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Modified Simulated Annealing Algorithm for Discrete Sizing Optimization of Truss Structure

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ABSTRACT

The main goal of structural optimization is to minimize the weight of structures while satisfying all design requirements imposed by design codes. In this paper, the Modified Simulated Annealing Algorithm (MSAA) is implemented to minimize the weight of truss structures with discrete sizing variables. MSSA is a newly improved version of the simulated annealing (SA) algorithm with three modifications: preliminary exploration, search step and a new probability of acceptance. The reliability of the MSAA is demonstrated through five optimization problems of truss structures with discrete design variables. Numerical results indicate that MSAA can minimize the overall weight of truss structures subjected to stress and displacement constraints.

KEYWORDS: Modified simulated annealing algorithm (MSAA), Discrete sizing optimization, Structural optimization, Truss structures.

INTRODUCTION

Structural optimization has become one of the most active branches of structural engineering in the past decade. The number of design variables, size of search area and number of design constraints are factors that influence the time needed by designers to find optimized designs. The structural optimization problem is non-convex, due to non-convex nature of the objective function or the complex geometry of the feasible domain shaped by design constraints, especially for the case that one or more of the previous difficulties are involved (Li and Ma, 2014). Therefore, deterministic approaches are difficult and time-consuming to be applied to these optimization problems. Also, a good starting point is vital for these methods to obtain successful outcome. Under such circumstances, meta-heuristic algorithms can serve as appropriate alternatives due to the ability to search local minima in highly modal and multi-dimensional spaces.

One of the major challenges in structural design is to introduce new meta-heuristic algorithms with higher potential and simpler usage. Several researchers have introduced and implemented different meta-heuristic algorithms for global optimization in structural design, including genetic algorithms (GA) (Rajeev and Krishnamoorthy, 1992; Kameshki and Saka, 2007); ant colony optimization (ACO) (Camp and Bichon, 2004; Kaveh and Talatahari, 2009); harmony search (HS) (Lee and Geem, 2004; Lee et al., 2005); particle swarm optimization (PSO) (Li et al., 2009; Luh and Lin, 2011); charged system search (CSS) (Kaveh et al., 2015); artificial bee colony (ABC) (Sonmez, 2011); teaching-learning-based optimization (TLBO) (Degertekin and Hayalioglu, 2013), colliding bodies optimization (CBO)

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(Kaveh and Mahdavi, 2014), big bang–big crunch (BB-BC) (Camp, 2007) and symbiotic organisms search (SOS) (Cheng and Prayogo, 2014), among others.

The Modified Simulated Annealing Algorithm (MSAA) was recently introduced for solving global optimization problems (Millán et al., 2014; Millán and Begambre, 2016). MSSA is a newly improved version of the simulated annealing (SA) algorithm with three modifications. Firstly, a preliminary exploration is realized to choose the starting point of search. Secondly, the transition from the start point to the new point is done by a search step. Thirdly, the range of probability of accepting a worse solution is reduced. The details of these improvements will be presented in the following sections of the paper. The modifications allow a balance between intensification and diversification during a search. Diversification (exploration) ensures, usually by randomization, that the algorithm efficiently explores the search space. Intensification (exploitation) aims to identify the best solution and select during the process a succession of best solutions.

In the present study, the MSAA is employed for the first time to solve truss optimization with discrete design variables. The robustness and performance of the MSAA are verified through five numerical examples. Numerical results indicate that in most of the cases, the MSAA is more efficient than other methods in the literature in terms of solution quality.

This study is structured as follows: The next section presents the formulation of the discrete sizing optimization problem. It is followed by a section that describes MSAA in detail. Then, MSAA truss design parameters are presented. After that, the test problems are described and the optimization results are discussed. The conclusions of the study are presented in the last section.

Discrete Structural Optimization Problems

Discrete sizing optimization attempts to find the optimal cross-section of system elements in order to minimize structural weight. However, the minimum design must also satisfy inequality constraints that limit design variable sizes and structural responses (Lee et al., 2005). The discrete structural optimization problem for a truss structure maybe expressed as:

Find

$$X = [X_1, X_2, \quad \dots, X_{ng}]$$
$$X_i \in D_i, \; D_i = [d_{i,1}, \quad d_{i,2}, \dots, d_{i,r(i)}]$$

to minimize $W(X) = \sum_{i=1}^{nm} \gamma_i . X_i . L_i$

subject to

$$\delta_{min} \le \delta_i \le \delta_{max}, \quad i = 1,2,\dots,m$$
$$\sigma_{min} \le \sigma_i \le \sigma_{max}, \quad i = 1,2,\dots,nm$$

where X is the vector containing the design variables; D_i is an allowable set of discrete values for the design variable X_i; ng is the number of design variables or the number of member groups; r(i) is the number of available discrete values for the i^{th} design variable; W(X) is the weight of the structure; m is the number of nodes; nm is the number of members forming the structure; γ_i is the material density of member i; L_i is the length of member i; δ_i is the nodal displacement/deflection at node i; σ_i is the stress developed in the i^{th} element; and min and max represent the lower and upper bounds, respectively.

