better state of harmony. Jazz improvisation seeks musically pleasing harmony similar to the optimum design process which seeks optimum solutions. The pitch of each musical instrument determines the aesthetic quality, just as the objective function value is determined by the set of values assigned to each design variable. In the process of musical production a musician selects and brings together number of different notes from the whole notes and then plays these with a musical instrument to find out whether it gives a pleasing harmony. The musician then tunes some of these notes to achieve a better harmony. Similarly it is then checked whether this candidate solution improves the objective function or not. This candidate solution is then checked to find out whether it satisfies the objective function or not, similar to the process of finding out whether euphonic music is obtained or not. The HS consists of five basic steps which can be summarized as follows [22]:

A possible range for each design variable is specified. The number of solution vectors in harmony memory (HM) or size of HM (HMS), the harmony considering rate (HMCR), the pitch adjusting rate (PAR) and the maximum number of searches are also specified.

An initial harmony memory matrix (HM) is produce. The HM is a matrix in which each row contains the values of design variables which are randomly selected from the design space. If the optimization problem includes  $n$  design variables the HM has the following form:

$$\text{HM} = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^j \\ \vdots \\ X^{HMS-1} \\ X^{HMS} \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_i^1 & \dots & x_{n-1}^1 & x_n^1 \\ x_1^2 & x_2^2 & \dots & x_i^2 & \dots & x_{n-1}^2 & x_n^2 \\ \vdots & \vdots & & \vdots & & \vdots & \vdots \\ x_1^j & x_2^j & \dots & x_i^j & \dots & x_{n-1}^j & x_n^j \\ \vdots & \vdots & & \vdots & & \vdots & \vdots \\ x_1^{HMS-1} & x_2^{HMS-1} & \dots & x_i^{HMS-1} & \dots & x_{n-1}^{HMS-1} & x_n^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & \dots & x_i^{HMS} & \dots & x_{n-1}^{HMS} & x_n^{HMS} \end{bmatrix} \tag{9}$$

where  $x_i^j$  is the value of the  $i$ th design variable in the  $j$ th solution vector.

To improvise new HM, a new harmony vector is generated. Thus the new value of the  $i$ th design variable can be chosen from the possible range of  $i$ th column of the HM with the probability of HMCR or from the entire possible range of values with the probability of  $1 - \text{HMCR}$  as follows:

$$x_i^{\text{new}} = \begin{cases} x_i^j \in \{x_i^1, x_i^2, \dots, x_i^{HMS}\}^T & \text{with the probability of HMCR} \\ x_i \in A_i & \text{with the probability of } (1 - \text{HMCR}) \end{cases} \tag{10}$$

where  $A_i$  is the set of the potential range of values for  $i$ th design variable. The HMCR is the probability of choosing one value from the significant values stored in the HM, and  $(1 - \text{HMCR})$  is the probability of randomly choosing one practical value not limited to those stored in the HM.

Components of the new harmony vector, is examined to determine whether it should be pitch-adjusted. Pitch adjusting is performed only after a value has been chosen from the HM as follows:

$$\text{pitch adjustment of } x_i^{\text{new}}? \begin{cases} \text{Yes} & \text{with the probability of PAR} \\ \text{No} & \text{with the probability of } (1 - \text{PAR}) \end{cases} \tag{11}$$

If the pitch-adjustment decision for  $x_i^{\text{new}}$  is "Yes", then a neighboring value with the probability of  $\text{PAR} \times \text{HMCR}$  is taken for it as follows:

$$x_i^{\text{new}} \leftarrow \begin{cases} x_i^{\text{new}} \pm u(-1,+1) \times bw & \text{with the probability of } \text{PAR} \times \text{HMCR} \\ x_i^{\text{new}} & \text{with the probability of } \text{PAR} \times (1 - \text{HMCR}) \end{cases} \tag{12}$$

where  $u(-1,+1)$  is a uniform distribution between  $-1$  and  $+1$ ; also  $bw$  is an arbitrary distance bandwidth for the continuous design variables.

This operation increases the chance of reaching the global optimum.

After selecting the new values for each design variables the objective function value is calculated for the new harmony vector. In this case  $x_i^{\text{new}}$  is analyzed using FEM and its objective function value is determined. If  $x_i^{\text{new}}$  is better than the worst vector in the HM, the new harmony is substituted by the existing worst harmony. The HM is then sorted in



descending order by the objective function value.

The optimization process of HS is repeated by continuing improvising new harmonies until a termination criterion is satisfied.

### 5.2 Firefly Algorithm

The FA is a new meta-heuristic optimization algorithm inspired by the flashing behavior of fireflies. FA is a population-based meta-heuristic optimization algorithm. Fireflies communicate, search for prey and find mates using bioluminescence with varied flashing patterns [23]. In order to develop the firefly algorithm, natural flashing characteristics of fireflies have been idealized using the following three rules:

All of the fireflies are unisex; therefore, one firefly will be attracted to other fireflies regardless of their sex.

Attractiveness of each firefly is proportional to its brightness, thus for any two flashing fireflies, the less bright firefly will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly.

The brightness of a firefly is determined according to the nature of the objective function.

