70(8A): 1-479; 2022. DOI: 10.18311/jmmf/2022/32021

Print ISSN : 0022-2755

Journal of Mines, Metals and Fuels

Contents available at: www.informaticsjournals.com/index.php/jmmf

Optimal Design of Steel Planar Trusses Using Ant Lion Algorithm

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Abstract

This paper elaborates on optimized design of steel structures directed towards the sustainability of materials. The case in point is steel trusses that are extensively used structural components. Though copious research is available on use of conventional optimization methods, nature-inspired optimization algorithms have received scarce attention particularly in optimal design of planar trusses. In this paper, the development of Ant Lion algorithm for the optimal design models for steel trusses is elaborated. A comprehensive comparison with the optimized sectional weights obtained by other nature inspired optimization algorithms implemented in earlier research by the author. They include elitism based genetic algorithm (EBGA), ant colony optimization (ACO), artificial honeybee optimization (AHBO), and Particle swarm optimization (PSO) algorithm. Four steel trusses with different articulations have been considered for this purpose. It is found that the optimal weights obtained by Ant Lion algorithm are almost on par with those obtained by PSO. The other three algorithms vary marginally. However, the convergence to overall weight of trusses is different for different algorithms. ALO took 100-200 iterations for the convergence. In fact, the convergence to optimized weights are faster in case of ALO and PSO in relation to other algorithms.

1.0 Introduction

Optimized material usage while developing articulations is not new in engineering design practices. Optimization by itself has a wide horizon of applications in almost every field of science and technology. In general, it could be minimization of cost, the effort, quantum of material, weight or energy consumption. In the same token, it could be maximization of strength, efficiency, performance, output and profit. This is driven by the fact that, for any engineering endeavour, the budget, resources and time is always limited. Therefore, optimization has gained a coveted place in all facets of engineering (Koziel and Yang, 2011). Optimal design of steel structures in general and steel trusses have gained huge significance and importance. As far as steel trusses are concerned, optimization would connote determination of ideal sectional areas and to obtain minimal weight of the members. Thus, such an optimization would result in reduction in overall weight of the truss without trading off the strength. To achieve this, an optimal solution should comply with the code provisions, the constraints, serviceability requirements and safety. Several traditional optimization methods such as gradient search (Zhu, 2009), linear programming (Kristen and Meteren, 1998), quadratic programming (Momo et all, 1994), and Newton method (Perez et all,1998). These methods however are cumbersome, and computationally intensive. They may not effectively handle practical operating constraints with non-convex, and non-differentiable objective functions. Above all they may not promise the global optima (Henh and Arora, 1989).

It has been established that meta-heuristic algorithm can obviate this. In a broader perspective of including various natural processes, the meta heuristic algorithms are grouped depending based on their development.

- Human based
- Swarm behaviour based
- Natural evolution based
- Music based
- Plant based

However quite recently swarm-based algorithms have gained huge popularity and applications. Swarm intelligence-based algorithms vaguely mimic community of creatures like fish, birds, bacteria, insect colonies and animal herds (Yang and Karmanagolu, 2013). These algorithms have received wide acceptance owing to their flexibility, versatility, simplicity. For the sake of information and completeness, a list of such collective intelligence-based optimization algorithms of recent origin (2015-2019) is provided in Table 1.

Among the several bio-inspired optimization algorithms listed, ALO stands out to be widely applied across all disciplines of engineering since it was developed in 2015 (Hussien and Amin, 2020).

In view of the nature of research, and to have a focussed presentation, a summary of applications of meta-heuristic algorithms for the optimization of trusses is presented in Table 2. Though algorithms used by researchers are different, literature survey revealed that the major concern is the minimization of overall weight of the truss.