Modified Simulated Annealing Algorithm (MSAA)

Prior to summarizing the characteristics of the MSAA, the functioning of basic Simulated Annealing (SA) is briefly described. SA (Kirkpatrick et al., 1983; Balling, 1991) has been developed from the statistical thermodynamics to simulate the behavior of atomic arrangements in liquid or solid materials during the annealing process. The material reaches the lowest energy level (globally stable condition) as temperature decreases. SA includes a rather simple optimization strategy. A trial design is randomly generated and problem functions are evaluated at that point. If the trial point is infeasible, it is rejected and a new trial point is evaluated. If the trial point is feasible and the cost function is smaller than the current best record, then the point is accepted and the best record is updated (Lamberti, 2008). If the trial point is feasible but the cost function is higher than the best value, then the point is accepted or rejected based on a probabilistic criterion which estimates whether the design may improve in the next function evaluations. In order to compute probability, a parameter called ‘‘temperature” is utilized. Temperature can be a target value (estimated) for the cost function corresponding to a global minimizer. Initially, a larger target value is selected. As the trials progress, the target value is reduced based on a cooling schedule (Lamberti, 2008). The acceptance probability steadily decreases to zero as temperature is reduced and is calculated using the following equation:

$$P(\Delta f, T) = e^{(\Delta f/T)} \quad (1)$$

where P is the probability of accepting the new state; Δf is the difference of the evaluations of the function for each state; T is the system temperature and e is the Euler number. The Pseudo code of classical SA is as follows:

Setting initial temperature ($T_{initial}$)
Setting final temperature (T_{final})
Setting maximum number of perturbations at the same temperature ($np_{\max}$)
Generate Initial Solution (S) chosen randomly
$T = T_{initial}$
While ($T > T_{final}$) do //Temperature Cycle
    For $np = 1$ to np_{max} //Metropolis Cycle
    Generate S' chosen randomly
    Obtain difference between S' and S
    If (difference ≤ 0) then
    Accept S'
    else
    Boltzmann Probability = exp (difference/ T)
    If (Boltzmann Probability > random (0, 1)) then
    Accept S'
    end if
    end if
    end while
    Decrease T by cooling function $T_{k+1} = T_k \cdot \alpha$
end while
Shown best solution (S_{best})

The MSSA introduced by Millán (Millán et al., 2014) has 3 fundamental characteristics that differentiate it from the basic SA. These characteristics are as follows:

Preliminary Exploration

In this phase, the algorithm performs a scan in the search space and is given by the following matrix:

$$X_{PxN} = I_{PxN} X_L + rand_{PxN}(X_U - X_L) \quad (2)$$

where P is the size of the search population; N is the number of dimensions of the problem; I_{PxN} is an identity matrix of size PxN; X_L is the lower limit of the problem; X_U is the upper limit of the problem and $rand_{PxN}$ is a PxN matrix of random numbers (pure randomness) between 0 and 1.

To start the optimization process with MSAA, all points generated by equation (2) are evaluated in the objective function of the problem and the smallest value (in the case of searching the minimum value of the function) is chosen as the starting point of the search.

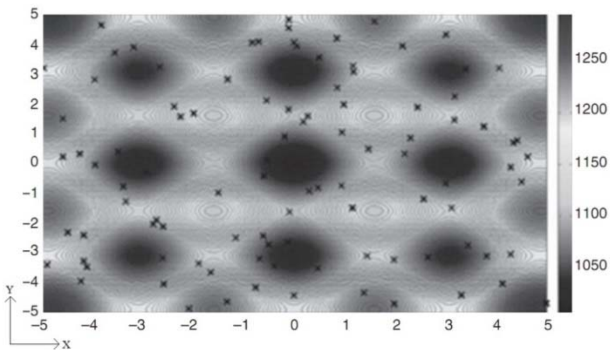

Figure (1): Exploration in the search space

Search Step

From the start point determined in the previous step, a step of search is generated to determine the neighbor state. This step depends on a radius of action that is gradually reduced as the temperature of the system decreases. That is, when the algorithm is at a certain temperature, with radius of action defined by equation (3), the transition from the start point to the new point (search step) is done by adding random numbers that are between zero and the value of the radius. This allows the algorithm to perform a global exploration at high temperatures and a local exploration at low temperatures, giving a balance between exploration and exploitation of the algorithm.

$$R_{i+1} = R_i \cdot \alpha \quad (3)$$

where R_i is the initial radius cycle and α is the radius reduction coefficient.

Probability of Acceptance

The probability of accepting a worse solution is given by:

$$P = \frac{1}{1+e^{(\Delta f/T)}} \quad (4)$$

where P is the probability of accepting the new state; Δf is the difference of the evaluations of the function for each state; T is the system temperature and e is the Euler number.

This probability is in a range between 0 and ½, which allows the algorithm to have a lower acceptance range of worse solutions.