The attractiveness of a firefly is determined by its brightness or light intensity which is obtained from the objective function of the optimization problem. However, the attractiveness  $\beta$ , which is related to the judgment of the beholder, varies with the distance between two fireflies. The attractiveness  $\beta$  can be defined by [23]:

$$\beta = \beta_0 e^{-\gamma r^2} \quad (13)$$

where  $r$  is distance of two fireflies,  $\beta_0$  is the attractiveness at  $r=0$ , and  $\gamma$  is the light absorption coefficient.

The distance between two fireflies  $i$  and  $j$  at  $X_i$  and  $X_j$  respectively, is determined as follows:

$$r_{ij} = \|X_i - X_j\| = \sqrt{\sum_{k=1}^d (x_{i,k} - x_{j,k})^2} \quad (14)$$

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

In the FA, the movement of a firefly  $i$  towards a more attractive (brighter) firefly  $j$  is determined by the following equation:

$$X_i = X_i + \beta_0 e^{-\gamma r_{ij}^2} (X_j - X_i) + \alpha(\text{rand} - 0.5) \quad (15)$$

where the second term is related to the attraction, while the third term is randomization with  $\alpha$  being the randomization parameter. Also rand is a random number generator uniformly distributed in [0, 1].

In this paper, the modified equation proposed in [22] for computing  $\alpha$  is employed as follows:

$$\alpha = \alpha_{max} - \frac{\alpha_{max} - \alpha_{min}}{t_{max}} \cdot t \quad (16)$$

where  $\alpha_{max}=1$  and  $\alpha_{min}=0.2$ . Also,  $t_{max}$  and  $t$  are the numbers of maximum iterations and present iteration, respectively.

### 5.3 Harmony Search-Firefly Algorithm

In the present study, HS and FA are hybridized to propose an efficient algorithm having for optimization of scallop domes for earthquake loadings. At first, a preliminary optimization is performed by HS to explore the design space with  $HMS = n$ . The optimum solution found by HS, say  $X_{HS}$ , is directly transformed to the optimal initial population. To complete the optimal initial population other individuals, say  $X_{mdi}$ ,  $i=1, 2, \dots, n-1$  are selected on the random basis. Thus, the optimal population can be defined as:

$$I_p = [X_{HS}, X_{md1}, X_{md2}, \dots, X_{mdn-1}] \quad (17)$$

where  $I_p$  is the optimal initial population.

This method of generation of the optimal initial population is inspired by Salajegheh and Gholizadeh [23]. Now the process of FA begins by employing the optimal initial population. The proposed optimization algorithm is called, harmony search-firefly algorithm (HSFA).

## 6. NUMERICAL RESULTS

In the present work, two double layer scallop domes with 8 and 10 segments are considered. For both the scallop domes the span is 50.0 m, the height is 10 m and the layer thicknesses is 1.5 m. The configuration of the mentioned scallop domes is shown in Fig 6. Young's modulus, mass density, yield stress and ultimate stress are  $2.1 \times 10^{10}$  kg/m<sup>2</sup>, 7850 kg/m<sup>3</sup>,  $2.4 \times 10^6$  kg/m<sup>2</sup>, and  $3.6 \times 10^6$  kg/m<sup>2</sup>, respectively. The computational time is measured in terms of CPU time of a PC Pentium IV 3000 MHz. A uniformly distributed load of 250 kg/m<sup>2</sup> is applied on the horizontal projection of the top layer. In this study, vertical component of Bam earthquake (Iran-2003) is considered. This component of the earthquake contains 13310 points with the PGA of 9.885 m/s<sup>2</sup>. Here a portion of the earthquake with 1500 points shown in Fig 6 is considered. The maximum deflection of top node of the domes is limited to 5 cm and the overall stability of the structures during the optimization process is checked. Thus, in the present work, limitation on maximum deflection and keeping the overall stability are considered as the design constraints.

