Scientia Iranica A (2013) 20(6), 1612–1625

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

A new accelerated firefly algorithm for size optimization of truss structures

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Received 7 July 2012; received in revised form 18 April 2013; accepted 28 May 2013

KEYWORDS
Firefly algorithm;
Truss structures;
Size optimization;
Metaheuristics.

Abstract. An Accelerated Firefly Algorithm (AFA) for fast size optimization of truss structures is proposed in this paper. Metaheuristic firefly algorithm has been recently developed and its effectiveness in solving practical problems such as sizing optimization of truss structures has not been thoroughly explored. The numerical experiments show that although the standard Firefly Algorithm (FA) is a powerful approach for truss optimization, it suffers from slow rate of convergence, and hence it should be modified to solve real-life problems. The proposed AFA imposes some improvements on the searching procedure by both reduction of randomness and scaling the random term in fireflies' motion. The effectiveness and robustness of the algorithm are investigated by solving some benchmark problems. The results revealed that the proposed AFA remarkably enhances the rate of convergence and stability of standard firefly algorithm.

1. Introduction

Trusses are among the most widely-used structures in civil engineering projects. The overall cost of a truss can be reduced by optimizing size, topology and configuration of the truss. Hence, optimization of truss structures has usually been an interesting subject for many researchers. For many years, the most popular and sophisticated optimization method, in engineering applications in general, and in truss optimization in particular, has been Genetic Algorithm (GA) [1-7]. Recently, other nature-inspired metaheuristic algorithms such as Ant Colony Optimization (ACO) [8-10] and Particle Swarm Optimization (PSO) [11-15] are gradually taking the place of traditional GA because of their robustness and simplicity at the same time. Other well-known population-based optimization methods include Harmony Search (HS) [16-18], Simulated Annealing (SA) [19-20], and Charged System Search algorithm (CSS) [21].

All aforementioned evolutionary optimization methods start the search with initial solution candidates. These candidates are technically called chromosomes (in GA), particles (in PSO) and so on; depending on the algorithm being used. The collection of candidates is called population (in GA), swarm (in PSO) and so on. Then, the algorithm tries to modify the solution via an iterative procedure to enhance the fitness of the objective function. Unfortunately, most iterative optimization algorithms undergo slow rate of convergence even in simple practical problems with a few design variables. For real-life problems such as planar or spatial trusses with many members, the searching space is very extensive. Therefore, the computational effort of finding the optimal solution is high and hence, the optimization algorithm may fail to find the solution even after a large number of iterations. For this reason, many researchers are tried to enhance the

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iterative optimization methods to make them suitable to solve practical problems [12,13,17,18,22].

Firefly Algorithm (FA) is one of the most recently developed nature-inspired metaheuristic algorithms. The algorithm was first developed by Yang (2008) [22] inspired by the light attenuation over the distance and fireflies' mutual attraction. Despite of having very attractive strategy, very few articles can be found in the literature concerning the application of firefly algorithm in structural optimization problems. Gandomi et al. [23] used firefly algorithm to solve mixed continuous and discrete structural optimization problems. Gomes employed FA for shape and size optimization of structures including dynamic constraints [24]. Kazemzadeh Azad and Kazemzadeh Azad tried to improve the efficiency of firefly algorithm for optimization of trusses [25]. Gandomi et al. [26] introduced chaos in firefly algorithm to increase its global search mobility.

Similar to other iterative optimization techniques, firefly algorithm undergoes slow convergence rate. In this paper, an Accelerated Firefly Algorithm (AFA) is proposed in order to successfully overcome this intrinsic drawback of the algorithm and to turn it into a powerful tool for optimization of truss structures involving constraints. The new algorithm modifies the movement of fireflies by reduction of randomness as well as a simple scaling technique which are found to be very effective in reducing the number of iterations required to find the optimal solution. The effectiveness and robustness of the method are investigated by solving some benchmark problems. In order to separately investigate the effect of each modification on the search capability of the algorithm, all problems are solved using standard Firefly Algorithm (FA), standard firefly algorithm with reduction of randomness (FA-R), and the proposed Accelerated Firefly Algorithm (AFA). Standard tests including statistical studies are carried out for each problem to thoroughly investigate the effectiveness and stability of the proposed approach. The rest of the paper is organized as follows.

In Section 2 the problem of size optimization of truss structures is defined. In Section 3 an overview on standard firefly algorithm is presented. Section 4 describes the modifications needed to improve FA and presents the Accelerated Firefly Algorithm (AFA). Section 5 deals with penalty function formulation which will be used in all firefly algorithms for constrain handling. In Section 6 some design examples are presented and effectiveness of the proposed technique is investigated. Finally, in Section 7 summary and conclusion are included.

2. Problem formulation

Weight optimization of pin connected structures with axially loaded members involves optimizing cross sections A_i of the members such that the weight of the structure W is minimized and some constraints with respect to design criteria are satisfied as follows:

Minimize:

$$W(A) = \sum_{k=1}^{\mathrm{ng}} A_k \sum_{i=1}^{mk} \rho_i L_i. \tag{1}$$

Subject to:

$$\sigma_{\mathrm{low}} \leq \sigma_i \leq \sigma_{\mathrm{up}}, \qquad i = 1, 2, \cdots, \mathrm{nm}, \tag{2}$$

$$\sigma_i^b \leq \sigma_i \leq 0, \qquad i = 1, 2, \cdots, \mathrm{ncm}, \tag{3}$$

$$\delta_{\mathrm{low}} \leq \delta_i \leq \delta_{\mathrm{up}}, \qquad i = 1, 2, \cdots, \mathrm{nn}, \tag{4}$$

$$A_{\mathrm{low}} \leq A_i \leq A_{\mathrm{up}}, \qquad i = 1, 2, \cdots, \mathrm{ng}, \tag{5}$$

in which A is the vector containing the design variables (i.e. cross sections $A = \{A_1, A_2, \cdots, A_{\mathrm{ng}}\}$), $W(A)$ is the weight of the truss structure, ρ_i is the density of member i, L_i is the length of member i, nm is the number of members in the structure, ncm is the number of compression members, nn is the number of nodes, ng is the total number of member groups (i.e. design variables), A_k is the cross-sectional area of the members belonging to group k, mk is the total number of members in group k, σ_i is the stress of the ith member, σ_i^b is the allowable buckling stress for the ith member, δ_i is the displacement of the ith node, and low and up are the lower and upper bounds for stress, displacement and cross-sectional area.

3. An overview on firefly algorithm

The Firefly Algorithm (FA) is one of the latest metaheuristic algorithms. Firefly algorithm is a nature-inspired algorithm, which was first developed by Yang [22] inspired by the light attenuation over the distance and fireflies' mutual attraction. In the algorithm, fireflies try to move to a greater light source than their own. Firefly algorithm idealizes some of the characteristics of the firefly behavior in nature. They follow three rules:

i) All the fireflies are unisex.
ii) Attractiveness is proportional to their flashing brightness which decreases as the distance from the other firefly increases due to the fact that the air absorbs light. The most attractive firefly is the brightest one which convinces neighbors to move toward him. In case of no brighter one, it freely moves in any direction.
iii) Brightness of every firefly determines its quality of solution; in most of the cases, it is proportional to the objective function.