Table 1: Recent swarm optimization algorithms

Algorithm	Author, Year
The Ant Lion	S. Mirjilili, 2015.
Social Spider	Yu and Li, 2015.
Elephant Herding	Gai-Ge Wang et all, 2015.
Earthworm Optimization	Gai-GeWang et all, 2015.
Red Deer	Fard and Keshteli, 2016.
Shark Smell	Abedinia, 2016.
Dolphin Swarm	Tian-qi wu et al, 2016.
Crow Search	Alireza Askarzadeh,2016.
Spotted Hyena	Dhiman and Kumar,2017.
Gross Hopper	Shahrzad S et al.,2017.
Owl Search	Jain et al., 2018.
Tree Growth	Cheraghalipour et al., 2018.
Squirrel Search	Jain et all, 2019.
Bald Eagle search	Alsattar et al., 2019.
Harris Hawks	Heidari et al., 2019.

2.0 Method

In a nutshell, the methodology involved application of Ant Lion algorithm on four planar steel trusses and comparing the optimized weights with the results of EBGA, ACO, HBO and PSO obtained by the other in the earlier studies.

2.1 Ant Lion Algorithm

Ant lion is an insect larva which thrives for 2 to 3 years and they eat ants by trapping them. To trap the prey, cone shaped holes will be dug by them with their powerful jaws. The walls of the holes are laden with fine sand that can induce slippery and caving in. It waits for the prey generally ants to fall in or to get trapped. In order not to be noticed, it hides beneath the bottom of the cone. As soon as the prey gets into the trap, it starts throwing the sand towards upper portion of the trap, making sand to cave in, and thus engulfing the prey or burying the prey. After eating the prey, it throws the leftovers outside the trap and again goes to hiding. A typical view of a few such traps is shown in Figure 1. Figure 2 depicts the waiting Ant Lion and the preys moving above and towards the trap. Figure 3 shows the projection of movement patterns if Ant Lions and Ants beneath the trap (Adel Saad Ansari et all, 2020).

The natural processes considered in the algorithm are:

- Ants run randomly on the sand.
- Ant lions distinguish in the sand and dig a trap to hunt the ants.
- When the ant gets into the trap, the ant lion gathers it by moving the sand.

The mapping of the natural processes is done as follows:

- The objective function is the sand
- The solutions are Ant Lion positions
- The search agents are Ants.
- Before getting into the trap, the ant has a lot of variable decisions.
- The deeper it goes into the trap the smaller variable decisions it has.

2.2 ALO Algorithm Phases

ALO takes six phases, they are explained in brief (Mirjalili, 2015).

Step 1: In the search space, the locations of Ants and Ant Lions are randomly initialized and two matrices