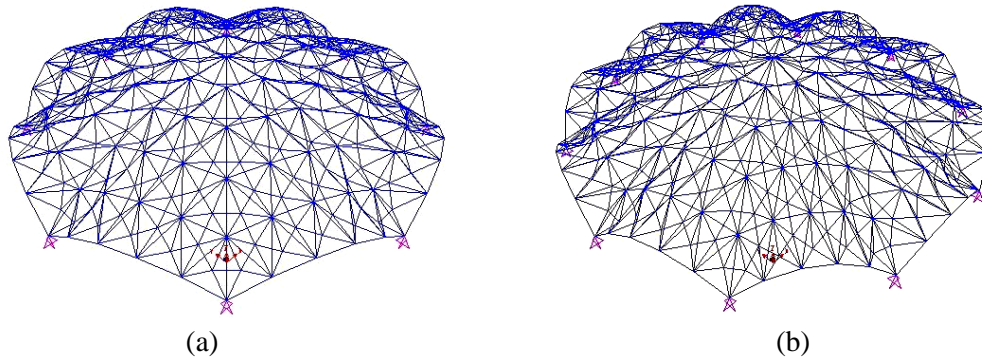


Figure 6. Double layer scallop dome with (a) 8 and (b) 10 segments

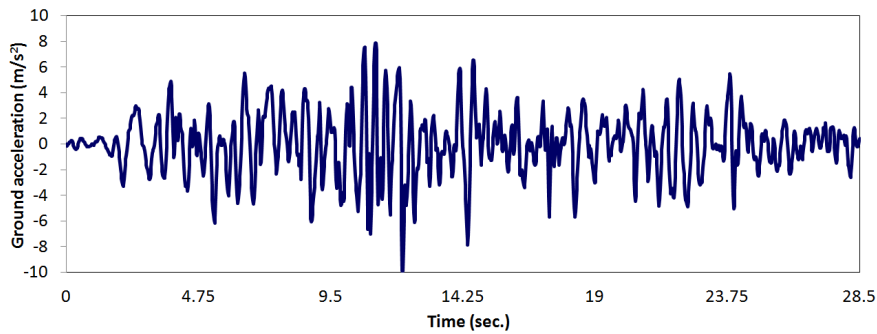


Figure 7. Vertical component of Bam earthquake (Iran-2003)

The number of individuals in initial population for all optimization algorithms is 25 and the maximum number of iterations for both algorithms is limited to 200. The discrete design variables are selected from a set of standard Pipe profiles listed in Table 1. In this table, cross-sectional area and radius of gyration are given by  $A$  and  $r$ , respectively.

Table 1: The available list of standard Pipe profiles (TUBO-)

NO.	Profile	$A$ ( $cm^2$ )	$r$ (cm)	NO.	Profile	$A$ ( $cm^2$ )	$r$ (cm)
1	D33.70x2.6	2.540	1.1000	14	D159.0x4.0	19.480	5.4814
2	D48.30x2.6	3.730	1.6200	15	D168.3x4.0	20.65	5.8102
3	D60.30x3.2	5.740	2.0200	16	D193.7x4.5	26.75	6.6922
4	D76.10x3.2	7.329	2.5799	17	D219.1x5.0	33.63	7.5716
5	D82.50x3.2	7.972	2.8060	18	D244.5x5.4	40.56	8.4557
6	D88.90x3.2	8.616	3.0321	19	D273.0x5.6	47.04	9.4570
7	D101.6x3.6	11.080	3.4672	20	D298.5x5.9	54.23	10.3471
8	D108.0x3.6	11.810	3.6934	21	D323.9x5.9	58.94	11.2450
9	D114.3x3.6	12.520	3.9161	22	D355.6x6.3	69.13	12.3536
10	D127.0x4.0	15.450	4.3504	23	D368.0x6.3	71.59	12.7895
11	D133.0x4.0	16.210	4.5629	24	D406.4x6.3	79.19	14.1475
12	D139.7x4.0	17.050	4.8004	25	D419.0x7.1	91.88	14.5645
13	D152.4x4.0	18.650	5.2483	26	D457.2x7.1	100.4	15.9150

For all examples, the structural elements of each layer are divided into three groups and therefore the optimization problem includes nine design variables:

$$X^T = \{A_{\text{Group1}}, A_{\text{Group2}}, A_{\text{Group3}}, A_{\text{Group4}}, A_{\text{Group5}}, A_{\text{Group6}}, A_{\text{Group7}}, A_{\text{Group8}}, A_{\text{Group9}}\} \quad (18)$$

During the nonlinear optimization process, for each element a strain-stress curve is considered according to its buckling stress. It is important to note that for all structural elements  $\sigma_y, \sigma_u$  and their corresponding strains are identical.

For presented numerical examples, optimization process is implemented by HS, FA and HSFA meta-heuristics and the results are compared. For implementation of HSFA, HS is employed in the first 100 generations and FA in the second 100 ones.

6.1. Example 1: A 8-Segment Double Layer Scallop Dome

The element groups of the 8-segment scallop dome are shown in Fig 8.