In summary, the 3 modifications have the purpose to improve the initial exploration, allow a balance between initial and final exploration and control the convergence in the final search stage. The Pseudo code of MSAA is as follows:

Setting initial temperature ($T_{initial}$)
Setting final temperature (T_{final})
Setting maximum number of perturbations at the same temperature (np_{max})
Generate Initial Solution (S) chosen by the preliminary exploration
$T = T_{initial}$
While ($T > T_{final}$) do //Temperature Cycle
For $np = 1$ to np_{max} //Metropolis Cycle
Generate S' by search step
Obtain difference between S' and S
If (difference ≤ 0) then
Accept S'
else
Boltzmann Probability = 1/(1+exp(difference/ T))
If (Boltzmann Probability > random(0, 1/2)) then
Accept S'
end if
end if
end while
Decrease T by cooling function $T_{k+1} = T_k \cdot \alpha$
end while
Shown best solution (S_{best})

MSAA Truss Design Parameters

All applications of the MSAA truss design use the same size of the search population, initial temperature, final temperature, maximum number of perturbations at the same temperature (temperature cycle), cooling function, attenuation coefficient (which controls the cooling speed of T) and search step. Numerical experiments indicate that a population of 100 (preliminary exploration); initial temperature $T_{initial} = 1$; final temperature $T_{final} = 1x10^{-3}$; maximum number of perturbations $np_{max} = 2000$; cooling function $T_{k+1} = T_k \cdot \alpha$; attenuation coefficient $\alpha = 0.8$; and search step $R = 8$ are adequate to provide good results.

The MSAA is applied to the design of several benchmark truss optimization problems and results are compared with those from other methods. To estimate the general performance of the MSAA, each benchmark truss design problem was run independently 100 times. While the number of runs is arbitrary, it should be adequate to provide reliable statistics on the general quality of the solutions and the convergence of the MSAA. It is also important to note that all presented MSAA designs are feasible.

Numerical Examples

In this section, five truss optimization examples with discrete variables are optimized with the MSAA. Detailed information about geometrical, material and structural constraints for all examples are provided in each problem description. The algorithms were coded in

Matlab and structures were analyzed using the finite element (direct stiffness) method.

Planar 10-bar Truss

This problem has effectively become the standard benchmark problem in structural optimization. The configuration of the structure is depicted in Fig. 2. The modulus of elasticity is 10000 ksi and density of material 0.1 lb/in^3. The allowable stress for all members is set to ±25 ksi and the maximum nodal deflection (in both the vertical and horizontal directions) is ±2.0 in. A single loading condition P_1=100 kips was used. There are 10 design variables and the discrete variables are selected from the set L= {1,62; 1,80; 1,99; 2,13; 2,38; 2,62; 2,63; 2,88; 2,93; 3,09; 3,13; 3,38; 3,47; 3,55; 3,63; 3,84; 3,87, 3,88; 4,18; 4,22; 4,49; 4,59; 4,80; 4,97; 5,12; 5,74; 7,22; 7,97; 11,5; 13,5; 13,9; 14,2; 15,5; 16,0; 16,9; 18,8; 19,9; 22,0; 22,9; 26,5; 30,0; 33,5} (in^2). This problem has been investigated by different researchers (Sonmez, 2011; Camp, 2007; Camp and Farshchin, 2014; Li et al., 2009; Barbosa et al., 2008) using different approaches.

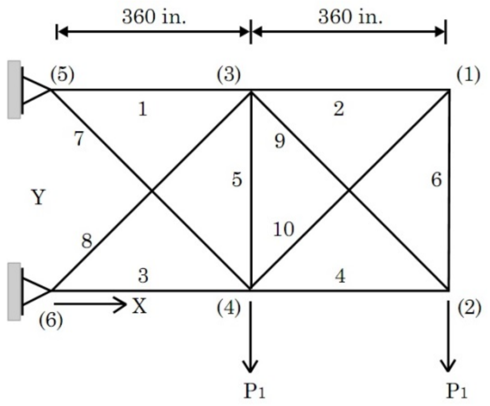

Figure (2): Schematic of the planar 10-bar truss structure

Table 1 lists the best design developed by the proposed MSAA, a truss weighing 5490.74 lb, which is identical to that found in previous studies. From statistical point of view, MSAA has provided a lower standard deviation (SD) and a lower mean value than other techniques. For instance, the SD of MSAA is about three times lower than the SD provided by Camp and Farshchin (2014) and the mean value is about 12 kg lighter. Fig. 3 shows the convergence curve of the best result obtained by the proposed algorithm for this truss design problem.

