

Sharif University of Technology Scientia Iranica Transactions A: Civil Engineering www.scientiairanica.com



Layout optimization of double-layer grids using modified genetic algorithm based on fuzzy inference system

P. Torkzadeh^a, T. Jaffari^b and S. Shojaee^{a,*}

a. Department of Civil Engineering, Faculty of Engineering, Shahid Bahonar University of Kerman, Kerman, Iran. b. Department of Civil Engineering, Graduate University of Advanced Technology, Kerman, Iran.

Received 1 Jun 2014; received in revised form 11 November 2014; accepted 28 Jan 2015

KEYWORDS

Optimization; Genetic algorithm; Space structures; Design space search; Fuzzy inference system. Abstract. In weight optimizitaion of double-layer grids, various parameters, such as members cross-sectional areas, the height between two layers, structure meshing in two directions and the topology of the structure should be considered. In this study, for simultaneous optimization of size, shape and topology of double-layer grids, a genetic algorithm is employed and is modified based on the fuzzy inference system. First, to efficiently search in design space at each stage, some solutions are generated in the neighborhood of the best sample, which enhances searching operation in the neighborhood of the optimum solution. Then, in order to achieve the possible solutions, penalties for violation of constraints, and the number of violated constraints are considered in order to choose the next generation. The value of objective function and the values of genetic algorithm parameters have a great effect on the result of the algorithm. For adaptive setting of these parameters, the fuzzy inference system is employed. The efficiency of these improvements has been confirmed by presenting some examples of truss structures and comparison with the other algorithms.

© 2015 Sharif University of Technology. All rights reserved.

1. Introduction

Structural optimization means the design of structures, so that all the design criteria are considered while the structural weight or cost is minimum. In the recent years, many studies have been performed on meta-heuristic algorithms to reduce the mathematical calculations and to enhance the ability of finding the global solution. In order to improve the above mentioned, many studies have been done in the field of structural optimization.

Lee and Geem proposed a new structural optimization method by harmony search algorithm [1]. Truss optimization was presented using Big Bang-Big Cranch method [2]. Kaveh and Shojaei optimized skeletal structures using ant colony algorithm [3]. Particle swarm optimization algorithm was used for structural design optimization [4]. Modified particle swarm optimization algorithms (PSO-HPSO-PSOPC) were presented for truss optimization [5]. DHPSACO approach was proposed by combination of Particle Swarm Optimization Passive Congregation (PSOPC), Ant Colony Optimization (ACO) and Harmony Search algorithm (HS) for truss optimization with discrete variables [6]. A two-stage method was presented using GA with discrete variables and was applied for optimization of truss structures [7]. Double-layer grids were optimized using back propagation neural networks [8]. Salajegheh and Gholizadeh performed optimization of space structures using modified genetic

^{*.} Corresponding author. Tel.: +98 3433222559; Fax: +98 3433220054 E-mail address: saeed.shojaee@uk.ac.ir (S. Shojaee)

algorithm and radial basis function neural network [9]. Gholizadeh et al. proposed shape optimization of double-layer grids using quantum behaved particle swarm optimization (QPSO) and neural networks [10]. Shape optimization of structures was implemented by sequential harmony search algorithm [11]. Also, layout optimization of truss structures was carried out by hybridizing cellular automata and particle swarm optimization [12].

In weight optimization of double-layer grids, structural design variables should be assigned so that the structure has a minimum weight. In this study, design variables such as members crosssectional areas, thickness of the double layer, the structure meshing in two directions and topology of the structure are assigned using improved GA. Since optimization of every system consists of two basic steps including searching the design space and evaluation of the search vectors, in order to have a proper searching in design space, some improvements are applied on optimization algorithm.

2. Formulation of the optimization problem

The optimization problem of truss structures is defined in general form by Eq. (1) in which all the design constraints are satisfied, and the total weight of the structure has the lowest value [13]:

minimize:
$$W(\{X\}) = \sum_{i=1}^{n} \gamma_i A_i L_i$$

subjected to : $g_i(\{X\}) \le 0; \quad i = 1, 2, ..., m$

$$h_i(\{X\}) \le 0; \quad j = 1, 2, ..., k$$

 $\{X_L\} \le \{X\} \le \{X_u\},$ (1)

where $W({X})$ is total weight of the structure (objective function), n is the number of structural elements, h_i and g_i are the design constraints. Some of the design constraints in structures are limitation of the stress, elements slenderness and node displacements. X_L and X_u are the upper and the lower bounds of variations.