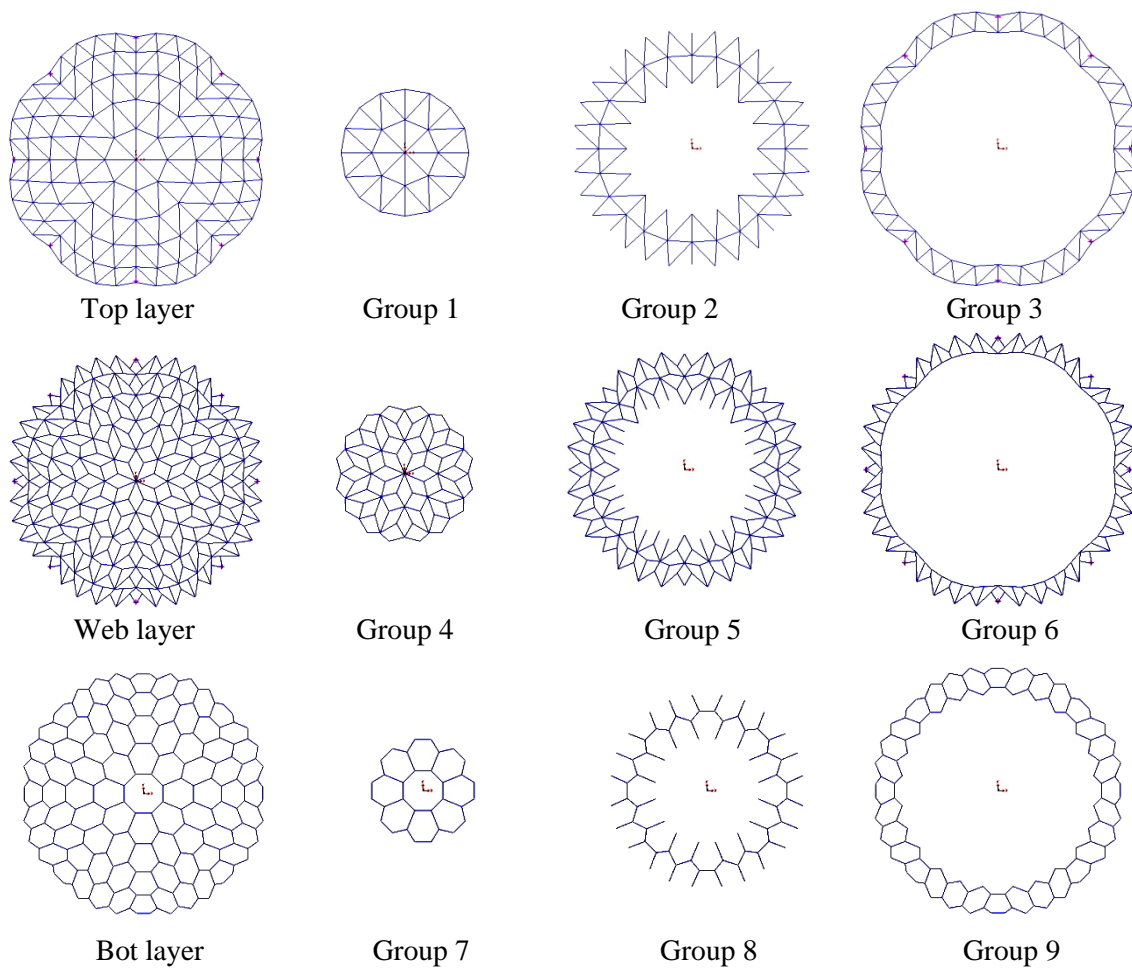


Figure 7. The 8-segment scallop dome with its relative element groups

The optimization processes considering nonlinear behavior using HS, FA and HSFA are achieved and the results are given in Table 2 in terms of Pipe profiles number of Table 1.

Table 2: Comparison of nonlinear optimal designs for 8-segment double layer scallop dome

Design variables	Nonlinear Optimum Design		
	HS	FA	HSFA
$A_{\text{Group1}}$	22	24	22
$A_{\text{Group2}}$	18	13	18
$A_{\text{Group3}}$	21	20	18
$A_{\text{Group4}}$	5	10	8
$A_{\text{Group5}}$	5	8	8
$A_{\text{Group6}}$	9	13	11
$A_{\text{Group7}}$	7	8	7
$A_{\text{Group8}}$	6	8	8
$A_{\text{Group9}}$	15	15	10
Weight (kg)	92902.25	90459.27	87519.56
Number of generations	200	200	168
Overall time (min.)	14322.12	14322.12	12030.58
Maximum deflection (cm)	4.9974	5.0000	5.0000

The results of Table 2 indicate that the optimum weight of HSFA is 5.79% and 3.25% lighter than those of HS and FA, respectively. In the mean time, HSFA converges in 168 generations while HS and FA require 200 generations for convergence. All of these indicate that HSFA possesses better computational performance compared with both HS and FA in terms of optimum structural weight and the required number of nonlinear structural analyses.

The time history deflections of nodes 1 to 5 in top layer of 8-segment optimum double layer scallop dome found during the optimization process using HSFA is represented in Fig. 8.

In order to find the factor of safety (FS) of the optimum structure found by HSFA, the PGA of the applied earthquake record is increased and nonlinear time history analysis is conducted. It is observed that when the PGA is 2.56 times of the original record PGA the optimum structure keeps its overall stability and for slightly larger values, say 2.561, the structure losses its overall stability and therefore FS for this structure is equal to 2.56. The time history deflections of node 1 in top layer of the optimum structure subject to earthquake loading with PGA of 2.56 times of the original one is shown in Fig. 9.