Table 1. Optimal design comparison for the 10-bar truss problem

Variables (in^2)	Camp (2007)	Barbosa et al. (2008)	Li et al. (2009)	Sonmez (2011)	Camp and Farshchin (2014)	MSAA
A1	33.50	33.50	30.00	33.50	33.50	33.50
A2	1.62	1.62	1.62	1.62	1.62	1.62
A3	22.90	22.90	22.90	22.90	22.90	22.90
A4	14.20	14.20	13.50	14.20	14.20	14.20
A5	1.62	1.62	1.62	1.62	1.62	1.62
A6	1.62	1.62	1.62	1.62	1.62	1.62
A7	22.90	22.90	7.97	7.97	22.90	7.97
A8	7.97	7.97	26.50	22.90	7.97	22.90
A9	1.62	1.62	22.00	22.00	1.62	22.00
A10	22.00	22.00	1.80	1.62	22.00	1.62
Weight (lb)	5490.74	5490.74	5531.98	5490.74	5490.74	5490.74
Mean (lb)	5494.17	5534.98	-	5510.35	5503.21	5491.37
SD (lb)	12.42	-	-	-	20.33	6.35
Number of runs	100	-	-	20	100	100

Note: 1 in^2= 6.452 cm^2 and 1 lb = 4.45 N.

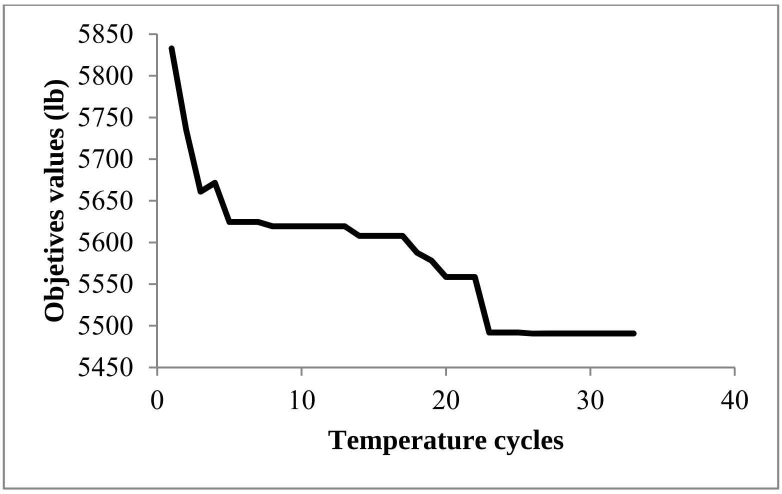

Figure (3): Convergence curve of the best result for the 10-bar truss

Table 2. Optimal design comparison for the 15-bar truss problem

Variables (mm^2)	Li et al. (2009)	Sabour et al. (2011)	Dede (2014)	MSAA
A1	113.20	113.20	113.20	113.20
A2	113.20	113.20	113.20	113.20
A3	113.20	113.20	113.20	113.20
A4	113.20	113.20	113.20	113.20
A5	736.70	736.70	736.70	736.70
A6	113.20	113.20	113.20	113.20
A7	113.20	113.20	113.20	113.20
A8	736.70	736.70	736.70	736.70
A9	113.20	113.20	113.20	113.20
A10	113.20	113.20	113.20	113.20
A11	113.20	113.20	113.20	113.20
A12	113.20	113.20	113.20	113.20
A13	113.20	113.20	113.20	113.20
A14	334.30	334.30	334.30	334.30
A15	334.30	334.30	334.30	334.30
Weight (kg)	105.74	105.74	105.74	105.74
Mean (kg)	-	105.74	-	105.74
SD (kg)	-	0.00	-	0.00
Number of runs	-	26	20	100

Planar 15-bar Truss Structure

Fig. 4 shows the geometry and the loading condition of the planar 15-bar truss structure, previously studied by Li et al. (2009), Sabour et al. (2011) and Dede (2014).The material density is 7800 kg/m^3 and the modulus of elasticity is 200GPa. The maximum allowable stress for all members is ±120 MPa and maximum displacements for all free nodes in both the vertical and horizontal directions must not exceed 10 mm. This test problem includes 15 discrete design variables that can be selected from the following discrete set: L={113,2; 143,2; 145,9; 174,9; 185,9; 235,9; 265,9; 297,1; 308,6; 334,3; 338,2; 497,8; 507,6; 736,7; 791,2; 1063,7} (mm^2). The vertical loads used in this example are: P_1=35 kN, P_2=35 kN and P_3=35 kN.

The design vectors and the corresponding weights of the optimal structures found by different methods are summarized in Table 2. In the 100 runs of this algorithm, the average weight of the truss designs was 105.74 kg with an SD of 0.00 kg. Fig. 5 shows the convergence curve of the best result obtained by the proposed algorithm for the 15-bar truss.