Table 2: Summary of literature survey

Author, Year	Brief description of the work
Tayfun Dede et al (2011)	Binary encoded genetic algorithm (GA) has been used for weight minimization of the trusses. Binary encoding has improved the speed of the algorithm run and memory requirement. The results were found to be encouraging.
Herbert Martin Gomes, (2011).	Particle swarm optimization (PSO) is used to optimize the sizes of four space trusses. The constraints were based on natural frequencies. The algorithm produced same results as that of other conventional methods and found to be better in some cases.
Degertekin and Hayalioglu (2013)	A new genre algorithm namely Teaching-learning-based optimization (TLBO) is used for optimal design of truss structures.The algorithm vaguely mimics the learning process of students.The role of the teacher is simulated in terms of guiding the learner population in the searchspace. The method was applied in developing optimal design of fourtrusses. Results have shown that the method ended up in slightly heavier designs as compared withsimilar designs obtained by other bio – inspired algorithms. It isalso reported that in a few cases, the availed results from the algorithm was relatively betterthan the results obtained by other bio-inspired algorihms in terms quick convergence.
Bekadas et al (2015)	The minimization of weights and sizing of members of the truss have been attempted using Flower pollination algorithm (FPA). The results proved the efficiency of FPA in combining both local and global searches. The said algorithm was implemented on three 2D and 3D trusses. The algorithm was found to be competitive with other meta heuristic algorithms.
Bureerat and Pholdee (2016)	Differential evolution concepts have been employed for optimization. Apart from this a novel methodology for handling constraints has also been found. The optimization also proved to be powerful and compares almost similar to best of the evolutionary algorithms with fast convergence and near global solution.
Kazemzadeh Azad et al, (2016)	The meta heuristic algorithm named big-bang crunch (BB-BC) is used algorithm is used for the optimal design of 38 member steel truss, i.e., overall weight minimization. The algorithm showed exponential run time when compared with other algorithms.
GhanashyanTejani et al. (2018)	Symbiotic organisms searchalgorithm (MOASOS) is implemented solving trussoptimization. A pair of objectivefunctions one for elemental stress and the other related to discretecross-sectional areas have beenproposed. The first objective function captured the behaviour and the other captured the constraints respectively. Different shaped space trusses with design variables that are discrete have been considered. The algorithms exercised adaptive control of parameters and the concurrent results have shown that this control over the parameters resulted in solutions that are competitive.
Masoud Salar, and Babak Dizangian (2019)	ALO is implemented size optimization in case of space truss-structures. The efficiency and performance of the ALO is examined by considering 22 bar and 25 bars spatial truss examples. The obtained results are compared with those published by other researchers. Results prove capability of the ALO for finding global optimum of tested examples. Furthermore, it is found that the convergence rate of the ALO algorithm is not satisfactory to achieve the best solution
Ali Kavehand Ataollah (2020)	The algorithm used in this work istermed Shuffled shepherd optimization algorithm (SSOA).The truss layout optimization is done. This recent algorithm isinspired by the shepherd's pattern of behaviour. The results of thealgorithm on 25 bar,47 bar and 272 bar space trusses have shown that SSOA is comparable withbest of the heuristic algorithms.

Author, Year	Brief description of the work
Ali Kavehand Masoud Khosravian (2022)	Vibrating Particles System (VPS) optimization algorithm is applied to topology optimization of trusses. The essence of the method is simulation of single degree freedom viscous-damped systems. The algorithm starts with population vibrating particles, which attain equilibrium by adjusting positions in the space. The position that provides a state of equilibrium will be the best position. Four trusses are considered for the evaluation of performance of the algorithm in terms of its convergence to the optimal values of the variables. The proposed algorithm is proved to be an efficient method for small number of members in the truss
M.A.Jayaram (2022)	Four bio-inspired optimization algorithms are proposed. The EBGA, ACO, HBO, and PSO has been attempted. The size of the members of the truss are optimized. Planar steel trusses with 8, 11 , 12, and 13 bars were considered and optimal weights are determined. The results show marginal variation across the algorithms in terms of optimized weights. Marked differences were noticed in the pattern of convergence of total weight. In this context, quick convergence was noticed with PSO. The algorithms have also shown lower values of standard deviation in overall weight.

M_{ant} and $M_{antlion}$ are generated. The rows of these matricies the coordinates or the position vectors of the Ants and Ant Lions respectively. The number of rows indicate the population of Ants and Ant Lions.

$$M_{ant} = \begin{bmatrix} A_{11} \; A_{12} \ldots\ldots \; A_{1N} \\ A_{21} \; A_{22} \ldots \; A_{2N} \\ ---\\ ----\\ ----\\ A_{M1} \; A_{M2} \ldots\ldots A_{MN} \end{bmatrix} \quad \ldots (1)$$

Figure 1: Ant Lion conical shaped traps

$$M_{antlion} = \begin{bmatrix} AL_{11} \; AL_{12} \ldots\ldots \; AL_{1N} \\ AL_{21} \; AL_{22} \ldots \; AL_{2N} \\ ---\\ ----\\ ----\\ AL_{M1} \; AL_{M2} \ldots\ldots AL_{MN} \end{bmatrix} \quad \ldots (2)$$

Step 2: The positions of ants and ant lions are used to evaluate the objective function. Two fitness vectors F_{ant} and $F_{antlion}$ will be generated.