Since the genetic algorithm is used in unconstraint optimization problems, in this study, penalty function method is employed to transform the constrained function to unconstrained function. In penalty function, if the constraints are in the allowable range, the penalty rate will be zero. Otherwise, the penalty rate is obtained from the following equations [14]:

$$\begin{cases} \sigma_i^{\min} \leq \sigma_i \leq \sigma_i^{\max} \qquad \Rightarrow \ \phi_{\sigma}^i = 0\\ \sigma_i < \sigma_{\min} \text{ or } \sigma_i > \sigma_{\max} \quad \Rightarrow \ \phi_{\sigma}^i = \frac{\sigma_i - \sigma_i^{\max/\min}}{\sigma_i^{\max/\min}}\\ i = 1, 2, ..., m \end{cases}$$
(2)

$$\begin{cases} \delta_{j}^{\min} \leq \delta_{j} \leq \delta_{j}^{\max} \qquad \Rightarrow \ \phi_{\delta}^{j} = 0\\ \delta_{j} < \delta_{\min} \text{ or } \delta_{j} > \delta_{\max} \quad \Rightarrow \ \phi_{\delta}^{j} = \frac{\delta_{j} - \delta_{j}^{\max/\min}}{\delta_{j}^{\max/\min}} \quad (3)\\ j = 1, 2, ..., k \end{cases}$$

$$\begin{cases} \lambda_n^{\min} \le \lambda_n \le \lambda_n^{\max} & \Rightarrow & \phi_{\lambda}^n = 0\\ \lambda_n < \lambda_{\min} \text{ or } \lambda_n > \lambda_{\max} & \Rightarrow & \phi_{\lambda}^n = \frac{\lambda_n - \lambda_n^{\max/\min}}{\lambda_n^{\max/\min}}\\ n = 1, 2, ..., p \end{cases}$$
(4)

$$AFW^{k} = \varepsilon_{1}W^{k} + \varepsilon_{2} \left(\phi_{\sigma}^{k} + \phi_{\delta}^{k} + \phi_{\lambda}^{k}\right)^{\varepsilon_{3}}, \qquad (5)$$

where $\sigma_i^{\max/\min}$ and σ_i are, respectively, the existing stress and the allowable stress in *i*th member; $\delta_j^{\max/\min}$ and δ_j are, respectively, the existing and the allowable displacement of *j*th node; $\lambda_n^{\max/\min}$ and λ_n are, respectively, the existing and the allowable slenderness of the *i*th member; ϕ_{σ}^k , ϕ_{δ}^k and ϕ_{λ}^k are the summation of the penalties calculated for stress, displacement and slenderness constraints, respectively; and ε_1 , ε_2 and ε_3 are coefficients of the penalty function. In this study, ε_1 and ε_3 are equal to 1, and ε_2 is obtained from Eq. (6). AFW^k is additional function due to addition of penalty to the weight of the structure.

$$\varepsilon_2 = 0.015 \times W \times i < 2 \times W, \tag{6}$$

where W is the weight of the structure, and i is the number of iteration loops in optimization process. The coefficient of penalty function, ε_2 , is directly proportional to the number of iteration loops and $W \times i$ is relatively a high value. For reduction of the penalty coefficient, the value of 0.015, which is the optimal value obtained by optimization of several truss structures, is used. The 0.015 $\times W \times i$ value considers a smaller penalty in initial stages of the optimization and increases subsequently by increasing the number of iteration loops. This procedure results in a better search of the algorithm. To avoid a large penalty value in higher loops, the penalty value is limited to the $2 \times W$ value.

3. Genetic algorithm

Genetic algorithm is one of the optimization methods which is a member of the large family of evolutionary algorithms. This algorithm establishes a search method by natural inheritance principle of survival of the stronger members and analyzing the members to create better members. In this algorithm, variables are encoded by means of numerical strings in binary system, which are called genes. By taking together the strings of each variable, fixed-length string is generated which is called chromosome. Each chromosome represents a solution point in the search space. In this algorithm, the initial population is randomly selected, and by evaluating the chromosomes, calculating the fitness function by Eq. (7), selecting the parents, and applying host and mutation operators, new children are generated. Using the fitness of the chromosomes, the population of the next generation is selected. The algorithm will continue to approach a convergence [15].

$$F_{i} = \exp\left(-\beta \times \frac{\text{AFW}_{i}}{\text{AFW}_{\text{max}} + 1}\right), \qquad i = 1, 2, \dots, n,$$
(7)

where n is the number of members of current population, F_i is a parameter which shows the level of *i*th members fitness, and β is a selection pressure coefficient.

3.1. Improvement of search space in genetic algorithm

Fundamental characteristic of meta-heuristic algorithms is to search in the design space. Depending on the manner of searching the space, algorithms exhibit different performance. The more appropriate the manner of searching the space, the more the likelihood of achieving the optimum solution increases. One of the drawbacks of GA is unsuccessful mutations. For example, if the problem has four variables, according to Table 1, and chromosome 1 is the best possible solution, and chromosomes 2 and 3 are random chromosomes obtained in the algorithm implementation process, objective function value will be near to the global optimum. Applying several different mutations indicates that there is a little chance to reach the final optimum. Sample space variables are as follows:

$$X = [1, 2, 3, \dots, 31, 32].$$
(8)