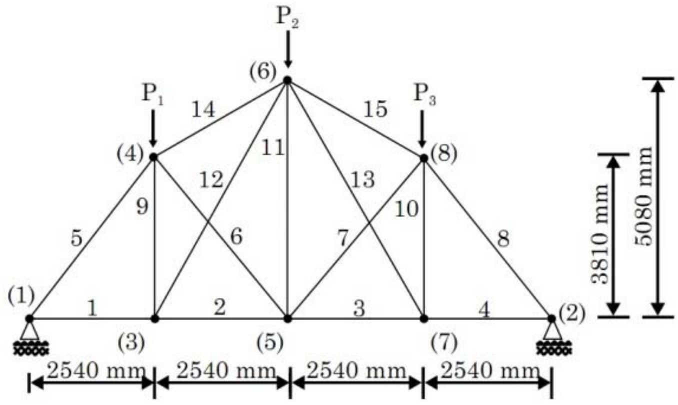

Figure (4): Schematic of the planar 15-bar truss structure

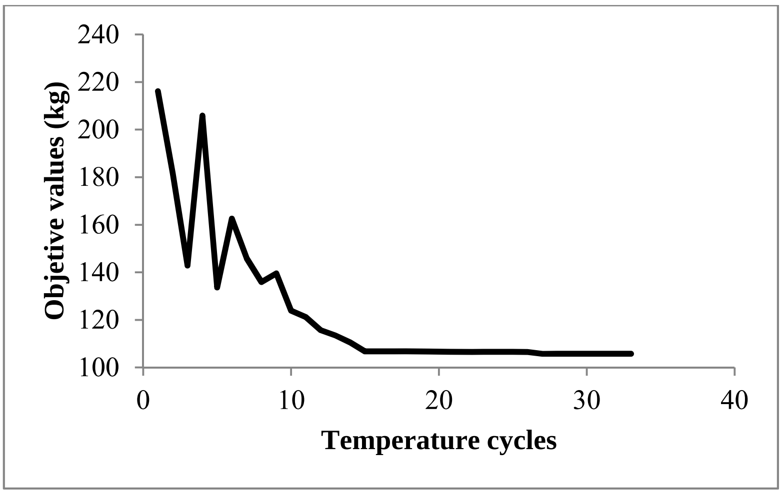

Figure (5): Convergence curve of the best result for the 15-bar truss

Planar 52-bar Truss Structure

The 52-bar planar truss structure shown in Fig. 6 has been analyzed by Lee et al. (2005), Li et al. (2009), Kaveh and Talatahari (2009) and Kaveh et al. (2015). The members of this structure are divided into 12 groups: (1) A1-A4, (2) A5-A10, (3) A11-A13, (4) A14-A17, (5) A18-A23, (6) A24-A26, (7) A27-A30, (8) A31-A36, (9) A37-A39, (10) A40-A43, (11) A44-A49 and (12) A50-A52. The material density is 7860.0 kg/m^3 and the modulus of elasticity is 207 GPa. The maximum allowable stress for all members in terms of both tension and compression is 180 MPa. Loads P_X=100 kN and P_Y=200 kN are both considered. Discrete values of cross-sectional areas can be selected from Table 3.

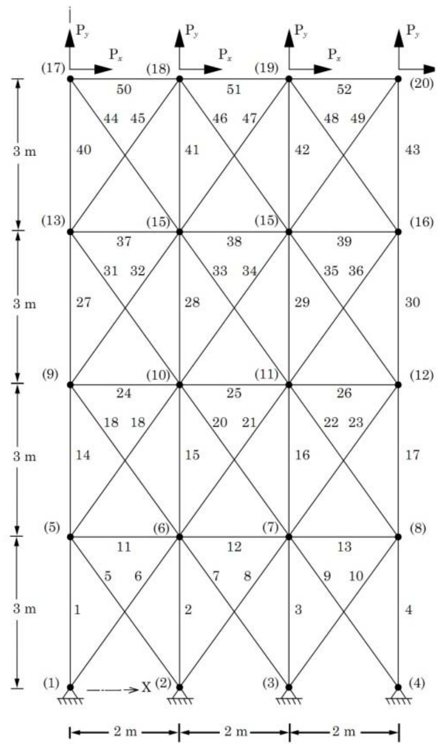

Figure (6): Schematic of the planar 52-bar truss structure

Table 4 shows the results obtained from the MSAA compared to other published designs. The results show that the MSAA has generated the lightest truss design compared to other published optimization methods. The best design weight of 1902.61 kg is the same as the best weight reported in literature (Kaveh et al., 2015) and 0.15% lighter than the best weight reported by Li et al. (2009). The SD provided by the MSAA shows the stability of the proposed algorithm. Fig. 7 shows the convergence curve of the best result obtained by the MSAA for the 52-bar truss.