Firefly algorithm starts with initializing a swarm of fireflies, each of which is determined by the flashing light intensity. During the loop of pairwise comparison of light intensities, the firefly with lower light intensity moves toward the higher one. The moving distance depends on the attractiveness. After moving, the new firefly is evaluated and updated for the light intensity. During pairwise comparison loop, the best-so-far solution is iteratively updated. The pairwise comparison process is repeated until termination criteria are satisfied. Finally, the best-so-far solution is visualized.

To define the most important parameters in firefly algorithm suppose a night with absolute darkness where the only visible light is the light produced by fireflies. The light intensity of each firefly is proportional to the quality of the solution it is currently located at. In order to improve his own solution, the firefly needs to advance towards the fireflies that have brighter light emission than his own.

Although the theoretical background of firefly algorithm can be found in Yang's article [22], a brief overview is presented as follows.

In firefly algorithm it is assumed that the attractiveness β of a firefly is determined by its brightness I which in turn is associated with the objective function. The attractiveness β varies with the distance r_{ij} between firefly i and firefly j. Moreover, from a physical point of view, light intensity decreases with the distance from its source, and light is also absorbed in the media. Hence, the light intensity $I(r)$ can be assumed to vary according to inverse square law [22]:

$$I(r) = \frac{I_s}{r^2}, \tag{6}$$

in which I_s is the intensity at the source. For a medium with a fixed light absorption coefficient, γ, the light intensity I varies with the distance as:

$$I(r) = I_0 \exp(-\gamma r), \tag{7}$$

where I_0 is the original light intensity. To avoid singularity at $r = 0$ in Eq. (6), the combined effect of both the inverse square law and absorption is approximated by the following Gaussian form:

$$I(r) = I_0 \exp(-\gamma r^2). \tag{8}$$

Since the attractiveness of a firefly is proportional to the light intensity observed by neighbor fireflies, the attractiveness, β, of a firefly is defined as:

$$\beta = \beta_0 \exp(-\gamma r^2), \tag{9}$$

in which, β_0, is the attractiveness in distance $r = 0$ and γ is light absorption coefficient in the range $[0, \infty)$. The distance r between firefly i and j at x_i and x_j, is defined as Cartesian distance:

$$r = r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2}, \tag{10}$$

where $x_{i,k}$ is the kth component of the spatial coordinate, x_i, of the ith firefly and d is the number of dimensions. Finally, the movement of firefly i which is attracted by a more attractive or brighter firefly j is given by the following equation:

$$x_i = x_i + \beta_0 \exp(-\gamma r^2)(x_j - x_i) + \alpha(\epsilon - 0.5), \tag{11}$$

where the second term is due to the attraction. The third term is randomization with α being the randomization parameter such that $\alpha \in [0, 1]$, and ϵ is a vector of random numbers drawn from a Gaussian distribution or uniform distribution in the range $[0, 1]$. Furthermore, for most problems, one can take $\beta_0 = 1$.

In the case of size optimization of trusses, the cross-sectional areas of bars are considered as design variables to be optimized with d being the number of bars in the truss. The formulation of standard firefly algorithm, i.e. Eq. (11), is denoted by FA throughout the manuscript.

4. Accelerated Firefly Algorithm (AFA)

Similar to most other metaheuristic optimization techniques, the standard firefly algorithm suffers from slow rate of convergence. This means that for real-world problems with many design variables, the structure should be analyzed several times with no guaranty to achieve the optimal solution. Our experiments on standard firefly algorithm revealed that even for simple truss structures a large number of iterations (about 3000 iterations) are required to obtain a solution. If the initial population has a number o,f say, 50 fireflies, the overall 150,000 structural analyses are needed.

In this section some modifications on standard firefly algorithm are proposed that can remarkably improve the performance and the rate of convergence of the firefly algorithm. These modifications include gradual reduction of randomness and scaling the random term. The aforementioned procedures are presented in the following subsections.

4.1. Gradual randomness reduction

The first modification of firefly algorithm is to adjust the randomization parameter, α, in Eq. (11), so as it gradually decreases as the solution is approached. Consider:

$$\alpha = \alpha_0 \theta^t, \tag{12}$$

in which $t \in [0, t_{\max}]$ is the simulation time (iteration) and $t_{\max}$ is the maximum number of iterations.

Moreover, α_0 is the initial randomization parameter and $\theta \in (0,1]$ is the randomization reduction constant. Applying Eq. (12) in Eq. (11) gives:

$$x_i = x_i + \beta_0 \exp(-\gamma r^2)(x_j - x_i) + \alpha_0 \theta^t (\epsilon - 0.5). \tag{13}$$

The formulation of Eq. (13), which imposes reduction of randomness in the standard firefly algorithm, is denoted by FA-R in this paper.

The idea of decreasing randomization, as the iteration proceeds, is actually not new and it has been already employed [23,26].

4.2. Scaling the random term

The main new idea in improving the rate of convergence of firefly algorithm is scaling. The random term (third term in Eq. (13)) can be further modified by defining a scaling parameter λ as the difference between lower bound and upper bound of design variables as:

$$\lambda = (\text{Upper variable boundary} - \text{lower variable boundary}). \tag{14}$$

This is a general formula proposed for λ which can be used in any optimization problem. For the problem at hand, according to the variables boundary defined in Eq. (5), the above equation can be written as:

$$\lambda = A_{\text{up}} - A_{\text{low}}. \tag{15}$$

Then, the random term in Eq. (13) can be further modified using λ as:

$$x_i = x_i + \beta_0 \exp(-\gamma r^2)(x_j - x_i) + \lambda \alpha_0 \theta^t (\epsilon - 0.5). \tag{16}$$

Eq. (16) is the basic formula for the proposed Accelerated Firefly Algorithm (AFA). The pseudo code for accelerated firefly algorithm is given in Table 1.