$$F_{ant} = \begin{bmatrix} f(A_{11} \; A_{12} \ldots\ldots \; A_{1N}) \\ f(A_{21} \; A_{22} \ldots \; A_{2N}) \\ ---\\ ----\\ ----\\ f(A_{M1} \; A_{M2} \ldots\ldots A_{MN}) \end{bmatrix} \quad \ldots (3)$$

$$F_{antlion} = \begin{bmatrix} f(AL_{11} \; AL_{12} \ldots\ldots \; AL_{1N}) \\ f(AL_{21} \; AL_{22} \ldots \; AL_{2N}) \\ ---\\ ----\\ ----\\ f(AL_{M1} \; AL_{M2} \ldots\ldots AL_{MN}) \end{bmatrix} \quad \ldots (4)$$

Step 3: The fittest Ant Lion that has high objective function value *f(AntLion)* will be selected as the *elite* one.

Step 4: Roulette wheel algorithm is used to choose the Ant Lion randomly for each ant.

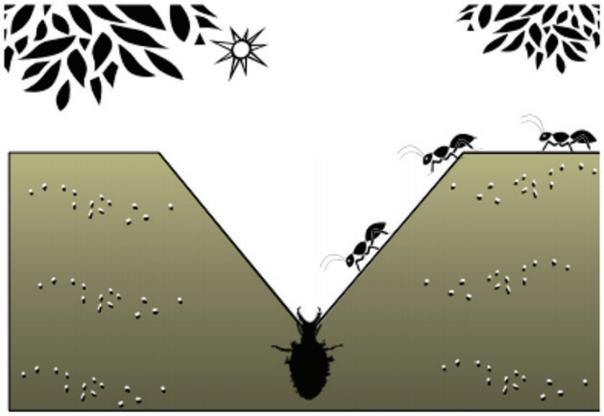

Figure 2: Hunting behaviour

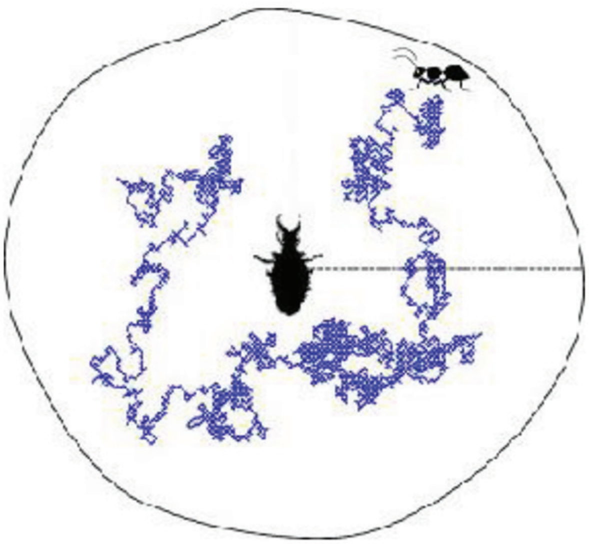

Figure 3: The search space

Begin:
Input the population size and other parameters
Randomly create initial populations of Ants and Ant Lions.
Compute the values of fitness function of Ants and Ant Lions.
Choose the fittest Ant Lion deemed to be elite.
While It < N
For each Ant
Select the Ant lion by Roulette wheel operator.
The limits of parameters the upper and the lower are updated.
The positions of Ant and Antlions are updated.
End For.
Compute fitness values of all ants and place them in F_{ant} matrix.
Change the Ant Lion with the Ant if Ant lion has greater fitness value than that of Ant
Modify the value of the elite Ant Lion's previous value if current value is better.
End While.
Provide the best elite ant's value as the

Figure 4: Pseudo code of ALO algorithm

Step 5: Ants will be allowed make random walks in the search space.

$$X = \begin{bmatrix} 0 \\ CS(2*r1-1) \\ CS(2*r2-1) \\ ---- \\ ---- \\ CS(2*r(IT)-1 \end{bmatrix} \quad \ldots (5)$$

Here, *r(IT)* is a stochastic function, and *r* is the random function with a uniform distribution in the range [0,1]. When the ant gets in to the trap, the ant lion pushes the sand to attract it so that the decision variables will get reduced. The random walks will be normalized.