It is to be noted that the values of X_i (i = 1, 2, ..., 4)(all chromosomes are in the neighborhood of each other, but comparison between chromosomes 1 and 2 and chromosomes 1 and 3 shows that to transform chromosome 2 to chromosome 1, the number of 12 bits and to transform chromosome 3 to chromosome 1, 6 bits of chromosomes should be changed. This case is less likely to occur. To solve this problem, the method of generating new children in the neighborhood of the best solution is used. In this method, after finding the optimal chromosome at the end of iteration, sampling interval for each variable by using Eq. (9) is reduced, and new children are randomly generated from the given distance interval.

$$\begin{bmatrix} \operatorname{number}(\Psi_i^l), \operatorname{number}(\Psi_i^u) \end{bmatrix} \\ = \begin{bmatrix} \operatorname{number}\left(X_i^{[fav]}\right) - \lambda, \operatorname{number}\left(X_i^{[fav]}\right) + \lambda \end{bmatrix},$$
(9)

where $X_i^{[fav]}$ i = 1, 2, 3, 4 is the value of chromosome variables with the highest fitness; number $\left(X_i^{[fav]}\right)$ is the number corresponding to $X_i^{[fav]}$ from variable search space; number $\left(\Psi_i^l\right)$ and number $\left(\Psi_i^u\right)$ are, respectively, the upper and the lower bound number of variable search space, and λ is the distance coefficient which is assumed to be equal to 1. For example, since for chromosome 2 the value and its corresponding number in selected sampling interval are the same, sampling interval based on $\lambda = 1$ for chromosome 2 variables is obtained as follows:

 $[\operatorname{number}(\Psi_1^l), \operatorname{number}(\Psi_1^u)] = [5-1, 5+1] = [4, 6]$

 $\left[\text{number}(\Psi_2^l), \text{number}(\Psi_2^u) \right] = [9-1, 9+1] = [8, 10]$

 $[\text{number}(\Psi_1^l), \text{number}(\Psi_1^u)] = [17 - 1, 17 + 1]$

= [16, 18],

 $[\operatorname{number}(\Psi_1^l), \operatorname{number}(\Psi_1^u)] = [31 - 1, 31 + 1]$

$$= [30, 32]. \tag{10}$$

The sampling interval should be in the range of initial sampling interval. It is clear that the global optimum is located at a distance of the above sampling intervals. So, if the sampling of chromosomes is randomly generated, the probability of obtaining the global optimum is high. This method improves the algorithm search in the obtained optimal neighborhood.

 Table 1. Sample of chromosomes.

| Chromosome | Variables no. | Binary state | | | | D | ecodi | ng sta | te |
|------------|---------------|--------------|-------|-------|-------|-------|-------|--------|-------|
| | | X_1 | X_2 | X_3 | X_4 | X_1 | X_2 | X_3 | X_4 |
| 1 | 4 | 00011 | 00111 | 01111 | 11111 | 4 | 8 | 16 | 32 |
| 2 | 4 | 00100 | 01001 | 10000 | 11110 | 5 | 9 | 17 | 31 |
| 3 | 4 | 00011 | 00110 | 10000 | 11111 | 4 | 7 | 17 | 32 |

3.2. Using possible solutions to choose the next generation

In large-scale structures, due to the long duration of structural analysis and duration of obtaining the final optimum, the priority is to achieve the results that can satisfy all the constraints. In this study, in addition to considering the fitness function, in case of violation of the constraints, the following three rules are used to select the next generation.

- 1. Every possible solution is preferred to impossible solution.
- 2. Between two possible solutions, the solution which has a better objective function will be chosen.
- 3. Between two impossible solutions, the solution which violates fewer constraints will be accepted.

This procedure makes the algorithm dependent on the number of violated constraints in addition to its dependence on objective function. Since the solution obtained by the algorithm must satisfy all the required constraints, the algorithm is greatly conducted to the possible solutions by using penalty function and the above three rules.

3.3. Modifying the parameters of GA using fuzzy inference system

Selection of GA parameters and the manner to control them have a great influence to find the best solution. Maintaining the population diversity in GA prevents the premature convergence and also increases the likelihood of achieving the optimum solution. During the implementation of the algorithm with respect to the mean variance of fitness value, selection pressure coefficient, percent of elite population and mutation rate are determined dynamically using fuzzy inference system to increase the chances of finding the best solution of algorithm. As the algorithm parameters change at each iteration, the adaptation feature of algorithm parameters reduces. As a result, the algorithm parameters should be kept constant for a specific number of iterations (12 iterations in this study). Based on the algorithm performance (mean value of fitness of iterations) in this number of iterations, mutation rate of previous stage and iteration loop counters, algorithm parameters (selection pressure coefficient, percent of elite population and mutation rate) are computed.

Eq. (10) is used to calculate the variance, and Eq. (11) is employed to determine the improvement of algorithm performance by specific number of iterations. In this equation, if the obtained value is a number greater than zero, the algorithm has been improved or the algorithm has a better performance; otherwise the algorithm has a worse performance.

variance =
$$\frac{G_{\max} - G_{\max}}{G_{\max} - G_{\min}}$$
, (11)

$$AP = \frac{G_{better}^{k-1} - G_{better}^{k}}{G_{better}^{k}}$$

$$\Rightarrow \begin{cases} \text{if AP} > 0 & \text{then algorithm has better} \\ \text{performance} \\ \text{else if AP} < 0 & \text{then algorithm has worse} \end{cases}$$

else if
$$AP \leq 0$$
 then algorithm has worse (12) performance

The membership functions are defined using triangular, trapezoidal, Gaussian and bell-shaped function. Input and output membership functions are illustrated in Figures 1-7.