5. Constraints handling

Most optimization problems contain specified constraints which should be satisfied. In the case of truss structures, according to Eqs. (2) through (5), some constraints have been defined. The problem-specified constraints (Eqs. (2)-(4)) usually dictate constraints on the magnitude of stress within the bar elements or nodal displacements. Variable constraints (Eq. (5)) usually indicate that the design variables should be chosen within a specified range due to availability of cross-sectional areas of bars. The most popular

Table 1. The pseudo code for Accelerated Firefly Algorithm (AFA).

```
Objective function f(x), x = (x_1, x_2, ..., x_d)^T   d = no. of design variables
Generate initial population of fireflies randomly X^i, i = 1, 2, ..., n   n = no. of fireflies
Light intensity I_i at x^i is determined by f(x^i)
Define light absorption coefficient γ
Define randomness reduction constant θ
Define initial randomization parameter α_0
Define attractiveness at (r = 0), β_0
Calculate scaling parameter λ = (upper variable boundary − lower variable boundary)
while t maximum number of generation or convergence criteria met
Calculate α = α_0 θ^t
    for i = 1 to n
        for j = 1 to n
            if (I_i > I_j)
                Calculate the distance r_ij = ||x^i − x^j||
                Calculate β = β_0 exp(−γ r_ij^2)
                Generate random number vector ε_i
                Update design variable x^i = x^i + β(x_j − x_i) + αλε_i
            end if
        end for j
    end for i
    Rank the fireflies and find the current global best
end while
Postprocess results and visualization
```

method for handling constraints in optimization algorithms is penalty function formulation. The method has been already employed successfully to deal with constraints [11,23-25]. The main reason of popularity of the method is its simplicity and its direct applicability regardless of the optimization method being used. Therefore, the method can also be used in firefly algorithm. This formulation utilizes general information of the swarm of fireflies, such as the average of the objective function and the level of violation of each constraint in each iteration, in order to define different penalties for different constraints. The basic equation is [11]:

$$f'(x) = \begin{cases} f(x) & \text{if } x \text{ is feasible} \\ f(x) + \sum\limits_{i=1}^{m} k_i \bar{g}_l(x) & \text{otherwise} \end{cases} \tag{17}$$

in which k_i is penalty parameter and is calculated in each iteration by:

$$k_i = \left|\bar{f}(x)\right| \frac{\bar{g}_i(x)}{\sum_{j=1}^{m} \left[\bar{g}_j(x)\right]^2}, \tag{18}$$

with $f(x)$ being the objective function and m being the number of constraints. Moreover, in firefly algorithm $g_i(x)$ is specific constraint value so that violated constraints have values greater than zero, $\bar{f}(x)$ is the average of objective function in current fireflies and $\bar{g}_i(x)$ is the violation of the ith constraint averaged over the current swarm of fireflies.

The illustration of Eq. (17) is that the problem is actually solved as an unconstrained one, where in minimization case, the objective function is designed such that non-feasible solutions are characterized by high function values.

6. Design examples

To study the effectiveness of the proposed accelerated firefly algorithm in optimal design of truss structures, three benchmark problems are presented and are fully discussed in various aspects in terms of computational effort, stability and optimal results. Moreover, from a technical point of view, in order to study the effect of each modification on the results and to distinguish the strategies, each problem is optimized using three different algorithms, i.e. standard firefly algorithm (FA, Eq. (11)), firefly algorithm with the reduction of randomness (FA-R, Eq. (13)), and the proposed accelerated firefly algorithm (AFA, Eq. (16)). Generally, the parameters of firefly algorithm depend on the optimization problem and appropriate values should be found to suit the problem by a trial and error procedure. For most problems in sizing optimization of truss structures, we found that the values of $\theta = 0.97$, $\gamma = 0.05$, $\beta_0 = 1$ and $\alpha_0 = 1$ are suitable to be used in the algorithm. Furthermore, in all examples, the initial swarm contains 100 fireflies.

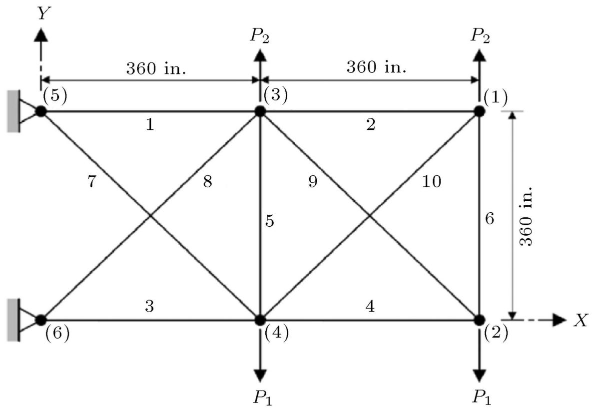

Figure 1. A 10-bar planar truss structure.

A finite element code was developed to analyze the planar and spatial trusses. The results are compared with the results obtained by other researchers as well.

6.1. 10-bar planar truss

The well-known planar 10-bar truss shown in Figure 1 has been analyzed by many researchers to test the efficiency and robustness of various optimization algorithms [11,12,16-18,27-31]. The material density of all members was 0.1 lb/in^3 and the Young's modulus of elasticity was 10,000 ksi. The maximum allowable stress in all bars was ±25 ksi with nodal displacement limitations of ±2.0 inches for both directions. The minimum cross-sectional area of each bar element was 0.1 in^2. The weight optimization of truss have been studied for two cases: Case 1 with $p_1 = 100$ kips and $p_2 = 0$; Case 2 with $p_1 = 150$ kips and $p_2 = 50$ kips.

Table 2 reports the results of optimizing the truss using FA, FA-R and AFA and the results found by other studies for Case 1. The cross-sectional areas found by each algorithm are included for comparison. As reported in Table 2 for Case 1, the weight of optimal structure is 5060.14 lb, 5060.07 lb, and 5059.22 lb for FA, FA-R and AFA, respectively. The results show that the proposed AFA leads to a lighter structure than FA and FA-R. The structure found by AFA is the lightest structure among the structures reported in Table 2 for Case 1. Moreover, the structural analyses required to obtain the optimal structure is dramatically reduced from 62675 analyses for FA to 23325 analyses for FA-R, and only 8000 analyses for AFA. The table also shows that although the reduction of randomness in firefly algorithm (FA-R) can improve the rate of convergence of FA, it is not yet competitive with AFA from this aspect. The rates of convergence of the three algorithms are compared in Figure 2. As the figure shows, the rate of convergence of FA-R is lower than

Table 2. Comparison of optimal designs for the 10-bar planar truss structure (Case 1).

Variables		Sedaghati [27]	Farshi and Alinia-ziazi [28]	Lamberti and Pappalettere [29]	Li et al. [12]			Degertekin [17]		This study		
		Optimal cross-sectional areas (in^2)										
		HS	PSO	IHS	PSO	PSOPC	HPSO	EHS	SAHS	FA	FA-R	AFA
1	A_1	30.5218	30.5208	30.5222	33.469	30.569	30.704	30.208	30.394	30.968	30.374	30.301
2	A_2	0.1000	0.1000	0.1000	0.110	0.100	0.100	0.100	0.100	0.100	0.100	0.100
3	A_3	23.1999	23.2040	23.2005	23.177	22.974	23.167	22.698	23.098	23.215	23.766	23.203
4	A_4	15.2229	15.2232	15.2232	15.475	15.148	15.183	15.275	15.491	15.043	15.050	15.207
5	A_5	0.100	0.1000	0.1000	3.649	0.100	0.100	0.100	0.100	0.100	0.100	0.100
6	A_6	0.5514	0.5515	0.5513	0.116	0.547	0.551	0.529	0.529	0.591	0.621	0.5366
7	A_7	7.4572	7.4669	7.4572	8.328	7.493	7.460	7.558	7.488	7.453	7.390	7.441
8	A_8	21.0364	21.0342	21.0368	23.340	21.159	20.978	21.559	21.189	20.866	20.742	20.984
9	A_9	21.5284	21.5294	21.5288	23.014	21.556	21.508	21.491	21.342	21.461	21.652	21.739
10	A_{10}	0.1000	0.1000	0.1000	0.190	0.100	0.100	0.100	0.100	0.100	0.100	0.100
Weight (lb)		5060.85	5061.40	5060.82	5529.50	5061.00	5060.92	5062.39	5061.42	5060.14	5060.07	5059.22
No of analyses		N/A	N/A	N/A	150000	150000	125000	9791	7081	62675	23325	8000