Step 6: The fitness function evaluation corresponding to each selected Ant *f(Ant)* and Ant *lion f(Ant Lion)* evaluation are carried out. The positions of Ant Lion and Ant will be updated based on two conditions;

If $f(Ant_{Selected}) > f(AntLion_{rws})$
$AntLion_{new} = Ant_{selected}$
If $f(AntLion_{new} > AntLion_{elite})$
$AntLion_{newelite} = AntLion_{new}$

Step 7: Repeat step 4 to step 6 until any one of the following is reached.

- Specified number of iterations
- Predefined tolerance value

The pseudo code of the algorithm (Dian Setiya Widodo, 2020) is provided in Figure 4.

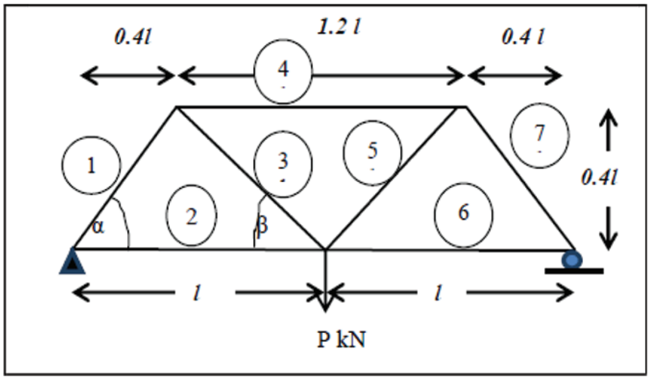

Figure 5: A typical 7- bar steel planar truss

2.3. The Objective Function

As a typical case, a framework for development of objective function which could generate cross sections that are optimal is elucidated. For the sake of clarity and completeness, a truss with 7 members has been chosen. For the formulation of the problem generalized linear dimensions are considered. The said truss is shown in Figure 5.

In order to make the development of objective function lucid, the length l is assumed to be unity (1 m). The sectional areas of seven bars are treated as the decision variables. Because of symmetry, some of the areas of cross sections will become equal and the decision variables would reduce to just four, i.e., A1 = A_7, A_2 = A_6, A_5 = A_3, and A_4. The objective function becomes,

Table 3: The member forces

(- compression, + tension)

Bars	Axial force	Members	Axial force
1 & 7	$-0.5\ P\ coseea$	3 and 5	$0.5Pcosee\beta$
2 & 6	$+0.5P\ cot\alpha$	4	$-0.5P(cot\alpha + cot\beta)$

$$Min\ f(A_i)= 1.132A_1 l + 2A_2 l + 1.8A_3 l + 1.2A_4 l \quad \text{... (6)}$$

The axial forces generated due to applied load is provided in Table 3.

In the first level constraints are developed by allowing the axial tensile (σ_{at}) and compressive (σ_{ac}) to befit the working stress levels. This constraint is predicated by the standard code of practice. Such constraints are in order.

$$\frac{0.5\ Pcosee\ \alpha}{A_1} \leq \sigma_{ac} \quad \text{... (7)}$$

$$\frac{0.5Pcot\ \alpha}{A_2} \leq \sigma_{at} \quad \text{... (8)}$$

$$\frac{0.5Pcosee\ \beta}{A_3} \leq \sigma_{at} \quad \text{... (9)}$$

$$\frac{0.5P\ (cot\alpha + cot\ \beta)}{A_4} \leq \sigma_{ac} \quad \text{... (10)}$$

The next type of constraints has their origin in the overall stability of the truss. However, this needs to be considered for the members that are in compression. Thus, the bars numbered 1, 4 and 7 will be in compression. As the limiting stress is at working level, the buckling loads as predicated by Euler's equation need be considered. Here, both ends are assumed to be hinged.

$$0.5Pcoseea \leq \frac{\pi E A_1^2}{1.28 l^2} \quad \text{... (11)}$$

$$0.5P(cot\alpha + cot\beta) \leq \frac{\pi E A_4^2}{5.76 l^2} \quad \text{... (12)}$$