If-Then rules are used to formulate the fuzzy conditional statements. The fuzzy rules are given in



Figure 1. Input membership function of mean-variance.



Figure 2. Input membership function of previous iteration mutation rate.



Figure 3. Input membership function of improved algorithm.



Figure 4. Input membership function of loop counters.



Figure 5. Output membership function of selection pressure coefficient.

Table 2. All the rules are combined with "and" logical operator. Phase-field model has been used for inference system. For defuzzification of the fuzzy output, the centroid method is employed.



Figure 6. Output membership function of elite population percent.



Figure 7. Output membership function of mutation rate.

4. Simultaneous optimization of size, shape, and topology of double-layer grids

In double-layer grids, various parameters, such as the member cross-sectional areas, the height between

| | | Input | | | Output | |
|----------------------|-------------------------|----------|----------------------------|--------|----------------------------|--------|
| Ave var ^a | AP^{b} | Mu^{c} | It^{d} | Beta | Pe^{e} | Mu |
| Low | - | - | Not very high | High | High | - |
| Medium | - | - | Not very high | Medium | Medium | - |
| High | - | - | - | Low | Low | - |
| - | Worse | Medium | Low | - | - | High |
| - | Worse | Medium | Medium | - | - | High |
| - | Worse | Medium | High | - | - | High |
| - | Worse | Medium | Very high | - | - | High |
| - | Worse | High | Low | - | - | Medium |
| - | Worse | High | Medium | - | - | Medium |
| - | Worse | High | High | - | - | Medium |
| - | Worse | High | Very high | - | - | Medium |
| - | Worse | Low | Low | - | - | Medium |
| - | Worse | Low | Medium | - | - | Medium |
| - | Worse | Low | High | - | - | Medium |
| - | Worse | Low | Very high | - | - | Low |
| - | Better | Medium | - | - | - | Medium |
| - | Better | High | - | - | - | High |
| - | Better | Low | - | - | _ | Low |

Table 2. If-Then rules used for fuzzy inference system.

 $\overline{}^{a}$ Ave var = Average variance; $\overline{}^{b}$ AP = Algorithm performance; $\overline{}^{c}$ Mu = Mutation;

 $^{\rm d}$ It = Iteration; and $^{\rm e}$ Pe = Percent of elite.

two layers, the structure meshing in two directions and topology of the structures are necessary which should be assigned to optimize the weight of the structure and satisfy all the design constraints. In this study, the mentioned variables are considered as design variables. Structural members and the nodes are grouped to achieve the desired results and to reduce the design space. In grouping the lower layer nodes, the geometrically symmetrical grouping is considered. The members are grouped based on internal forces which obtain from FE analysis in each iteration. Allowable domain of considered constraints during the optimization process is obtained from the following equations:

1. Stress constraints [16]:

$$\bar{\sigma}_i = 0.6F_y$$
 (for tensional members) (13)

$$\bar{\sigma}_i = \bar{\sigma_c}$$
 (for compressive members) (14)

$$\overline{\sigma_c} = \begin{cases} \left[\left(1 - \frac{\lambda_i^2}{2C_c^2}\right) F_y \right] / \left(\frac{5}{3} + \frac{3\lambda_i}{8C_c} - \frac{\lambda_i^3}{8C_c^3}\right) & \text{for } \lambda_i < C_c \\ \frac{12\pi^2 E}{23} & \text{for } \lambda_i \ge C_c \\ C_c = \sqrt{\frac{2\pi^2 E}{F_y}} & \end{cases}$$
(15)

In the above equations, F_y is the yield stress of material, E is the modulus of elasticity, C_c is the boundary slenderness between elastic and inelastic buckling, and λ is slenderness ratio of the members.

2. Slenderness ratio constraints [16]:

$$\lambda_i = K_i L_i / r_i \le 300 \quad \text{(for tensional members)}$$
(16)

$$\lambda_i = K_i L_i / r_i \le 200 \quad \text{(for compressive members)}$$
(17)

where r_i is radius of gyration, and K_i is buckling length coefficient of *i*th member. In truss structures, the member buckling length coefficient (K_i) is considered equal to unit.

3. Displacement constraints: the maximum displacement for double-layer grids is of small span.

To take into account the structural stability, where determinant of the structural stiffness matrix is equal to zero, a large penalty value is assigned to the structures to avoid the selection of unstable structures in the next stages of the algorithm.

5. Numerical examples

In order to verify the efficiency of the proposed method, two examples of truss structures are discussed and



Figure 8. 52-bar planar truss structure.

then, one example of simultaneous optimization of the size, shape, and topology of space structures is presented. In all examples presented, 85 percent of the next generation chromosomes are obtained using host and mutation operators, and the remaining 15 percent are obtained through the generation of new chromosomes in the neighborhood of optimum sample.