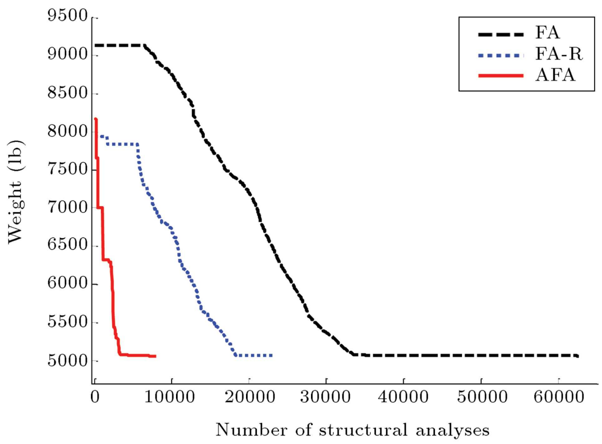

Figure 2. Comparison of the convergence rates of the three algorithms for the 10-bar planar truss structure (Case 1) .

AFA and higher than FA. To study the robustness of the algorithms, the statistical results of 50 independent runs of these three algorithms for Case 1 are reported in Table 3. Figure 3 compares the optimal weights found by each algorithm after these 50 independent runs. As it is clear from Table 3, AFA gives the best performance among the aforementioned algorithms. The mean value of the weight and number of structural analyses are considerably decreased by employing AFA. The least values of the standard deviation of weight and the associated coefficient of variations after 50 runs indicate better stability of the proposed algorithm than FA and FA-R. Figure 3 shows that the proposed AFA is more stable than FA and FA-R. Table 4 reports the optimal

Table 3. Comparison of statistical results for fifty independent runs of the three algorithms for the 10-bar planar truss structure (Case 1).

		Mean	Standard deviation	Coefficient of variation (%)
FA	Weight (lb)	5081.242	9.431	0.185
	No of analyses	53196	14088.48	26.48
FA-R	Weight (lb)	5071.448	7.665	0.151
	No of analyses	19483.5	4347.201	22.31
AFA	Weight (lb)	5061.791	2.955	0.058
	No of analyses	8720	3028.81	34.73

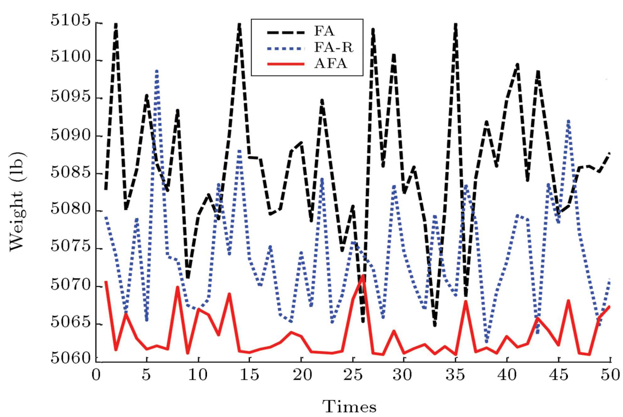

Figure 3. Comparison of the stability of the three algorithms for the 10-bar planar truss structure (Case 1).

Table 4. Comparison of optimal designs for the 10-bar planar truss structure (Case 2).

Variables		Optimal cross-sectional areas (in^2)											
		Lee and Geem [16]	Schmit and Farshi [30]	Kaveh and Talatahari [18]	Rizzi [31]	Li et al. [12]			Degertekin [17]		This study		
		HS		HPSACO		PSO	PSOPC	HPSO	EHS	SAHS	FA	FA-R	AFA
1	A_1	23.25	24.29	23.194	23.53	22.935	23.743	23.353	23.589	23.525	23.891	23.702	23.707
2	A_2	0.102	0.100	0.100	0.100	0.113	0.101	0.100	0.100	0.100	0.100	0.100	0.100
3	A_3	25.73	23.35	24.585	25.29	25.355	25.287	25.502	25.422	25.429	25.598	25.371	25.352
4	A_4	14.51	13.66	14.221	14.37	14.373	14.413	14.250	14.488	14.488	14.234	14.285	14.270
5	A_5	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
6	A_6	1.977	1.969	1.969	1.97	1.990	1.969	1.972	1.975	1.992	1.988	1.997	1.969
7	A_7	12.21	12.67	12.489	12.39	12.346	12.362	12.363	12.362	12.352	12.375	12.446	12.352
8	A_8	12.61	12.54	12.925	12.83	12.923	12.694	12.894	12.682	12.698	12.773	12.843	12.691
9	A_9	20.36	21.97	20.952	20.33	20.678	20.323	20.356	20.322	20.341	20.043	20.143	20.408
10	A_{10}	0.100	0.100	0.101	0.100	0.100	0.103	0.101	0.100	0.100	0.100	0.100	0.100
Weight (lb)		4668.81	4691.84	4675.78	4676.92	4679.47	4677.70	4677.29	4679.02	4678.84	4678.64	4678.09	4677.01
No of analyses		15000	N/A	9925	N/A	150000	150000	125000	11402	7267	64800	30625	7760

Table 5. Comparison of statistical results for fifty independent runs of the three algorithms for the 10-bar planar truss structure (Case 2).

		Mean	Standard deviation	Coefficient of variation (%)
FA	Weight (lb)	4738.081	83.312	1.758
	No of analyses	54893.00	15437.20	28.12
FA-R	Weight (lb)	4711.657	37.602	0.798
	No of analyses	18754.50	5286.56	28.19
AFA	Weight (lb)	4685.650	4.575766	0.097
	No of analyses	7668.8	2280.29	29.73

cross-sectional areas obtained by this study and other studies for Case 2. The weights of structures are 4678.64, 4678.09, and 4677.01 for FA, FA-R and AFA, respectively. The results are very satisfactory and close to those found by using other techniques. The rates of convergence of FA, FA-R and AFA for 10-bar planar truss are compared in Figure 4 for Case 2. As Figure 4 shows, AFA has improved the rate of convergence of both FA and FA-R. Statistical results reported in Table 5 for the three algorithms after 50 independent runs also indicate better performance of AFA than FA and FA-R for this case as well. Figure 5 compares the weight of the structure obtained using each of the algorithms for 50 independent runs to investigate the stability of each algorithm. As the figure indicates, the stability of AFA is more than both FA-R and FA by producing very close results after each run.

