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Sizing Optimization of Trusses Structures Using Improved Modified Simulated Annealing Algorithm

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Abstract

This paper presents the size optimization of trusses structures using the recently developed Improved Modified Simulated Annealing Algorithm (I-MSAA). I-MSAA was recently introduced for solving global optimization problems and is a newly improved version of the Modified Simulated Annealing Algorithm (MSAA) with two modifications: i) reduction of probability of accepting worse solutions; ii) the starting point is chosen randomly. I-MSAA was evaluated in five benchmark problems of truss size optimization. The results were compared by those reported by other metaheuristic algorithms and indicated that I-MSAA is stable and efficient to optimize this type of problems.

Keywords: Improved Simulated Annealing Algorithm, size optimization, truss structure, metaheuristics

1 Introduction

The design of trusses structures involves a set of design variables that must comply with certain design restrictions. In practice, the designs are based on the engineer's experience and no efforts are made to obtain optimized designs that allow a balance between safety and economy. In practice, optimization processes are performed through trial and error. This process requires a lot of time because the designer must evaluate many possible designs to find the one that satisfies the conditions of services and the design restrictions and it does not ensure that the design found is optimal.

In general, these design problems are highly nonlinear with complex constraints, and highly multimodal. These design constraints come from design requirements and security measures such as stresses on the members due to external loading, displacements in the nodes, among others. Because of this, deterministic approaches that require gradient information are not convenient to obtain optimized designs. Thus, metaheuristics techniques can serve as appropriate alternatives of conventional methods because they do not require the gradient and they use probabilistic transition rules, not deterministic rules. Furthermore, they do not even require an explicit relationship between the objective function and the constraints. Instead they are based on stochastic search strategies that make them quite effective and versatile to counter the combinatorial explosion of the possibilities.

Several metaheuristics have implemented for size optimization of trusses structures, for example, Genetic algorithms (GA) [1]; Simulated Annealing (SA) [2]; Particle Swarm Optimization (PSO) [3]; Harmony Search (HS) [4,5]; Mine Blast Algorithm (MBA) [6]; Artificial Bee Colony (ABC) [7]; Adaptive Dimensional Search (ADS) [8]; Symbiotic Organisms Search (SOS) [9]; Colliding Bodies Optimization (CBO) [10]; Teaching Learning Based Optimization (TLBO) [11,12] and several improved and hybridized versions of the algorithms [13–16].

Recently, the metaheuristic called Improved Modified Simulated Annealing Algorithm (I-MSAA) [17] was introduced to solve global optimization. I-MSAA is a newly improved version of the Modified Simulated Annealing Algorithm (MSAA) [18] with two modifications. Firstly, the starting point is chosen randomly. Secondly, the range of probability of accepting a worse solution is reduced. In this study, the I-MSAA is proposed for size optimization in trusses structures, with the objective of finding lightweight structures that meet the requested requirements and comply with design restrictions.

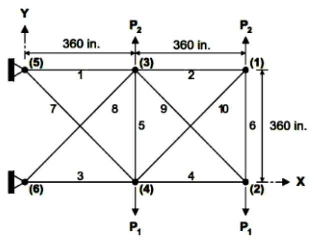
This study is structured as follows: Section 2 presents the methodology and the I-MSAA. Section 3 shows the results obtained with I-MSAA in the five benchmark designs. Section 4 presents the conclusions of this study.

2 Methodology

The algorithm I-MSAA was coded in MATLAB R2017a, and Windows platform using Intel(R) Core(TM) i5-3230M CPU@ 2.60 GHz processor speed with 8.00 GB RAM. The structures were analyzed using the finite element (direct stiffness) method. I-MSAA was evaluated in 5 benchmark designs. Table 1 shows the geometry and properties for each problem. Every problem was solved 100 times and the best design, weights and standard deviation are reported in the tables.

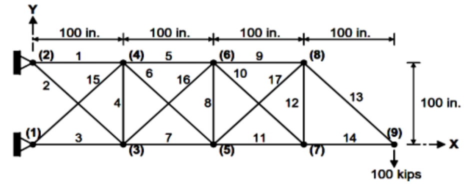
Table 1. Geometry and properties of trusses structures.