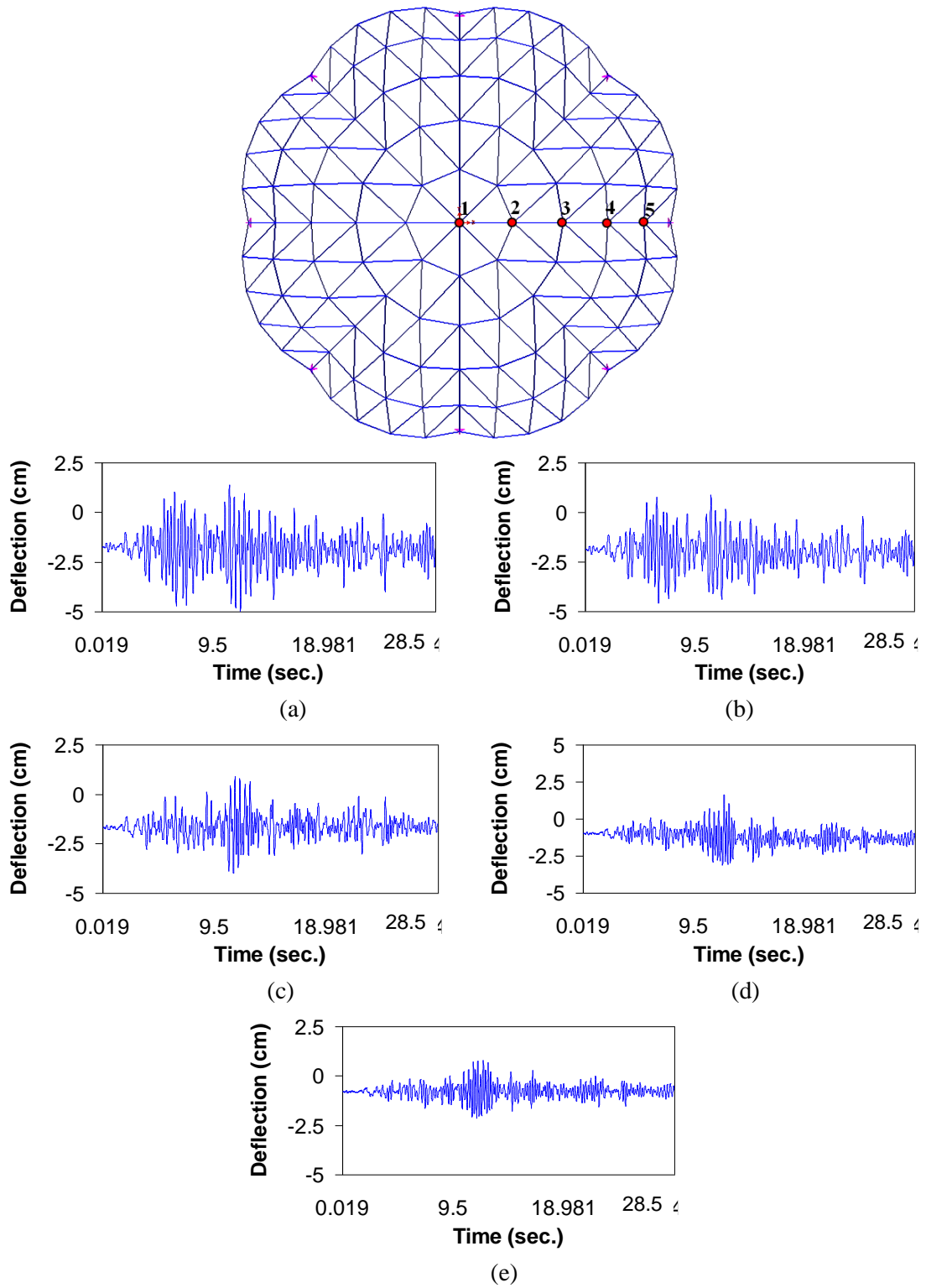


Figure 8. Time history deflection of nodes (a) 1, (b) 2, (c) 3, (d) 4 and (e) 5 of the optimum 8-segmented scallop dome found by HSFA

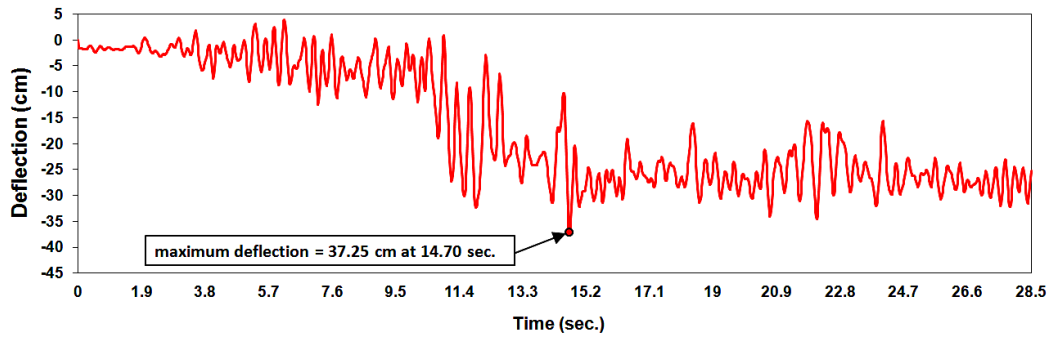


Figure 9. Time history deflection of node 1 of the optimum 8-segmented scallop dome found by HSFA for earthquake record with PGA of 2.58 times of the original one

6.2 Example 2: A 10-Segment Double Layer Scallop Dome

The element groups of the 10-segment scallop dome are shown in Fig 10.