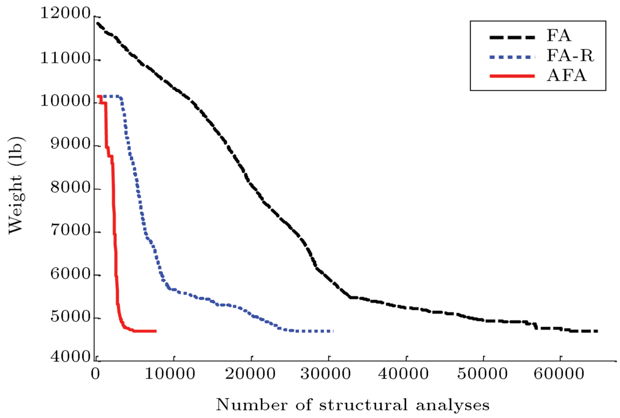

Figure 4. Comparison of the convergence rates of the three algorithms for the 10-bar planar truss structure (Case 2).

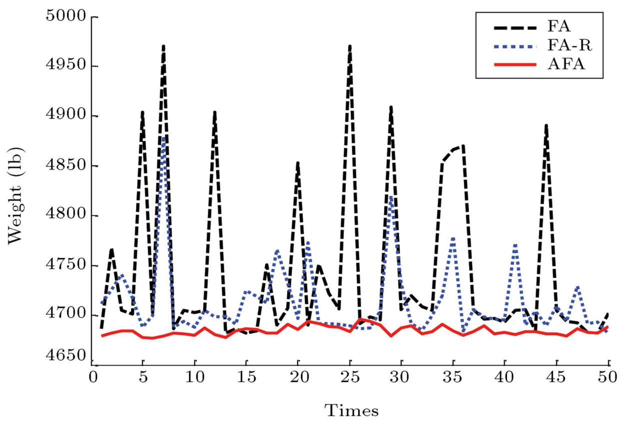

Figure 5. Comparison of the stability of the three algorithms for the 10-bar planar truss structure (Case 2).

6.2. 25-bar space truss structure

Figure 6 shows the 25-bar spatial truss in which modulus of elasticity of the material was 10,000 ksi and its density was 0.1 lb/in^3. Table 6 reports the two load cases examined for this example. The structure should satisfy the problem-specified constraints for both cases. The design variables of the structure are categorized in 8 groups, and the allowable stress values for all groups are listed in Table 7. All nodes in all directions are subjected to the displacement limits of ± 0.35 in. Moreover, the minimum cross-sectional area for each group of elements was 0.01 in^2.

Table 8 reports optimization results obtained for 25-bar truss by this study and by other researches [12,16-18,29,32]. As reported in Table 8, the optimal weight of 545.25 lb, 546.61 lb, and 544.75 lb were found by FA, FA-R, and AFA, respectively. The table shows that all three algorithms lead to very satisfactory results, close to results of other algorithms. However, the computational effort of AFA is very low compared to most other methods. Moreover, the optimal weight found by AFA is less than the weight of most other structures reported in Table 8. Figure 7 compares the rate of convergence of FA, FA-R and AFA, revealing remarkable improvement of FA in reducing the number of structural analyses required for convergence by using AFA. The results of optimal weights found by the three algorithms after 50 independent runs for 25-bar spatial truss structure is shown in Figure 8 and the associated statistical results are presented in Table 9. As Figure 8 and Table 9 show, AFA is very stable and robust compared to FA and FA-R.

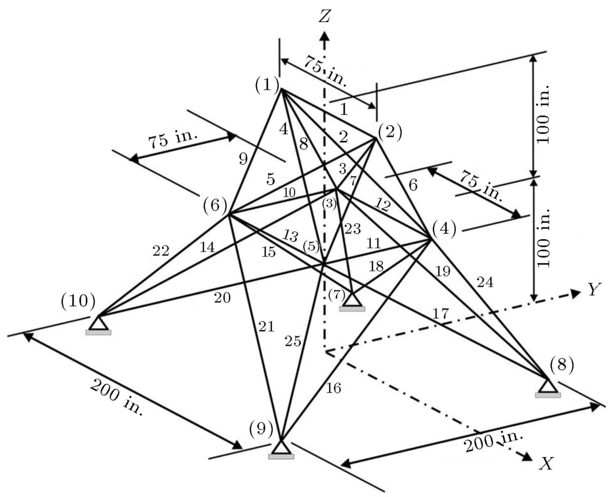

Figure 6. A 25-bar spatial truss structure .

Table 6. Load cases for the 25-bar spatial truss structure.

Node	Case 1 (Kips)			Case 2 (Kips)		
	P_x	P_y	P_z	P_x	P_y	P_z
1	0.0	20.0	-5.0	1.0	10.0	-5.0
2	0.0	-20.0	-5.0	0.0	10.0	-5.0
3	0.0	0.0	0.0	0.5	0.0	0.0
6	0.0	0.0	0.0	0.5	0.0	0.0

Table 7. Member stress limits for the 25-bar spatial truss structure.

Variables		Compressive stress limitations (Ksi)	Tensile stress limitations (Ksi)
1	A_1	35.092	40.0
2	$A_2 \sim A_5$	11.590	40.0
3	$A_6 \sim A_9$	17.307	40.0
4	$A_{10} \sim A_{11}$	35.092	40.0
5	$A_{12} \sim A_{13}$	35.092	40.0
6	$A_{14} \sim A_{17}$	6.759	40.0
7	$A_{18} \sim A_{21}$	6.959	40.0
8	$A_{22} \sim A_{25}$	11.802	40.0

6.3. 72-bar spatial truss

The problem of weight optimization of 72-bar spatial truss structure shown in Figure 9 is presented in this

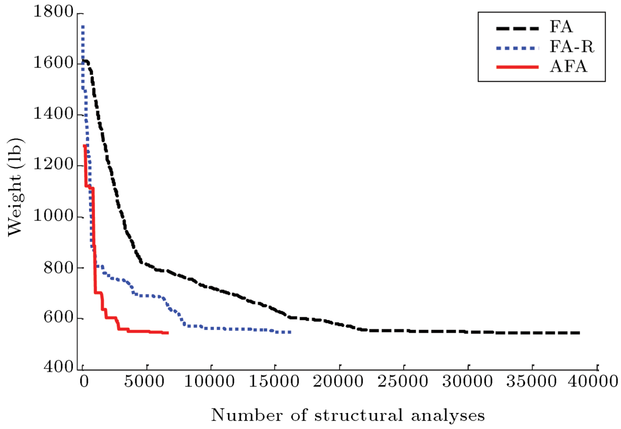

Figure 7. Comparison of the convergence rates of the three algorithms for the 25-bar spatial truss structure.

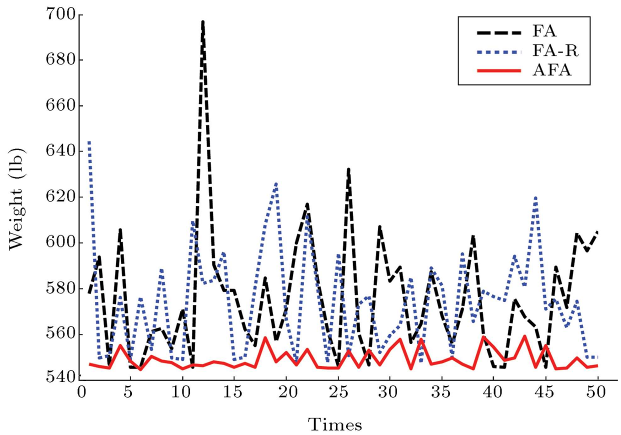

Figure 8. Comparison of the stability of the three algorithms for the 25-bar spatial truss structure.