Planar 10-bar Truss Structure



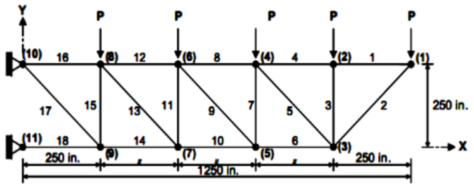
ρ=0.10 lb/in^3
E=10000 ksi
MAS=±25 ksi
DN=±2 in
P_1=150 kips
P_2=50 kips

Planar 17-bar Truss Structure



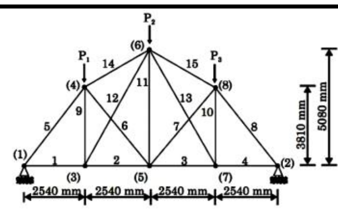
ρ=0.268 lb/in^3	MAS=±50 ksi
E=30000 ksi	DN=±2 in

Planar 18-bar Truss Structure



ρ=0.10 lb/in^3	MAS=±20 ksi
E=10000 ksi	P=20 kips

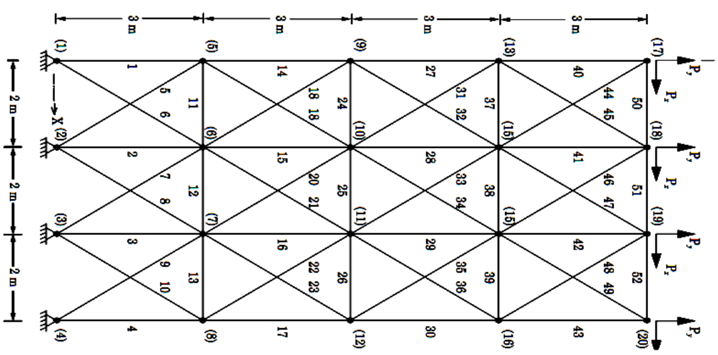
Planar 15-bar Truss Structure



ρ=7800 kg/m^3
E=200 GPa
MAS=±120 MPa
DN=±10 mm
P_1=35 kN
P_2=35 kN
P_3=35 kN

Planar 52-bar Truss Structure

ρ=7860 kg/m^3
E=207 GPa
MAS=±180 MPa
P_X=100 kN
P_Y=200 kN



ρ – material density
E – modulus of elasticity
MAS – maximum allowable stress for all members
DN – displacements for all free nodes

2.1 Improved Modified Simulated Annealing Algorithm (I-MSAA)

I-MSAA is based on the SA. SA is a method developed from the statistical thermodynamics to simulate the behavior of atomic arrangements in liquid or solid materials during the annealing process. I-MSAA was introduced by Suarez et al. [17] for global optimization and has the following characteristics: i) reduction of probability of accepting worse solutions; ii) the starting point is chosen randomly and not by means of the preliminary exploration. The probability of acceptance of a worse solution is between 0 and 1/3 and is calculated by:

$$P = \frac{1}{1+2\exp(\Delta f/T)} \quad (1)$$

The Pseudo code of I-MSAA is as follow:

```
Setting initial temperature (Ti)
Setting final temperature (Tf)
Setting maximum number of perturbations at the same temperature (npmax)
Generate Initial State (S) randomly
T=Ti
While (T> Tf) do //Temperature Cycle
For np=1 to npmax //Metropolis Cycle
Generate S' by search step
Obtain difference (Δf) between S' and S
If (Δf ≤ 0) then
Accept S'
else
Boltzmann Probability = 1/(1+2exp(Δf /T))
If (Boltzmann Probability > random(0, 1/3)) then
Accept S'
end if
end if
end while
Decrease T by cooling function Tk+1=αTk
end while
Shown best solution (Sbest)
```