Table 3. Available cross-sectional areas from the AISC design code

No.	in²	mm²	No.	in²	mm²
1	0.111	71.613	33	3.840	2477.414
2	0.141	90.968	34	3.870	2496.769
3	0.196	126.451	35	3.880	2503.221
4	0.250	161.29	36	4.180	2696.769
5	0.307	198.064	37	4.220	2722.575
6	0.391	252.258	38	4.490	2896.768
7	0.442	285.161	39	4.590	2961.284
8	0.563	363.225	40	4.800	3096.768
9	0.602	388.386	41	4.970	3206.445
10	0.766	494.193	42	5.120	3303.219
11	0.785	506.451	43	5.740	3703.218
12	0.994	641.289	44	7.220	4658.055
13	1.000	645.16	45	7.970	5141.925
14	1.228	792.256	46	8.530	5503.215
15	1.266	816.773	47	9.300	5999.988
16	1.457	939.998	48	10.850	6999.986
17	1.563	1008.385	49	11.500	7419.34
18	1.620	1045.159	50	13.500	8709.66
19	1.800	1161.288	51	13.900	8967.724
20	1.990	1283.868	52	14.200	9161.272
21	2.130	1374.191	53	15.500	9999.98
22	2.380	1535.481	54	16.000	10322.56
23	2.620	1690.319	55	16.900	10903.204
24	2.630	1696.771	56	18.800	12129.008
25	2.880	1858.061	57	19.900	12838.684
26	2.930	1890.319	58	22.000	14193.52
27	3.090	1993.544	59	22.900	14774.164
28	3.130	2019.351	60	24.500	15806.42
29	3.380	2180.641	61	26.500	17096.74
30	3.470	2,238,705	62	28.000	18064.48
31	3.550	2290.318	63	30.000	19354.8
32	3.630	2341.931	64	33.500	21612.86

Table 4. Optimal design comparison for the 52-bar truss problem

Element group (mm²)		Lee et al. (2005)	Li et al. (2009)	Kaveh and Talatahari (2009)	Kaveh et al. (2015)	MSAA
1	A1-A4	4658.06	4658.06	4658.06	4658.06	4658.06
2	A5–A10	1161.29	1161.29	1161.29	1161.29	1161.29
3	A11–A13	506.45	363.23	494.19	494.19	494.19
4	A14–A17	3303.22	3303.22	3303.22	3303.22	3303.22
5	A18–A23	940.00	940.00	1008.39	940.00	940.00
6	A24–A26	494.19	494.19	285.16	494.19	494.19
7	A27–A30	2290.32	2238.71	2290.32	2238.71	2238.71
8	A31–A36	1008.39	1008.39	1008.39	1008.39	1008.39
9	A37–A39	2290.32	388.39	388.39	494.19	494.19
10	A40–A43	1535.48	1283.87	1283.87	1283.87	1283.87
11	A44–A49	1045.16	1161.29	1161.29	1161.29	1161.29
12	A50–A52	506.45	792.26	506.45	494.19	494.19
Weight (kg)		1906.76	1905.50	1904.83	1902.61	1902.61
Mean (kg)		-	-	-	-	1902.66
SD (kg)		-	-	-	-	0.32
Number of runs			-	-	-	100

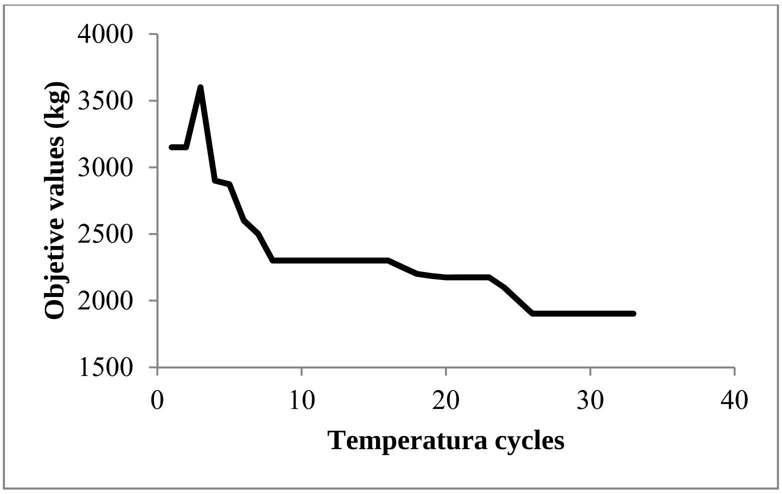

Figure (7): Convergence curve of the best result for the 52-bar truss

Spatial 25-bar Truss Structure

The 25-bar transmission tower shown in Fig. 8 is used widely in structural optimization to verify various design approaches and compare different numerical techniques. The material of the structure has a mass density of 0.1 lb/in^3 and an elastic modulus of 10 Msi. The stress limit in tension/compression is ±40 ksi and maximum nodal displacement is ±0.35 in. The structure includes 25 members categorized into the following 8 groups: (1) A1, (2) A2–A5, (3) A6–A9,(4) A10–A11,(5) A12–A13,(6) A14–A17,(7) A18–A21 and (8) A22–A25. Discrete values of cross-sectional areas were selected from the following set: L = {0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2, 2.3, 2.4, 2.6, 2.8, 3.0, 3.2, 3.4} (in^2). Loads are shown in Table 5. This problem has been studied by several researchers (Lee et al., 2005; Li et al., 2009; Camp, 2007; Camp and Farshchin, 2014).

Table 6 compares the optimized design with literature. It can be seen that the design provided for MSAA (484.85 lb) is identical to that found in previous studies. From statistical point of view, the SD and the mean value of MSAA are lower than those provided by Camp (2007). Fig. 9 shows the convergence history of 25-bar truss.