Table 8. Comparison of optimal designs for the 25-bar spatial truss structure.

		Optimal cross-sectional areas (in^2)											
Variables		Lee and Geem [16]	Lamberti [29]	Kaveh and Talatahari [18]	Camp [32]	Li et al. [12]			Degertekin [17]		This study		
		HS	**CMLPSA**	**HPSACO**	**BB-BC**	**PSO**	**PSOPC**	**HPSO**	**EHS**	**SAHS**	**FA**	**FA-R**	**AFA**
1	A_1	0.047	0.0100	0.010	0.010	9.863	0.010	0.010	0.010	0.010	0.0100	0.0100	0.0100
2	$A_2 \sim A_5$	2.022	1.9870	2.054	2.092	1.798	1.979	1.970	1.995	2.074	1.9722	1.7785	1.9995
3	$A_6 \sim A_9$	2.950	2.9935	3.008	2.964	3.654	3.011	3.016	2.980	2.961	3.0074	3.1628	2.9598
4	$A_{10} \sim A_{11}$	0.010	0.0100	0.010	0.010	0.100	0.100	0.010	0.010	0.010	0.0100	0.0100	0.0100
5	$A_{12} \sim A_{13}$	0.014	0.0100	0.010	0.010	0.100	0.100	0.010	0.010	0.010	0.0100	0.0100	0.0100
6	$A_{14} \sim A_{17}$	0.688	0.6840	0.679	0.689	0.596	0.657	0.694	0.696	0.691	0.6852	0.7079	0.6904
7	$A_{18} \sim A_{2}1$	1.657	1.6769	1.611	1.601	1.659	1.678	1.681	1.679	1.617	1.6836	1.7934	1.6824
8	$A_{22} \sim A_{25}$	2.663	2.6621	2.678	2.686	2.612	2.693	2.643	2.652	2.674	2.6564	2.5671	2.6531
Weight (lb)		544.38	545.15	544.99	545.38	629.08	545.27	545.19	545.49	545.12	545.25	546.61	544.75
No of analyses		15000	N/A	9875	20566	150000	150000	125000	10391	9051	38775	16225	6750

Table 9. Comparison of statistical results for fifty independent runs of the three algorithms for the 25-bar spatial truss structure.

		Mean	Standard deviation	Coefficient of variation (%)
FA	Weight (lb)	575.806	27.813	4.830
	No of analyses	30904	8936.75	28.92
FA-R	Weight (lb)	574.430	23.213	4.041
	No of analyses	13974	1663.69	11.90
AFA	Weight (lb)	549.024	4.279	0.779
	No of analyses	6593	1653.97	25.08

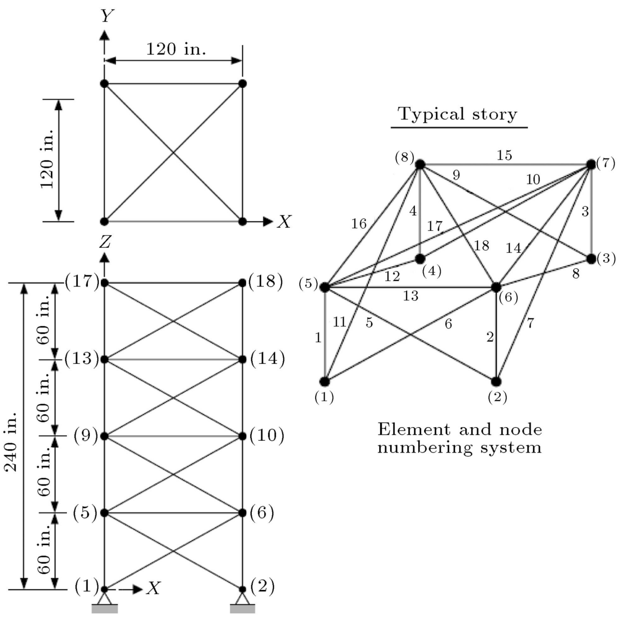

Figure 9. A 72-bar spatial truss structure.

section. This truss has been already investigated by many researchers [11,12,16-18,29,32,33]. The modulus of elasticity of the material was 10,000 ksi and material density was 0.1 lb/in^3. The cross-sectional areas of members as design variables are separated into 16 groups:

(1) A1-A4,	(2) A5-A12,
(3) A13-A16,	(4) A17-A18,
(5) A19-A22,	(6) A23-A30,
(7) A31-A34,	(8) A35-A36,
(9) A37-A40,	(10) A41-A48,
(11) A49-A52,	(12) A53-A54,
(13) A55-A58,	(14) A59-A66,
(15) A67-A70,	(16) A71-A72.

The maximum allowable stress in all members was equal in tension and compression and it was ± 25 ksi. Maximum allowable displacement of uppermost nodes was ± 0.25 inches in both x and y directions. Table 10 gives the two load cases for this example. This problem was analyzed for two cases: Case 1 in which minimum cross-sectional area of each members was 0.1 in^2, and Case 2 in which this value was 0.01 in^2.

Table 11 compares the optimal cross-sectional

Table 10. Load cases for the 72-bar spatial truss structure

Node	Case 1 (Kips)			Case 2 (Kips)		
	P_x	P_y	P_z	P_x	P_y	P_z
17	5.0	5.0	-5.0	0.0	0.0	-5.0
18	0.0	0.0	0.0	0.0	0.0	-5.0
19	0.0	0.0	0.0	0.0	0.0	-5.0
20	0.0	0.0	0.0	0.0	0.0	-5.0

Table 11. Comparison of optimal designs for the 72-bar spatial truss structure (Case 1).