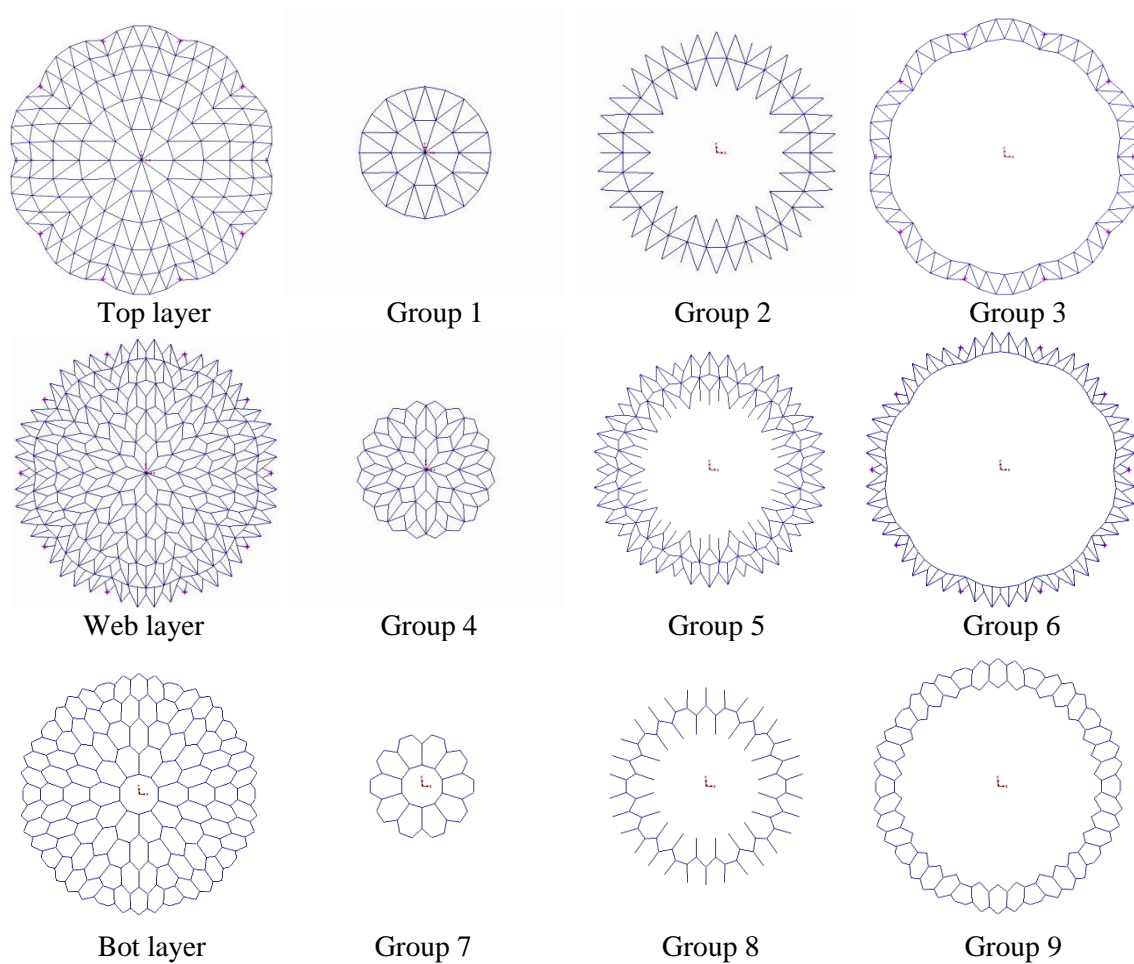


Figure 10. The 10-segment scallop dome with its relative element groups

The results of optimization using HS, FA and HSFA considering nonlinear behavior are given in Table 3.

It can be observed that the optimum weight of HSFA is 7.21% and 2.35% lighter than those of HS and FA, respectively. Furthermore, the number of required generations by HSFA is 172 while HS and FA require 200 generations for convergence. These results demonstrate the better performance of HSFA in comparison with HS and FA.

Table 3: Comparison of nonlinear optimal designs for 10-segment double layer scallop dome

Design variables	Nonlinear Optimum Design		
	HS	FA	HSFA
$A_{\text{Group1}}$	18	18	17
$A_{\text{Group2}}$	10	10	14
$A_{\text{Group3}}$	19	18	17
$A_{\text{Group4}}$	4	3	5
$A_{\text{Group5}}$	5	4	6
$A_{\text{Group6}}$	10	10	10
$A_{\text{Group7}}$	4	4	6
$A_{\text{Group8}}$	5	5	5
$A_{\text{Group9}}$	8	10	10
Weight (kg)	75063.45	71325.98	69650.91
Number of generations	200	200	172
Overall time (min.)	25754.09	25754.09	22148.72
Maximum deflection (cm)	4.9809	5.0000	4.9981

The time history deflections of nodes 1 to 5 in top layer of 10-segment optimum double layer scallop dome found during the optimization process using HSFA is represented in Fig. 11.

In order to find the FS of the optimum structure found by HSFA, as well as the first example, the PGA of the applied earthquake record is increased and nonlinear time history analysis is conducted. It is observed that when the PGA is 2.35 times of the original record PGA the optimum structure keeps its overall stability and for the larger values the structure losses its overall stability and therefore FS for this structure is equal to 2.35. The time history deflections of node 1 in top layer of the optimum structure subject to earthquake loading with PGA of 2.35 times of the original one is shown in Fig. 12.