The deflection criteria provide a crucial constraint. The magnitude of the deflection at the centre of the truss owing to the applied loads are limited to a value as suggested by the IS code.

$$\frac{Pl}{E}\left(\frac{0.567}{A_1} + \frac{0.500}{A_2} + \frac{2.236}{A_3} + \frac{2.700}{A_4}\right) \leq \delta_{ma:} \quad \text{... (13)}$$

The cross sectional areas should also be limited by the upper and lower bounds. As the area of cross sections are the decision variables, their bounds are also treated as as a constarint. Thus, the bounds of decision variables are:

$$LB \leq A_1, A_2, A_3, A_4 \leq UB \quad \text{... (14)}$$

The above listed are obviously inequality constraints, optimization of areas of cross sections, therefore the weights will nevertheless be a constrained optimization problem. To covert this problem into unconstrained one, suitable penalty function is to be chosen. The transformed formulation would be (Deb, 2013).

$$P\left(x^{(t)}, R^{(t)}\right) = f\left(x^{(t)}\right) + F((R^t, g(x^t)) \quad \text{... (15)}$$

The objective function is represented by $f(x)$, the constraints bearing inequality are denoted by $g(x)$, the penalty function is represented as $R(t)$. To terminate the iterative process of searching, a threshold parameter (ε) is designated.