Variables		Optimal cross-sectional areas (in^2)									
		Lee and Geem [16]	Perez and Behdinan [11]	Kaveh and Talatahari [18]	Camp [32]	Li et al. [12]	Degertekin [17]		This study		
		HS	PSO	HBB-BC	BB-BC	PSO	EHS	SAHS	FA	FA-R	AFA
1	$A_1 \sim A_4$	1.7901	1.7427	1.9042	1.8577	41.794	1.967	1.860	1.8898	2.0554	1.9046
2	$A_5 \sim A_{12}$	0.521	0.5185	0.5162	0.5059	0.195	0.510	0.521	0.5062	0.4894	0.5236
3	$A_{13} \sim A_{16}$	0.100	0.1000	0.1000	0.1000	10.797	0.100	0.100	0.1023	0.1042	0.1000
4	$A_{17} \sim A_{18}$	0.100	0.1000	0.1000	0.1000	6.861	0.100	0.100	0.1000	0.1003	0.1000
5	$A_{19} \sim A_{22}$	1.229	1.3079	1.2582	1.2476	0.438	1.293	1.271	1.2781	1.1904	1.2462
6	$A_{23} \sim A_{30}$	0.522	0.5193	0.5035	0.5269	0.286	0.511	0.509	0.5258	0.4865	0.5067
7	$A_{31} \sim A_{34}$	0.100	0.1000	0.1000	0.1000	18.309	0.100	0.100	0.1000	0.1000	0.1000
8	$A_{35} \sim A_{36}$	0.100	0.1000	0.1000	0.1012	1.220	0.100	0.100	0.1000	0.1000	0.1000
9	$A_{37} \sim A_{40}$	0.517	0.5142	0.5178	0.5209	5.933	0.499	0.485	0.5506	0.5217	0.4726
10	$A_{41} \sim A_{48}$	0.504	0.5464	0.5214	0.5172	19.545	0.501	0.501	0.5135	0.5276	0.5224
11	$A_{49} \sim A_{52}$	0.100	0.1000	0.1000	0.1004	0.159	0.100	0.100	0.1000	0.1000	0.1011
12	$A_{53} \sim A_{54}$	0.101	0.1095	0.1007	0.1005	0.151	0.100	0.100	0.1145	0.1322	0.1002
13	$A_{55} \sim A_{58}$	0.156	0.1615	0.1566	0.1565	10.127	0.160	0.168	0.1573	0.1548	0.1569
14	$A_{59} \sim A_{66}$	0.547	0.5092	0.5421	0.5507	7.320	0.522	0.584	0.5238	0.5534	0.5546
15	$A_{67} \sim A_{70}$	0.442	0.4967	0.4132	0.3922	3.812	0.478	0.433	0.4576	0.4352	0.3995
16	$A_{71} \sim A_{72}$	0.590	0.5619	0.5756	0.5922	18.196	0.591	0.520	0.5337	0.5743	0.5546
Weight (lb)		379.27	381.91	379.66	379.85	6818.67	381.03	380.62	380.50	381.30	379.54
No of analyses		20000	N/A	13200	19621	150000	15044	13742	72925	36500	12780

areas and overall weight of structures found by FA, FA-R and AFA and those obtained by other studies. As Table 11 shows for Case 1, the weights of 380.50 lb, 381.30 lb, and 379.54 lb were obtained using FA, FA-R, and AFA, respectively. AFA finds the optimal structure, which is lighter than most of structures reported in Table 11, after 12780 structural analyses. Figure 10 compares convergence rates of the algorithms. The figure shows that AFA outperforms the other two algorithms in fast optimization of structure. Tables 12 reports statistical results obtained after 50 independent runs of these three algorithms, and Figure 11 compares the stability of these algorithms for Case 1. As the results show, AFA is a very stable algorithm compared to FA and FA-R. The optimal results of 72-bar spatial truss structure for Case 2, by using various algorithms, are given in Table 13. As it is clear from the table,

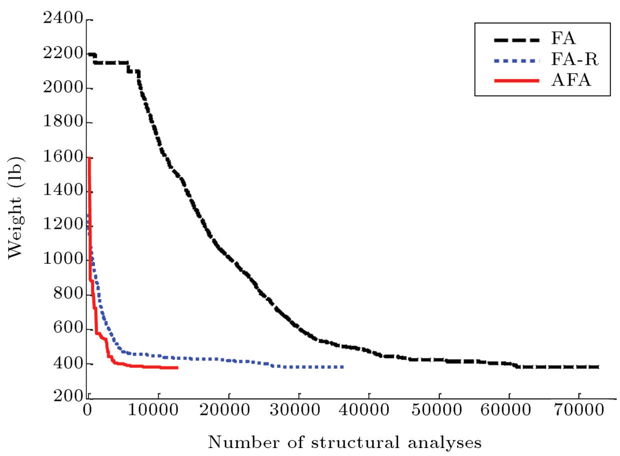

Figure 10. Comparison of the convergence rates of the three algorithms for the 72-bar spatial truss structure (Case 1).

Table 12. Comparison of statistical results for fifty independent runs of the three algorithms for the 72-bar spatial truss structure (Case 1).

		Mean	Standard deviation	Coefficient of variation (%)
FA	Weight (lb)	405.505	29.195	7.200
	No of analyses	71377	24783.75	34.72232
FA-R	Weight (lb)	392.412	13.162	3.354
	No of analyses	33318.4	7564.00	22.70
AFA	Weight (lb)	381.489	1.115	0.292
	No of analyses	13132.80	2999.74	22.84

Table 13. Comparison of optimal designs for the 72-bar spatial truss structure (Case 2).

		Optimal cross-sectional areas (in^2)											
Variables		**Lee and Geem [16]**	**Lamberti [29]**	**Samara [33]**		**Li et al. [12]**			**Degertekin [17]**		**This study**		
		HS	**CMLPSA**	**Simple GA**	**Simple GA**	**PSO**	**PSOPC**	**HPSO**	**EHS**	**SAHS**	**FA**	**FA-R**	**AFA**
1	$A_1 \sim A_4$	1.963	1.8866	2.141	1.732	40.053	1.652	1.907	1.889	1.889	1.8539	1.8927	1.9085
2	$A_5 \sim A_{12}$	0.481	0.5169	0.510	0.522	0.237	0.547	0.524	0.502	0.520	0.5123	0.5217	0.5130
3	$A_{13} \sim A_{16}$	0.010	0.0100	0.054	0.010	21.692	0.100	0.010	0.010	0.010	0.0100	0.0100	0.0100
4	$A_{17} \sim A_{18}$	0.011	0.0100	0.010	0.013	0.657	0.101	0.010	0.010	0.010	0.0100	0.0497	0.0100
5	$A_{19} \sim A_{22}$	1.233	1.2903	1.489	1.345	22.144	1.102	1.288	1.284	1.289	1.2889	1.1831	1.2553
6	$A_{23} \sim A_{30}$	0.506	0.5170	0.551	0.551	0.266	0.589	0.523	0.526	0.524	0.5406	0.5051	0.5142
7	$A_{31} \sim A_{34}$	0.011	0.0100	0.057	0.010	1.654	0.011	0.010	0.010	0.010	0.0100	0.0124	0.0100
8	$A_{35} \sim A_{36}$	0.012	0.0100	0.013	0.013	10.284	0.010	0.010	0.010	0.010	0.0100	0.0100	0.0100
9	$A_{37} \sim A_{40}$	0.538	0.5207	0.565	0.492	0.559	0.581	0.544	0.528	0.539	0.5151	0.5277	0.5487
10	$A_{41} \sim A_{48}$	0.533	0.5180	0.527	0.545	12.883	0.458	0.528	0.525	0.519	0.5183	0.5327	0.5194
11	$A_{49} \sim A_{52}$	0.010	0.0100	0.010	0.066	0.138	0.010	0.019	0.010	0.015	0.0100	0.0100	0.0100
12	$A_{53} \sim A_{54}$	0.167	0.1141	0.066	0.013	0.188	0.152	0.020	0.063	0.105	0.1012	0.1354	0.1050
13	$A_{55} \sim A_{58}$	0.161	0.1665	0.174	0.178	29.048	0.161	0.176	0.173	0.167	0.1686	0.1655	0.1670
14	$A_{59} \sim A_{66}$	0.542	0.5363	0.425	0.524	0.632	0.555	0.535	0.550	0.532	0.5198	0.5456	0.5343
15	$A_{67} \sim A_{70}$	0.478	0.4460	0.437	0.396	3.045	0.514	0.426	0.444	0.425	0.4131	0.4105	0.4500
16	$A_{71} \sim A_{72}$	0.551	0.5761	0.641	0.595	1.711	0.648	0.612	0.592	0.579	0.6577	0.6375	0.5925
Weight (lb)		364.33	363.818	372.40	364.40	5417.02	368.45	364.86	364.36	364.05	363.98	364.57	363.85
No of analyses		20000	N/A	N/A	N/A	150000	125000	125000	13755	12852	41085	21990	11000