Table 5. Loading condition for the 25-bar truss problem

Nodes	Loads		
	P_X (kips)	P_Y (kips)	P_Z (kips)
1	1.0	−10.0	−10.0
2	0.0	−10.0	−10.0
3	0.5	0.0	0.0
6	0.6	0.0	0.0

Table 6. Optimal design comparison for the 25-bar truss problem

Element group (in^2)		Lee et al. (2005)	Li et al. (2009)	Camp (2007)	Camp and Farshchin (2014)	MSAA
1	A1	0.10	0.10	0.10	0.10	0.10
2	A2–A5	0.30	0.30	0.30	0.30	0.30
3	A6–A9	3.40	3.40	3.40	3.40	3.40
4	A10–A11	0.10	0.10	0.10	0.10	0.10
5	A12–A13	2.10	2.10	2.10	2.10	2.10
6	A14–A17	1.00	1.00	1.00	1.00	1.00
7	A18–A21	0.50	0.50	0.50	0.50	0.50
8	A22 –A25	3.40	3.40	3.40	3.40	3.40
Weight (lb)		484.85	484.85	484.85	484.85	484.85
Mean (lb)		-	-	485.1	484.91	484.93
SD (lb)		-	-	0.44	0.17	0.18
Number of runs		-	-	100	100	100

Note: 1 in^2= 6.452 cm^2 and 1 lb = 4.45 N.

Spatial 72-bar truss structure

The five-test problem is the weight minimization of the 72-bar spatial truss schematized in Fig. 10. This test case was previously studied by Lee et al. (2005), Li et al. (2009), Kaveh and Talatahari (2009) and Kaveh and Mahdavi (2014a). Material properties are as follows: the material density is 0.1 lb/in^3, the modulus of elasticity is 10 Msi. Stresses developed in truss elements cannot exceed 25,000 psi in both tension and compression. Nodal displacements must be smaller than ±0.25 in. Loading conditions are listed in Table 7. The 72 structural members of this spatial truss are categorized into 16 groups using symmetry: 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 and (16) A71–A72. Discrete values of cross-sectional areas were selected from the following set: L = {0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, 2.9, 3.0, 3.1, 3.2} (in^2).

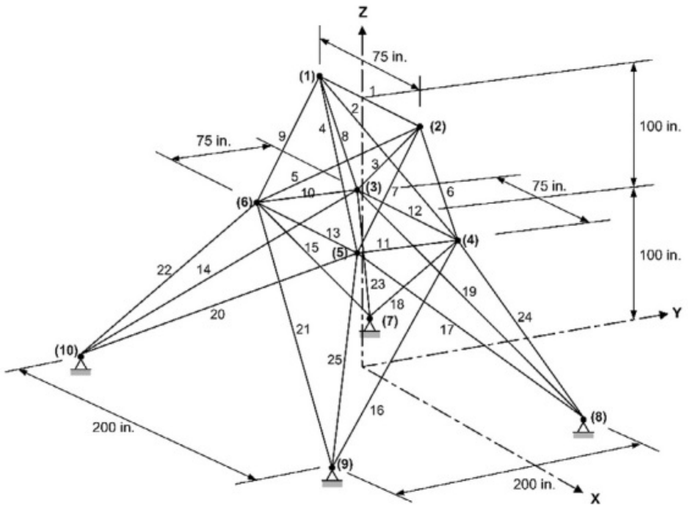

Figure (8): Schematic of the spatial 25-bar truss structure

Table 7. Loading condition for the 72-bar truss problem

Nodes	Loads		
	P_X (kips)	P_Y (kips)	P_Z (kips)
17	5.0	5.0	−5.0
18	0.0	0.0	0.0
19	0.5	0.0	0.0
20	0.6	0.0	0.0