2.2 Formulation of the optimization problem

The main objective is to optimize the cross-sections of the members in order to minimize the total weight of the structure, satisfying the restrictions that the optimization problem imposes. The structural optimization problem for a truss structure maybe expressed as:

$$\begin{aligned} &\text{minimize} && W(x) = \sum_{i=1}^{nm} \rho_i x_i L_i \\ &\text{subject to} && \begin{cases} \delta_L \leq \delta_i \leq \delta_U;\ i = 1, \dots, m \\ \sigma_L \leq \sigma_i \leq \sigma_U;\ i = 1, \dots, nm \end{cases} \end{aligned} \tag{2}$$

where x is the is the vector containing the design variables (discrete or continuous); W(x) is the weight of the structure; m is the number of nodes; nm is the number of members forming the structure; ρ_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 element i; and L and U represent the lower and upper bounds, respectively.

3 Results

Table 2 shows the results obtained with I-MSAA in the five design problems and they are compared with others reported in the literature. For the planar 10-bar truss structure, the minimum and maximum area for the cross section of the members were $0.1 \leq A_i\,(in^2) \leq 35$ (continuous variables).

Table 2. Optimal design comparison for the five benchmark design problems

Planar 10-bar Truss Structure

Algorithm	Variables (in^2)										Weight (lb)	Mean (lb)	SD (lb)
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**			
TLBO [11]	23.5	0.1	25.4	14.5	0.1	2.0	12.3	12.7	20.4	0.1	4678.3	4680.1	1.0
PSO [3]	22.9	0.1	25.4	14.4	0.1	2.0	12.3	12.9	20.7	0.1	4679.5	-	-
HS [5]	23.2	0.1	25.8	14.5	0.1	2.0	12.2	12.6	20.4	0.1	4668.8	-	-
I-MSAA	23.5	0.1	25.3	14.2	0.1	2.0	12.4	12.9	20.4	0.1	4677.0	4678.9	1.4

Planar 17-bar Truss Structure

Algorithm	Variables (in^2)									Weight (lb)	Mean (lb)	SD (lb)
PSO [3]	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	2724.4	-	-
	15.8	2.3	13.9	0.1	11.4	3.9	8.1	01	5.9			
	A10	**A11**	**A12**	**A13**	**A14**	**A15**	**A16**	**A17**				
	2.3	6.3	3.4	5.4	3.9	3.5	2.3	3.5				
HS [5]	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	2580.8	-	-
	15.8	0.1	12.0	0.1	8.2	5.5	11.8	0.1	7.9			
	A10	**A11**	**A12**	**A13**	**A14**	**A15**	**A16**	**A17**				
	0.1	4.1	0.1	6.7	4.1	5.7	0.1	5.6				
I-MSAA	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	2582.0	2582.9	0.68
	15.9	0.1	12.2	0.1	8.0	5.5	11.9	0.1	8.0			
	A10	**A11**	**A12**	**A13**	**A14**	**A15**	**A16**	**A17**				
	0.1	4.0	0.1	5.7	4.0	5.6	0.1	5.6				

Planar 18-bar Truss Structure

Algorithm	Variables (in^2)				Weight (lb)	Mean (lb)	SD (lb)
	G1	**G2**	**G3**	**G4**			
HS [5]	9.98	21.63	12.49	7.06	6421.88	-	-
ABC [7]	10.00	21.65	12.50	7.07	6430.53	-	-
I-MSAA	10.00	21.65	12.50	7.07	6430.53	6430.53	0.00

Planar 15-bar Truss Structure

Algorithm	Variables (mm^2)								Weight (kg)	Mean (kg)	SD (kg)
ICA [16]	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	105.7	105.7	0.0
	113.2	113.2	113.2	113.2	736.7	113.2	113.2	736.7			
	A9	**A10**	**A11**	**A12**	**A13**	**A14**	**A15**				
	113.2	113.2	113.2	113.2	113.2	334.3	334.3				
TLBO [12]	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	105.7	-	-
	113.2	113.2	113.2	113.2	736.7	113.2	113.2	736.7			
	A9	**A10**	**A11**	**A12**	**A13**	**A14**	**A15**				
	113.2	113.2	113.2	113.2	113.2	334.3	334.3				
I-MSAA	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	105.7	105.7	0.0
	113.2	113.2	113.2	113.2	736.7	113.2	113.2	736.7			
	A9	**A10**	**A11**	**A12**	**A13**	**A14**	**A15**				
	113.2	113.2	113.2	113.2	113.2	334.3	334.3				