5.1. Size optimization of a 52-bar planar truss structure

A 52-bar planar truss structure, shown in Figure 8, had been investigated by many researchers [6,7,17,18]. Members of this structure are divided to 12 groups: (1) $A_1 - A_4$, (2) $A_5 - A_{10}$, (3) $A_{11} - A_{13}$, (4) $A_{14} - A_{17}$, (5) $A_{18} - A_{23}$, (6) $A_{24} - A_{26}$, (7) $A_{27} - A_{30}$, (8) $A_{31} - A_{36}$, (9) $A_{37} - A_{39}$, (10) $A_{40} - A_{43}$, (11) $A_{44} - A_{49}$, and (12) $A_{50} - A_{52}$. The mass density of materials is 7860 kg/m³, and the elasticity modulus is 2.07×10^5 MPa. The members have a stress limitation of ±180 MPa. The loads $P_x = 100$ kN and $P_y = 200$ kN are applied at nodes 17, 181, 19, and 20. A

| A1 | $\mathbf{A2}$ | A3 | $\mathbf{A4}$ | $\mathbf{A5}$ | $\mathbf{A6}$ | $\mathbf{A7}$ | A 8 | A 9 | A10 |
|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| 0.111 | 0.141 | 0.196 | 0.25 | 0.307 | 0.391 | 0.442 | 0.563 | 0.602 | 0.766 |
| A11 | $\mathbf{A12}$ | $\mathbf{A13}$ | A14 | A15 | A16 | A17 | A18 | A19 | $\mathbf{A20}$ |
| 0.785 | 0.994 | 1 | 1.228 | 1.266 | 1.457 | 1.563 | 1.62 | 1.8 | 1.99 |
| A21 | $\mathbf{A22}$ | $\mathbf{A23}$ | A24 | A25 | A26 | A27 | $\mathbf{A28}$ | A29 | $\mathbf{A30}$ |
| 2.13 | 2.38 | 2.62 | 2.63 | 2.88 | 2.93 | 3.09 | 1.13 | 3.38 | 3.47 |
| A31 | $\mathbf{A32}$ | $\mathbf{A33}$ | $\mathbf{A34}$ | $\mathbf{A35}$ | $\mathbf{A36}$ | A37 | A38 | A39 | $\mathbf{A40}$ |
| 3.55 | 3.63 | 3.84 | 3.87 | 3.88 | 4.18 | 4.22 | 4.49 | 4.59 | 4.8 |
| $\mathbf{A41}$ | $\mathbf{A42}$ | $\mathbf{A43}$ | $\mathbf{A44}$ | $\mathbf{A45}$ | $\mathbf{A46}$ | $\mathbf{A47}$ | $\mathbf{A48}$ | $\mathbf{A49}$ | $\mathbf{A50}$ |
| 4.97 | 5.12 | 5.74 | 7.22 | 7.97 | 8.53 | 9.3 | 10.85 | 11.5 | 13.5 |
| A51 | $\mathbf{A52}$ | $\mathbf{A53}$ | $\mathbf{A54}$ | $\mathbf{A55}$ | A56 | A57 | $\mathbf{A58}$ | $\mathbf{A59}$ | $\mathbf{A60}$ |
| 13.9 | 14.2 | 15.5 | 16 | 16.9 | 18.8 | 19.9 | 22 | 22.9 | 24.5 |
| A61 | $\mathbf{A62}$ | $\mathbf{A63}$ | $\mathbf{A64}$ | | | | | | |
| 26.5 | 28 | 30 | 33.5 | | | | | | |

Table 3. List of the available cross sectional areas for 52-bar planar truss structure (in^2) .

Table 4. Comparison of optimal designs for 52-bar planar truss structure.

| $\mathbf{Elements}$ | \mathbf{GA} | HSH | PSO | PSOPC | HPSO | DHPSACO | Proposed |
|---------------------|---------------|----------|----------|----------|----------|----------|-------------------|
| group | [17] | [2] | [6] | [6] | [6] | [7] | \mathbf{method} |
| 1 | 4658.055 | 4658.055 | 4658.055 | 5999.988 | 4658.055 | 4658.055 | 4658.055 |
| 2 | 1161.288 | 1161.288 | 1374.19 | 1008.38 | 1161.288 | 1161.288 | 1161.288 |
| 3 | 645.16 | 506.451 | 1858.06 | 2696.77 | 363.225 | 494.193 | 494.193 |
| 4 | 3303.219 | 3303.219 | 3206.44 | 3206.44 | 3303.219 | 3303.219 | 3303.219 |
| 5 | 1045.159 | 940 | 1283.87 | 1161.29 | 940 | 1008.385 | 939.998 |
| 6 | 494.193 | 494.193 | 252.26 | 729.03 | 494.193 | 285.161 | 494.193 |
| 7 | 2477.414 | 2290.318 | 3303.22 | 2238.71 | 2238.705 | 2290.318 | 2238.705 |
| 8 | 1045.159 | 1008.385 | 1045.16 | 1008.38 | 1008.385 | 1008.385 | 1008.385 |
| 9 | 285.161 | 2290.318 | 126.45 | 494.19 | 388.386 | 388.386 | 494.193 |
| 10 | 1696.771 | 1535.481 | 2341.93 | 1283.87 | 1283.868 | 1283.868 | 1283.868 |
| 11 | 1045.159 | 1045.159 | 1008.38 | 1161.29 | 1161.288 | 1161.288 | 1161.288 |
| 12 | 641.289 | 506.451 | 1045.16 | 494.19 | 792.256 | 506.451 | 494.193 |
| Weight (kg) | 1970.142 | 1906.76 | 2230.16 | 2146.63 | 1905.495 | 1904.83 | 1902.606 |