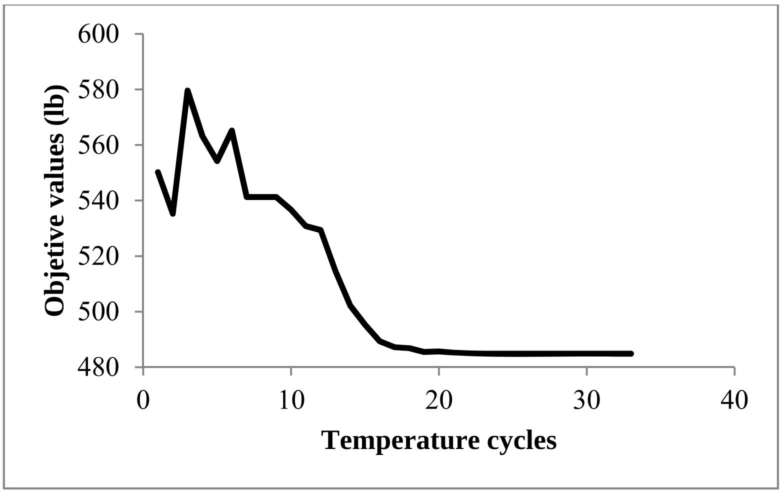

Figure (9): Convergence curve of the best result for the 25-bar truss

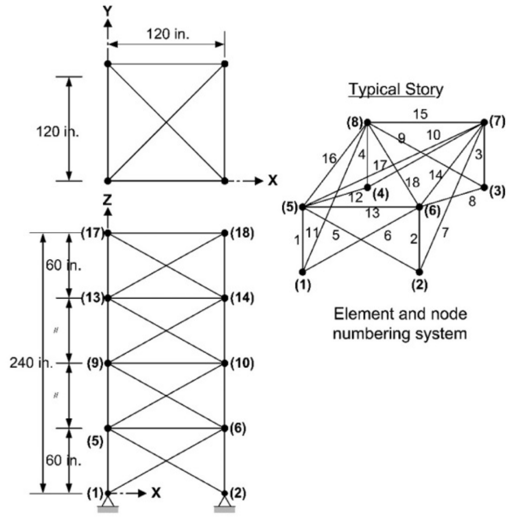

Figure (10): Schematic of the spatial 72-bar truss structure

Table 8 compares the results obtained by the MSAA and other optimization methods. In this case, the proposed algorithm obtained the same best weight as Kaveh and Talatahari (2009) (385.54 lb). Furthermore, the weight is about 3.4 lb and 2.4 lb lighter than best weight values reported by Li et al. (2009) and Lee et al. (2005), respectively. In over 100 runs of this algorithm, the average weight of the truss designs was 386.04 lb with a lower standard deviation of 1.16 lb. Fig. 11 shows the convergence curve of the best result obtained by the MSAA for the 72-bar truss.

Table 8. Optimal design comparison for the 72-bar truss problem

Element group (in^2)		Lee et al. (2005)	Li et al. (2009)	Kaveh and Talatahari (2009)	Kaveh and Mahdavi (2014a)	MSAA
1	A1–A4	1.90	2.10	1.90	1.90	1.90
2	A5–A12	0.50	0.60	0.50	0.50	0.50
3	A13–A16	0.10	0.10	0.10	0.10	0.10
4	A17–A18	0.10	0.10	0.10	0.10	0.10
5	A19–A22	1.40	1.40	1.30	1.40	1.40
6	A23–A30	0.60	0.50	0.50	0.50	0.50
7	A31–A34	0.10	0.10	0.10	0.10	0.10
8	A35–A36	0.10	0.10	0.10	0.10	0.10
9	A37–A40	0.60	0.50	0.60	0.50	0.50
10	A41–A48	0.50	0.50	0.50	0.50	0.50
11	A49–A52	0.10	0.10	0.10	0.10	0.10
12	A53–A54	0.10	0.10	0.10	0.10	0.10
13	A55–A58	0.20	0.20	0.20	0.20	0.20
14	A59–A66	0.50	0.50	0.60	0.60	0.60
15	A67–A70	0.40	0.30	0.40	0.40	0.40
16	A71–A72	0.60	0.70	0.60	0.60	0.60
Weight (lb)		387.94	388.94	385.54	385.54	385.54
Mean (lb)		-	-	-	-	386.04
SD (lb)		-	-	-	-	1.16
Number of runs		-	-	-	20	100

Note: 1 in^2= 6.452 cm^2 and 1 lb = 4.45 N.

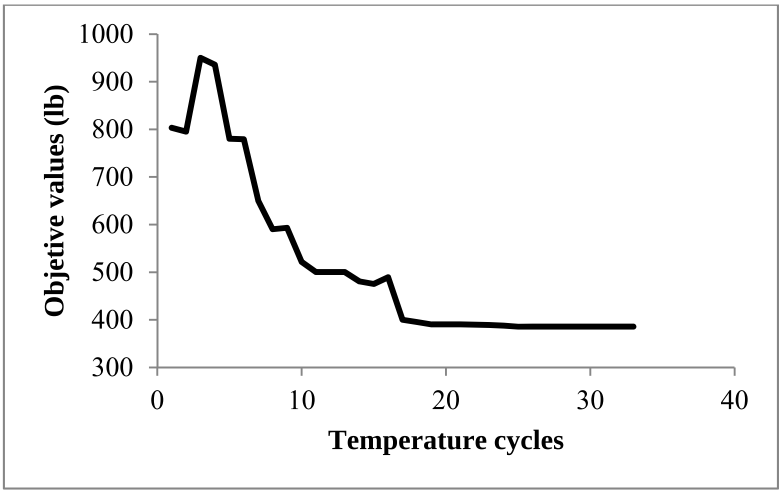

Figure (11): Convergence curve of the best result for the 72-bar truss

CONCLUSIONS

In this work, a recently new optimization algorithm called Modified Simulated Annealing Algorithm (MSAA) is employed for the discrete optimization of truss structures. Five truss structures taken from literature are analyzed in this paper to demonstrate the efficiency of the MSAA in discrete optimization. The results obtained by MSAA are compared with the results of other optimization methods. For all of the truss structures considered, the results obtained from this study are equal to or lighter than the other results of references given in comparison tables. It is concluded that the MSAA can be effectively used in weight minimization of truss structures. This method can be easily extended for the optimization of other structural design applications.

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