Planar 52-bar Truss Structure

Algorithm	Variables (mm^2)						Weight (kg)	Mean (kg)	SD (kg)
CBO [10]	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**	1899.35	1963.12	106.01
	4658.06	1161.29	388.39	3303.22	940.00	506.45			
	G7	**G8**	**G9**	**G10**	**G11**	**G12**			
	2238.71	1008.39	506.45	1283.87	1161.29	506.45			
TLBO [12]	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**	1902.61	-	-
	4658.06	1161.29	494.19	3303.22	940.00	494.19			
	G7	**G8**	**G9**	**G10**	**G11**	**G12**			
	2238.71	1008.39	494.19	1283.87	1161.29	494.19			
I-MSAA	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**	1902.61	1910.68	21.38
	4658.06	1161.29	494.19	3303.22	940.00	494.19			
	G7	**G8**	**G9**	**G10**	**G11**	**G12**			
	2238.71	1008.39	494.19	1283.87	1161.29	494.19			

The problem has 32 non-linear constraints (10 tension constraints, 10 compression constraints and 12 displacements constraints). For this problem, it can be seen that the optimal weight acquired by the I-MSAA (4677.0 lb) is better than the reported by other algorithms (4678.3 lb for TLBO and 4679.5 lb for PSO). In addition, the SD (1.4 lb) obtained by I-MSAA shows the stability of the algorithm.

The planar17-bar truss structure has 17 independent variables and 52 non-linear constraints. As seen, for this problem the I-MSAA obtained a structure with a weight of 2582.0 lb with a SD of 0.68 lb. It is important to mention that the weights reported with HS (2580.8 lb) and PSO (2724.4 lb) are lower than those of I-MSAA, this is because these designs violate some restrictions.

For the planar18-bar truss structure, the number of variables was reduced to four groups in the following manner: (G1) elements 1, 4, 8, 12, 16; (G2) elements 2, 6, 10, 14, 18; (G3) elements 3.7, 11, 15; (G4) elements 5,9, 13, 17. The minimum area was 0.10 in^2 and the maximum 50 in^2. The problem has 36 non-linear restrictions. From Table 2, it can be seen that the optimal weight acquired by the I-MSAA (6430.53 lb) agrees well with those given by the ABC [7]. In addition, the SD obtained with I-MSAA was 0.0 lb evidencing the capability of the algorithm for reach the optimal.
The planar15-bar truss structure 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). In the 100 runs of this algorithm, the average weight of the truss designs was 105.7 kg with an SD of 0.0 kg. These values were equal to those reported by ICA and TLBO.

For the planar 52-bar truss structure the members of the structure were divided into 12 groups: (G1) A1-A4, (G2) A5-A10, (G3) A11-A13, (G4) A14-A17, (G5) A18-A23, (G6) A24-A26, (G7) A27-A30, (G8) A31-A36, (G9) A37-A39, (G10) A40-A43, (G11) A44-A49 and (G12) A50-A52. Discrete values of cross-sectional areas can be selected from the AISC design code. The best weight found by I-MSAA (1902.61 kg) was equal to that reported by TLBO. Although the CBO (1899.35 kg) obtained a lower weight than I-MSAA, I-MSAA obtained an SD (21.38 lb), five times less than that reported by CBO (106.01 lb).

4 Conclusions

In this work the Improved Modified Simulated Annealing Algorithm (I-MSAA) was introduced, for the first time, in the sizing optimization of truss structure. The performance of I-MSAA was evaluated in 5 benchmark designs and the results were compared with those reported in the literature. The comparison showed that I-MSAA outperformed other algorithms, in some cases noticeably, both in terms of solution qualitity and standard deviation value. Finally, the I-MSAA is distinguished by its ability to fluently escape the traps of the local minima.

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