set of cross sections are selected from Table 3 for the design variables. The results obtained from the best 20 implementations and the results of previous studies are given in Table 4.

5.2. Size and topology optimization of a 10-bar planar truss structure

A 10-bar planar truss structure, shown in Figure 9, has been investigated by many researchers [19,21]. Variables considered in this example are the members cross sectional areas and the presence or absence of structural members. The load of -100 kips is applied at nodes 2 and 4 in the vertical direction. Mass density of materials is 0.1 lb/in³ and the elasticity modulus is 10⁷ psi. The members have a stress limitation of 25000 Psi. All nodes in y-direction have a displacement limitation of 2.05 in. Cross sections for the design variables are selected from Table 5. The results obtained from the best 20 implementations and



Figure 9. 10-bar planar truss structure.

| No. | Area (in^2) |
|-----|---------------|-----|---------------|-----|---------------|-----|---------------|
| 1 | 1.62 | 9 | 3.63 | 17 | 5.74 | 25 | 16 |
| 2 | 1.8 | 10 | 3.84 | 18 | 7.22 | 26 | 18.8 |
| 3 | 2.38 | 11 | 3.87 | 19 | 7.97 | 27 | 19.9 |
| 4 | 2.62 | 12 | 4.18 | 20 | 11.5 | 28 | 22 |
| 5 | 2.88 | 13 | 4.49 | 21 | 13.5 | 29 | 22.9 |
| 6 | 3.09 | 14 | 4.8 | 22 | 13.9 | 30 | 26.5 |
| 7 | 3.13 | 15 | 4.97 | 23 | 14.2 | 31 | 30 |
| 8 | 3.38 | 16 | 5.12 | 24 | 15.5 | 32 | 33.5 |

Table 5. List of the available cross sectional areas for 10-bar planar truss structure.

the results of previous studies are given in Table 6. Figure 10 shows the optimized structure.

5.3. A double-layer grid with $57m \times 57m$ dimensions

A double-layer grid with $57m \times 57m$ dimensions is selected. The members cross sectional areas, the height between two layers, the number of meshes in the x-

 Table 6. Comparison of optimal designs for the 10-bar
 planar truss structure.

| Elements | $\mathbf{G}\mathbf{A}$ | \mathbf{GA} | \mathbf{GA} | $\mathbf{Proposed}$ |
|-------------|------------------------|---------------|---------------|---------------------|
| group | [19] | [20] | [21] | \mathbf{method} |
| 1 | 30 | 30 | 30 | 26.5 |
| 2 | 0 | 0 | 0 | 0 |
| 3 | 19.9 | 26.5 | 19.9 | 26.5 |
| 4 | 15.5 | 14.2 | 15.5 | 13.9 |
| 5 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 |
| 7 | 7.22 | 7.97 | 7.22 | 5.74 |
| 8 | 22 | 19.9 | 19.9 | 22 |
| 9 | 22 | 18.8 | 22 | 19.9 |
| 10 | 0 | 0 | 0 | 0 |
| Weight (lb) | 4962.1 | 4921.25 | 4855.2 | 4833.832828 |



Figure 10. The optimum topology obtained for the 10-bar planar truss structure.

and y-direction and the presence or absence of nodes of the lower layer are considered as the design variables. The characteristics of the design variables are selected from Tables 7 and 8. The nodes around the lower grid are assumed to be connected to the supports. The elasticity modulus of steel is 2.1×10^6 kg/cm² and mass

 Table 7. Characteristics of the shape variables for double-layer grid.

| | No. of | No. of | Diameter |
|-----|-------------|-------------|----------------|
| No. | meshes in | meshes in | of layer |
| | x-direction | y-direction | (\mathbf{m}) |
| 1 | 25 | 25 | 5.25 |
| 2 | 23 | 23 | 5 |
| 3 | 21 | 21 | 4.75 |
| 4 | 20 | 20 | 4.5 |
| 5 | 19 | 19 | 4.25 |
| 6 | 17 | 17 | 4 |
| 7 | 15 | 15 | 3.75 |
| 8 | 14 | 14 | 3.5 |