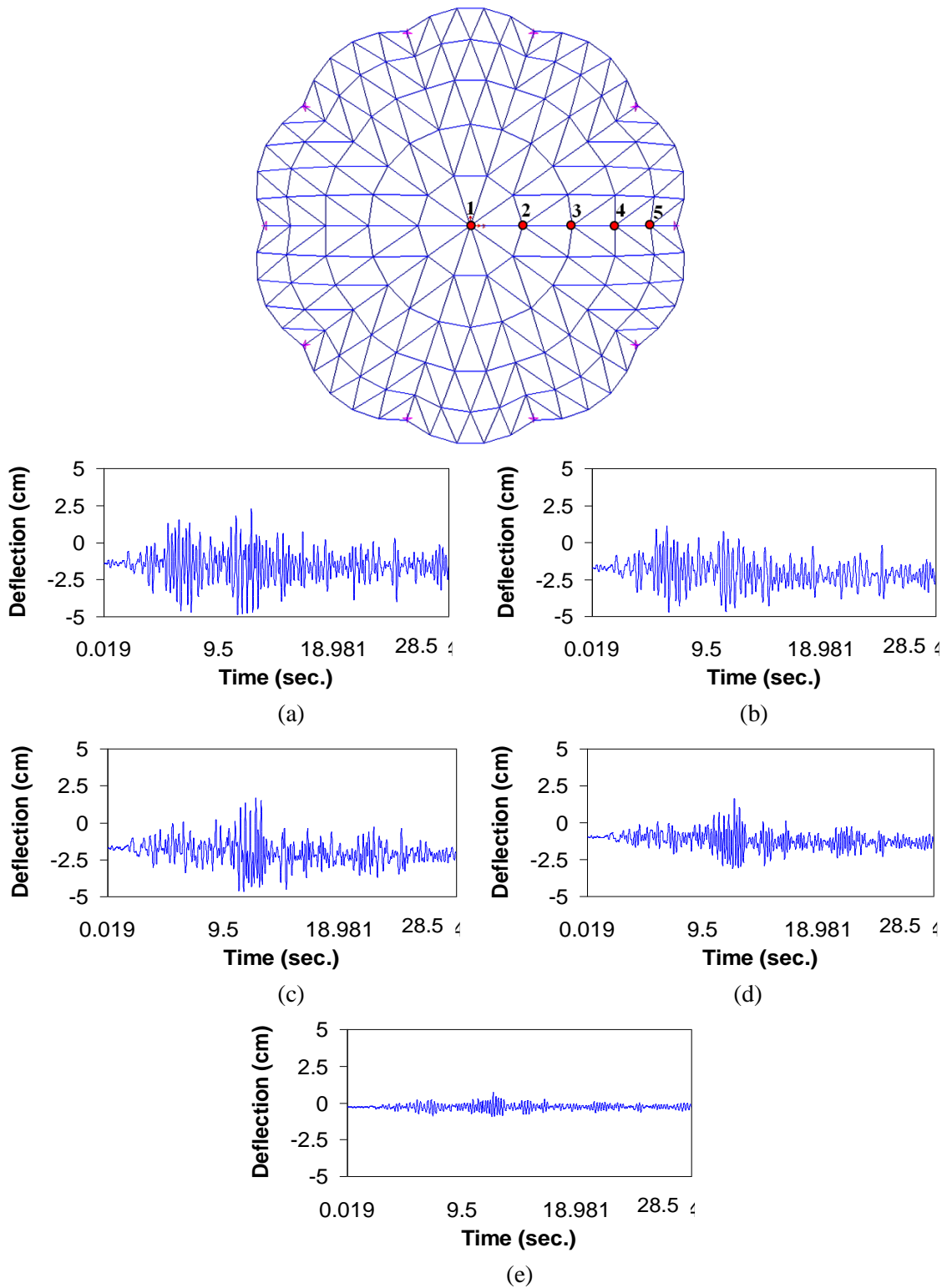


Figure 11. Time history deflection of nodes (a) 1, (b) 2, (c) 3, (d) 4 and (e) 5 of the optimum 10-segmented scallop dome found by HSFA

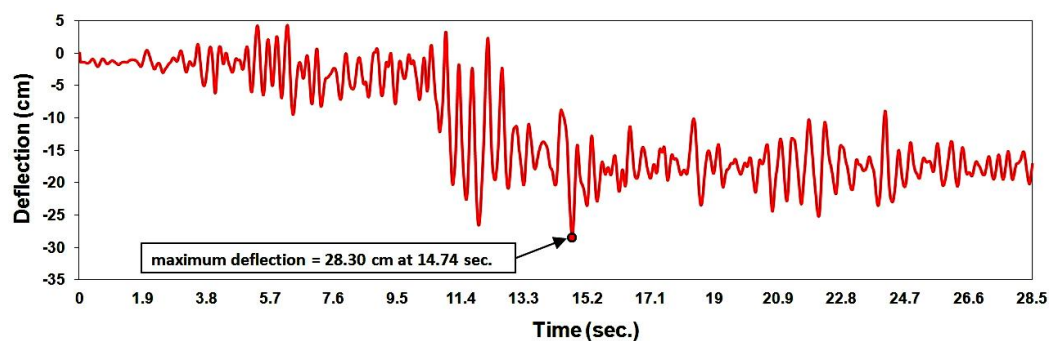


Figure 12. Time history deflection of node 1 of the optimum 10-segmented scallop dome found by HSFA for earthquake record with PGA of 2.35 times of the original one