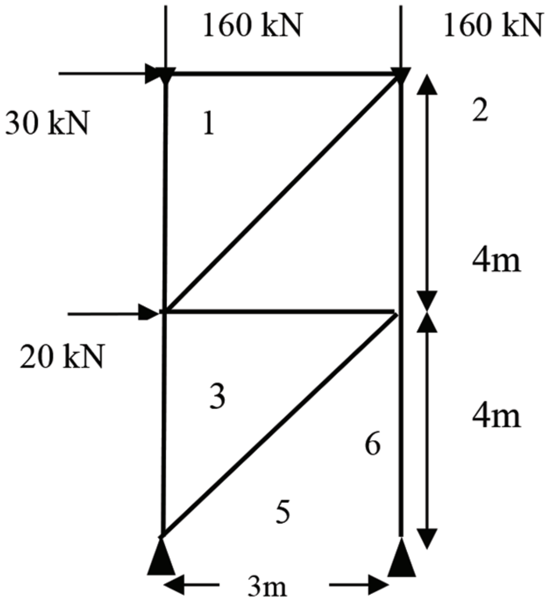

Figure 6: Truss 1-8 bars

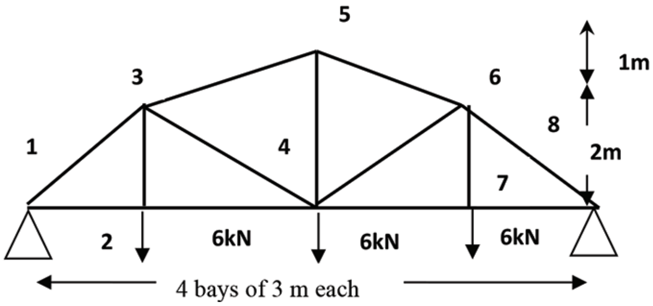

Figure 7: Truss 2-12 bars

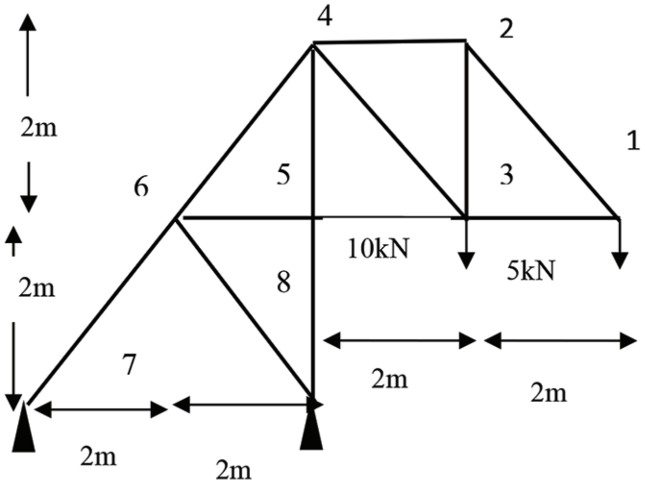

Figure 8: Truss 3-11 bars

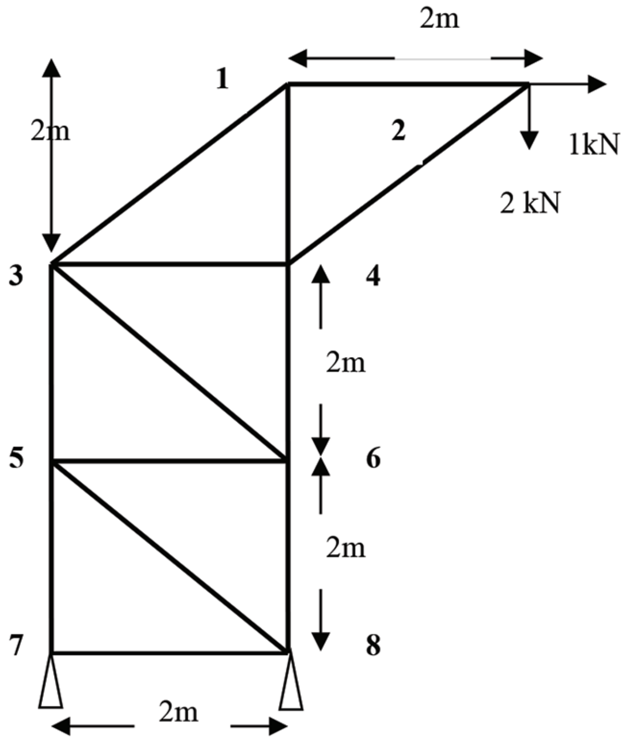

Figure 9: Truss 4-13 bars

Table 4: Various parameters considered

Parameter	Value
Unit weight	7850 kg/m^3
Elastic Modulus	2.1×105 N/mm^2(Mpa)
Permissible axialstress (compression and tension)	300 N/mm^2
Permissibledeformation (elongation & compression)	16% - 20%
Effective slendernessratio	180
Permissible deflection	Span/500 mm

3.0 Results and Discussion

In order to make in-depth application and comparative results of optimization, four topologies of trusses have been considered. These trusses are presented in Figures 6 to 9. The allowable stresses and other intricate parameters, 2m and physical properties are as per the provisions of Indian standard codes (IS 800, SP 6-1). Some of the salient physical properties and their values as obtained from code provisions are listed in 2m Table 4.

3.1 Example Trusses

Application of Ant lion algorithm performed for the trusses as shown in Figures 6 to 9. Optimization of size is performed by tagging to section nearest to the optimal area of cross section found in steel handbook (SP 61)). The optimization process was carried out in stages as specified in the steps and pseudo code of the algorithm. A constant population size of 20 Ants and Ant Lions was maintained for the sake of uniformity and for comparison with other algorithms. The ALO algorithm took 100-200 iterations for converging to optimal weight. This number depended on the configuration complexity of the trusses. The area of cross section obtained is rounded off to the nearest integer value. The results obtained by ALO algorithm is compared to those of the results obtained by other evolutionary algorithms (Jayaram, 2022) namely, Artificial Bee Colony Optimization (ABCO), Ant Colony Optimization (ACO), Elitist Genetic Algorithm (EGA) and Particle Swarm Optimization (PSO). Tabulation of the results obtained by afore mentioned methods for a comparative analysis on the four planar steel trusses considered is provided in Tables 5 to Table 8 along with ALO results. However, the elaboration on the four algorithms does not come under the purview of this paper.