 $\label{eq:table basis} \textbf{Table 8. List of the available profiles for double-layer grid.}$

| No | o. OD ^a | \mathbf{T}^{b} | No. | OD | т | No. | OD | Т |
|----|--------------------|---------------------------|-----|-------|------|-----|-------|------|
| 1 | 4.83 | 0.26 | 12 | 11.43 | 0.36 | 23 | 21.91 | 0.45 |
| 2 | 6.03 | 0.29 | 13 | 13.3 | 0.4 | 24 | 21.91 | 0.45 |
| 3 | 7.61 | 0.29 | 14 | 13.3 | 0.4 | 25 | 24.45 | 0.63 |
| 4 | 7.61 | 0.29 | 15 | 13.97 | 0.4 | 26 | 24.45 | 0.63 |
| 5 | 8.89 | 0.32 | 16 | 13.97 | 0.4 | 27 | 27.3 | 0.63 |
| 6 | 8.89 | 0.32 | 17 | 15.9 | 0.45 | 28 | 27.3 | 0.63 |
| 7 | 10.16 | 0.36 | 18 | 15.9 | 0.45 | 29 | 32.39 | 0.71 |
| 8 | 10.16 | 0.36 | 19 | 16.86 | 0.45 | 30 | 35.56 | 0.8 |
| 9 | 10.8 | 0.36 | 20 | 16.86 | 0.45 | 31 | 40.64 | 0.88 |
| 10 | 10.8 | 0.36 | 21 | 19.37 | 0.45 | 32 | 45.72 | 1 |
| 11 | 11.43 | 0.36 | 22 | 19.37 | 0.45 | | | |

^a: OD: Outer Diameter (cm); ^b: T: Thickness.

density is 7850 kg/m² and external uniform distributed load is assumed to be 180 kg/m². The results obtained from the best 20 implementations and the results of previous studies are given in Tables 9 and 10. Figure 11 shows the optimized structure.



Figure 11. The topology obtained for double-layer grid with 57m×57m dimensions: (a) Double-layer grid; (b) upper layer; (c) diagonal layer; and (d) lower layer.

The topology obtained for double-layer grid in terms of structural engineering is remarkable, because this optimum topology is similar to the plate topology demonstrated in Figure 12 which is obtained from Ref. [23].

6. Conclusions

In this study, in order to achieve the efficient results for optimization of truss structures, genetic algorithm has been improved. First, the design space has been efficiently searched in the neighborhood of optimum solution by generating the new samples in the neighborhood of the best obtained sample. For selecting the next generation, in addition to considering the fitness function of population, the possible solutions have also been considered. This makes the algorithm to have possible solutions which satisfy the constraints,



Figure 12. Topology optimization of plate: (a) Base structure; and (b) optimum structure.

| | ACO [22] | MMA-ACO [22] |] | Proposed meth | nod |
|-------------------------------------|---------------|-----------------|-----------|---------------|---------------|
| | The best | The best | Runs no. | Average | The best |
| | weight (kg) | weight (kg) | ituns no. | weight (kg) | weight (kg) |
| Size optimization | 97335 | 97335 | - | - | - |
| Size & topology optimization | 85036 | 81927 | - | - | - |
| Size, shape & topology optimization | - | - | 3 | 76204.47 | 73960.453 |

Table 9. Comparison of optimal designs for double-layer grid.

| Table 10. | Optimal | charact | eristics | for | doul | ble-layer | grid. |
|-----------|---------|---------|----------|-----|------|-----------|-------|
|-----------|---------|---------|----------|-----|------|-----------|-------|

| | MMA-ACO (size & topology) [22] | GA (size, shape & topology) |
|---------------------------------------|-----------------------------------|--------------------------------|
| Mesh no. in <i>x</i> -direction | 19 | 14 |
| Mesh no. in y -direction | 19 | 14 |
| Height between two layers | 450 | 500 |
| No. of groups of compressive members | 14 | 12 |
| No. of groups of tensional members | 3 | 5 |
| No. of nodes in initial topology | 841 | 481 |
| No. of nodes in optimized topology | 653 | 410 |
| No. of elements in initial topology | 3200 | 1800 |
| No. of elements in optimized topology | 2552 | 1226 |

so that there is no need to run again. This subject looks essential in large-scale structures which require a lot of analysis time. Also, adaptive setting of genetic algorithm parameters, based on fuzzy inference system, causes improvement of the algorithm to achieve the optimum solution and to avoid the premature convergence.

Efficient selection of design variables in doublelayer grids has a great influence on the weight of the structure. The most effective variables in double-layer grids are the height between two layers, the structure meshing in two directions, presence or absence of nodes and the members cross sectional areas. For this purpose, simultaneous optimization of size, shape and topology of double-layer grids has been performed using the mentioned modifications on GA. The results demonstrate that the proposed method for optimum design of double-layer grids is efficient and can be used in practical problems.