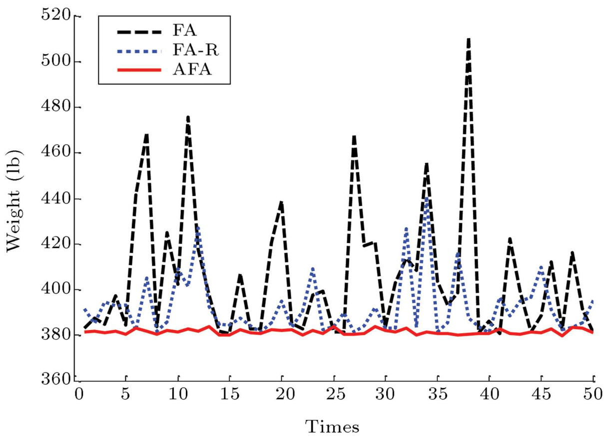

Figure 11. Comparison of the stability of the three algorithms for the 72-bar spatial truss structure (Case 1).

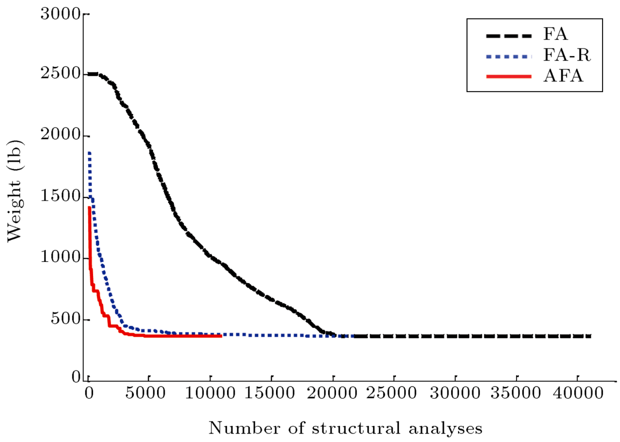

Figure 12. Comparison of the convergence rates of the three algorithms for the 72-bar spatial truss structure (Case 2).

the weights of 363.98 lb, 364.57 lb, and 363.85 lb were found using FA, FA-R, and AFA, respectively. The structure obtained by AFA is lighter than most other structures reported in the table. In addition, the proposed AFA requires very less computational effort than other techniques. It is worthy of remark that as it is clear from Tables 11 and 13, the well-known PSO algorithm has been practically unable to find a solution for both cases. This implies that the firefly algorithm might be superior to PSO in truss optimization, since in all our experiments satisfactory solutions were obtained by all versions of firefly algorithm. Figure 12 compares convergence rates of the algorithms for Case 2 of this problem. Table 14 gives statistical results obtained after 50 independent runs of these three algorithms and

Table 14. Comparison of statistical results for fifty independent runs of three algorithms for the 72-bar spatial truss structure (Case 2).

		Mean	Standard deviation	Coefficient of variation (%)
FA	Weight (lb)	373.602	15.634	4.185
	No of analyses	48306	12146.42	25.14
FA-R	Weight (lb)	369.533	4.082	1.104
	No of analyses	21546.70	4708.61	21.85
AFA	Weight (lb)	364.880	0.557	0.153
	No of analyses	10657.00	2210.46	20.74

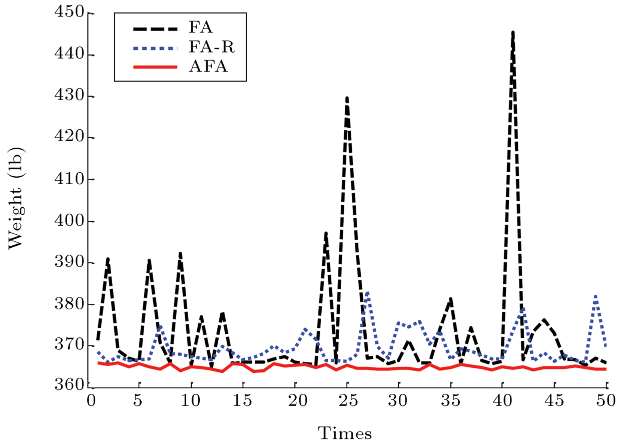

Figure 13. Comparison of the stability of the three algorithms for the 72-bar spatial truss structure (Case 2).

Figure 13 is presented to compare the stability of these algorithms for Cases 1 and 2, respectively. Superiority of AFA compared to FA and AFA in producing very close results after each independent run is obvious from these figures.

7. Summary, discussion and conclusion

The capability of firefly algorithm in weight optimization of truss structures was first investigated in this paper. Firefly algorithm is a recently developed technique and is not thoroughly tested in optimizing real-life problems. The studies showed that firefly algorithm is a robust approach and suitable for size optimization of truss structures. As indicated in this paper, in some cases, the standard PSO algorithm is not capable of finding the optimal solution for the problem contrary to firefly algorithm. More specifically, an asymptotic case of firefly algorithm is the standard PSO by approaching the light absorption coefficient to zero ($\gamma \to 0$). On the other hand, when $\gamma \to \infty$, attraction is almost zero in the sight of other fireflies, and hence, no firefly can be seen and fireflies randomly move in the search space and hence this extreme case is reduced to random search method. Since the range of variation of γ is extensive, appropriate value for this parameter should be found for each problem. As mentioned by Yang [22] and shown in this paper, it is possible to adjust the parameters γ and α such that FA outperforms PSO. However, the number of iterations required for convergence is still considerable. Therefore, in the second part of this paper, the standard FA was improved to accelerate the algorithm. The accelerated firefly algorithm (AFA) was based on gradually decreasing the randomness as the solution is approached, and scaling the random part of fireflies' movement. To clearly distinguish between these two modifications, two algorithms including the reduction only (indicated by FA-R) and both reduction and scaling (indicated by AFA) were examined. The effectiveness and stability of each algorithm were tested through optimizing some benchmark truss structures. The results show that the reduction of randomness imposed in FA-R can improve the stability and performance of the standard FA. However, significant improvement in computational effort, stability and performance can be achieved by considering both reduction and scaling in AFA. The enhanced efficiency of the proposed AFA is impressing in optimizing complicated real-life truss structures.

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