## 7. CONCLUSIONS

The main objective of present study is to design scallop domes subject to earthquake loading for optimal weight considering nonlinear behavior. The design variables (cross-sectional areas of the element groups) are selected from a set of available standard sections consequently the optimization problem is discrete. The dynamic nonlinear nature of the tackled problem necessitates that a powerful meta-heuristic optimization algorithm to be employed. As the standard version of meta-heuristics are not usually efficient for solving such complex problems, in the present study a combination of harmony search (HS) and firefly algorithm (FA) methods is proposed as harmony search firefly algorithm (HSFA) for dealing with the mentioned problem. Implementation of HSFA includes following phases: at first, a preliminary optimization is accomplished by HS then an optimal initial population is produced using the first phase results and finally, FA is employed to find optimum design using the produced optimal initial population. In order to demonstrate the efficiency of the proposed HSFA meta-heuristic, two numerical examples including a 1200-bar 8-segment and a 1500-bar 10-segment double layer scallop domes subject to earthquake loading are presented. The numerical results indicate that for both examples, the HSFA not only converges to better solution but also requires less computational efforts compared with HS and FA. Therefore, it can be concluded that the proposed HSFA can be effectively employed for design optimization of space structures subject to earthquake loading considering nonlinear behavior.

## REFERENCES

1. Gholizadeh S, Salajegheh E. Optimal design of structures for earthquake loading by self organizing radial basis function neural networks, *Adv Struct Eng*, 2010; **13**:339-56.
2. Gholizadeh S, Salajegheh E. Optimum design of structures by an improved genetic algorithm and neural networks, *Adv Eng Softw*, 2005; **36**:757-67.
3. Kaveh A, Farahmand Azar B, Hadidi A, Rezazadeh Sorochi F, Talatahari S. Performance-based seismic design of steel frames using ant colony optimization, *J Constr Steel Res*, 2010; **66**: 566-74.

4. Togan V, Daloglu AT. Optimization of 3d trusses with adaptive approach in genetic algorithms, *Eng Struct*, 2005; **28**:1019-1027.
5. Saka MP, Ulker M. Optimum design of geometrically nonlinear space trusses, *Comput Struct*, 1991; **41**:1387-1396.
6. Kamyab Moghdas R, Salajegheh E. Size optimization of nonlinear scallop domes by an enhanced particle swarm algorithm, *Int J Civil Eng*, 2013; **11**:77-89.
7. Nooshin H, Tomatsuri H, Fujimoto, M. Scallop domes. *IASS97 Symposium on Shell & Spatial Structures: Design, Performance & Economics*, Singapore, 1997.
8. Kamyab R, Salajegheh E. Prediction of nonlinear time history deflection of scallop domes by neural networks, *Int J Optim Civil Eng*, 2011; **1**: 419-32.
9. McKenna F, Fenves G. *The Opensees Command Language Manual*, University of California, Berkeley (opensees.ce.berkeley.edu), 2001.
10. Lee KS, Geem ZW. A new structural optimization method based on the harmony search algorithm, *Comput Struct*, 2004; **82**:781–98.
11. Yang XS. Firefly algorithms for multimodal optimization, in: *Stochastic Algorithms: Foundations and Applications* (Eds O. Watanabe and T. Zeugmann), SAGA 2009, Lecture Notes in Computer Science, 5792, Springer-Verlag, Berlin, 169–78, 2009.
12. The Language of Technical Computing. MATLAB. Math Works Inc, 2006.
13. Gholizadeh S, Salajegheh E. Optimal seismic design of steel structures by an efficient soft computing based algorithm, *J Constr Steel Res*, 2010; **66**: 85–95.
14. Gholizadeh S, Samavati OA. Structural optimization by wavelet transforms and neural networks, *Appl Math Model*, 2011; **35**: 915–29.
15. Arora JS, Optimization of structures subjected to dynamic loads, *Structural Dynamic Systems Computational Techniques and Optimization*, C.T. Leondes (Eds.), Gordon and Breach Science Publishers, 1999.
16. Federal Emergency Management Agency. NEHRP guidelines for the seismic rehabilitation of buildings, Rep. FEMA 273 (Guidelines) and 274 (Commentary), Washinton, DC, 1997.
17. Lowes L, Mitra N, Altoontash A. A Beam-Column Joint Model for Simulating the Earthquake Response of Reinforced Concrete Frames, PEER Report 2003/10, Pacific Earthquake Engineering Research Center, 2004.
18. Ibarra L, Medina R, Krawinkler H. Hysteretic models that incorporate strength and stiffness deterioration, *Earth Eng Struct Dyna*, 2005; **34**:1489–1511.
19. Black GR, Wenger BA, Popov EP. Inelastic Buckling of Steel Struts Under Cyclic Load Reversals. UCB/EERC-80/40, Earthquake Engineering Research Center, Berkeley, CA., 1980.
20. Uriz P, Mahin SA. Toward Earthquake-Resistant Design of Concentrically Braced Steel-Frame Structures, PEER Report 2008/08, Pacific Earthquake Engineering Research Center, College of Engineering, University of California, Berkeley, 2008.
21. AISC-LRFD. *Manual of Steel Construction-Load and Resistance Factor Design*, American Institute of Steel Construction, Chicago, USA, 2001.
22. Gholizadeh S, Barati H. A comparative study of three metaheuristics for optimum design of trusses, *Int J Optim Civil Eng*, 2012; **2**:423-41.
23. Gandomi AH, Yang XS, Alavi AH. Mixed variable structural optimization using firefly algorithm, *Comput Struct*, 2011; **89**:2325–2336.