References

- Lee, K.S. and Geem, Z.W. "A new structural optimization method based on the harmony search algorithm", *Computers & Structures*, 82(9), pp. 781-798 (2004).
- Camp, C.V. "Design of space trusses using Big Bang-Big crunch optimization", *Journal of Structural Engi*neering, 133(7), pp. 999-1008 (2007).
- Kaveh, A. and Shojaee, S. "Optimal design of skeletal structures using ant colony optimization", *International Journal for Numerical Methods in Engineering*, 70(5), pp. 563-581 (2007).
- Perez, R.E. and Behdinan, K. "Particle swarm approach for structural design optimization", Computers & Structures, 85(19), pp. 1579-1588 (2007).
- Li, L.J., Huang, Z.B. and Liu, F. "A heuristic particle swarm optimization method for truss structures with discrete variables", *Computers & Structures*, 87(7), pp. 435-443 (2009).
- Kaveh, A. and Talatahari, S. "A particle swarm ant colony optimization for truss structures with discrete variables", *Journal of Constructional Steel Research*, 65(8), pp. 1558-1568 (2009a).
- Dede, T., Bekiroğlu, S. and Ayvaz, Y. "Weight minimization of trusses with genetic algorithm", *Applied* Soft Computing, 11(2), pp. 2565-2575 (2011).
- Kaveh, A. and Servati, H. "Design of double-layer grids using backpropagation neural networks", *Computers & Structures*, 79(17), pp. 1561-1568 (2001).
- Salajegheh, E. and Gholizadeh, S. "Optimum design of structures by an improved genetic algorithm using neural networks", *Advances in Engineering Software*, 36(11), pp. 757-767 (2005).
- Gholizadeh, S., Torkzadeh, P. and Jabarzadeh, S. "Optimum shape design of double-layer grids by quantum behaved particle swarm optimization and neural

networks", International Journal of Optimization in Civil Engineering, $\mathbf{3}(1)$, pp. 85-98 (2013).

- 11. Gholizadeh, S. and Barzegar, A. "Shape optimization of structures for frequency constraints by sequential harmony search algorithm", *Engineering Optimization*, **45**(6), pp. 627-646 (2013).
- Gholizadeh, S. "Layout optimization of truss structures by hybridizing cellular automata and particle swarm optimization", *Computers & Structures*, **125**, pp. 86-99 (2013).
- Kirsch, U., Optimum Structural Design: Concepts, Methods, and Applications, McGraw-Hill New York (1981).
- Kaveh, A. and Talatahari, S. "Size optimization of space trusses using Big Bang-Big crunch algorithm", *Computers & Structures*, 87(17), pp. 1129-1140 (2009b).
- 15. Nezamabadi-pour, H., Genetic Algorithm: The Basic Concept and Advanced Topics, Shahid Bahonar University of Kerman (2010).
- 16. AISC Manual, American institute of steel construction (2005).
- Wu, Sh.J. and Chow, P.T. "Steady-state genetic algorithms for discrete optimization of trusses", Computers & Structures, 56(6), pp. 979-991 (1995).
- Lee, K.S., Geem, Z.W., Lee, S.H. and Bae, K.W. "The harmony search heuristic algorithm for discrete structural optimization", *Engineering Optimization*, **37**(7), pp. 663-684 (2005).
- Rajan, S.D. "Sizing, shape, and topology design optimization of trusses using genetic algorithm", *Journal of Structural Engineering*, **121**(10), pp. 1480-1487 (1995).
- 20. Tang, W., Tong, L. and Gu, Y. "Improved genetic algorithm for design optimization of truss structures with sizing, shape and topology variables", *International Journal for Numerical Methods in Engineering*, **62**(13), pp. 1737-1762 (2005).
- Rahami, H., Kaveh, A. and Gholipour, Y. "Sizing, geometry and topology optimization of trusses via force method and genetic algorithm", *Engineering Structures*, **30**(9), pp. 2360-2369 (2008).
- Mashayekhi, M. "Reliability-based topology optimization of space structures using advanced optimization methods", Ph.D. Thesis, Shahid Bahonar University of Kerman (2011).
- Luo, Y., Kang, Z., Luo, Z. and Li, A. "Continuum topology optimization with non-probabilistic reliability constraints based on multi-ellipsoid convex model", *Structural and Multidisciplinary Optimization*, **39**(3), pp. 297-310 (2009).

Biographies

Peyman Torkzadeh is Assistant Professor of Department of Civil Engineering, Faculty of Engineering, Shahid Bahonar University of Kerman. He has over 50 papers in various journals and conferences. His researches have been in structural optimization, numerical modeling and seismic design of structures, structural health monitoring and structural damage detection.

Taghi Jaffari received his MSc degree in Structural Engineering from Graduate University of Advanced Technology, Kerman, in 2013. His research interests include metaheuristic optimization techniques. He has published a number of papers in journals. Saeed Shojaee obtained his BS degree from Shahid Bahonar University of Kerman, in 2001, and his MS and PhD degrees in Structural Engineering from Iran University of Science and Technology in 2003 and 2007, respectively. He is currently Associate Professor in the Department of Civil Engineering at Shahid Bahonar University in Kerman, Iran. His main research interests include: optimal analysis and design of structures, metaheuristic optimization techniques and applications, computational mechanics and seismic design of structures.