A deeper perspective into the results of optimized weights of individual members in Table 5 to 8, broadly it can be concluded that the five algorithms in general and ALO in particular have descended to almost to identical values of cross sections. However, marginal differences exist. These differences are subtle when number of iterations consumed by the algorithms is

Table 5: The results of ALO and other 4 algorithms (Truss-1, Figure 6)

Area in mm2 of bars and other parameters	ALO	ABCO	ACO	EBGA	PSO
A1-2	110	118	111	108	112
A2-3	174	178	174	171	175
A1-3	173	171	171	168	171
A2-4	283	276	281	279	281
A3-4	896	894	897	892	896
A3-5	412	411	409	407	411
A4-6	536	539	541	538	541
A4-5	669	674	672	669	671
Total weight (Kg)	3253	3261	3256	3232	3258
Standard Deviation (Kg)	0.24	0.48	0.61	0.23	0.26

Table 6: The results of ALO and other 4 algorithms (Truss-2, Figure 7)

Area in mm2 of bars and other parameters	ALO	ABCO	ACO	EBGA	PSO
A1-2 & A7-8	48	51	49	48	47
A2-3 & A6-7	26	26	22	23	24
A1-3 & A6-8	54	58	56	57	55
A2-4 & A4-7	51	48	48	47	49
A3-4 & A4-6	9	8	8	7	7
A3-5 & A5-6	47	47	47	45	48
A4-5	31	31	32	29	29
Total weight (Kg)	266	269	262	256	259
Standard Deviation (Kg)	0.22	0.42	0.31	0.26	0.21

Table 7: The results of ALO and other 4 algorithms (Truss-3, Figure 8)

Area in mm2 of bars and other parameters	ALO	ABCO	ACO	EBGA	PSO
A1-2	27	26	23	24	25
A2-3	18	18	17	17	17
A1-3	19	18	19	18	18
A2-4	18	19	19	18	18
A3-4	83	81	81	79	81
A3-5	77	81	82	79	78
A4-6	97	98	99	97	98
A5-6	78	81	83	79	78
A4-5	54	53	54	51	53
A6-7	147	142	145	143	146
A6-8	52	51	53	49	51
A5-8	53	54	53	51	53
Total weight (Kg)	723	722	728	705	716
Standard deviation (Kg)	0.26	0.67	0.87	0.29	0.25

Table 8. The results of ALO and other 4 algorithms (Truss-4, Figure 9)

Area in mm2 of bars and other parameters	ALO	ABCO	ACO	EBGA	PSO
A1-2	12	12	13	11	12
A2-4	13	11	11	10	12
A1-4	13	12	12	10	12
A1-3	17	16	16	15	16
A3-4	8	8	8	7	8
A3-5	23	23	24	22	24
A3-6	6	6	7	5	6
A4-6	19	17	17	17	18
A5-6	6	5	5	4	6
A5-7	19	18	18	17	19
A6-8	17	15	16	14	15
A5-8	6	6	6	2	6
A7-8	5	5	6	4	5
Total weight (Kg)	164	154	159	138	159
Standard Deviation (Kg)	0.19	0.45	0.55	0.20	0.18

also considered. As far as ALO is concerned, it doled out results are almost identical to PSO algorithm with very timid difference. Another observation that merit consideration is that the algorithms have shown lower values of standard deviation suggesting that the searching in all the cases has landed in a location where a cluster of solutions are available. ALO's iterations counts for convergence varied between 100 and 200 depending on the truss. For 12-member truss (figure 7) it took maximum of 200 iterations to arrive at the optimized weight. As the population size was kept constant in order to have a fairer comparison among the algorithms, the different heuristic strategies used by the five algorithms must have led to different iteration sizes. Interestingly both EGA and PSO converged with in just 100 iterations.

Though it is pertinent to do an analysis in comparison with the results obtained in this work with the reported works by other researchers, it does not fit well as in most of the optimization related research, the space trusses have received greater attention. Only in a small number of reported research that planar trusses have been considered for optimization of weight. In some limited cases the topology optimization has also been attempted. Here

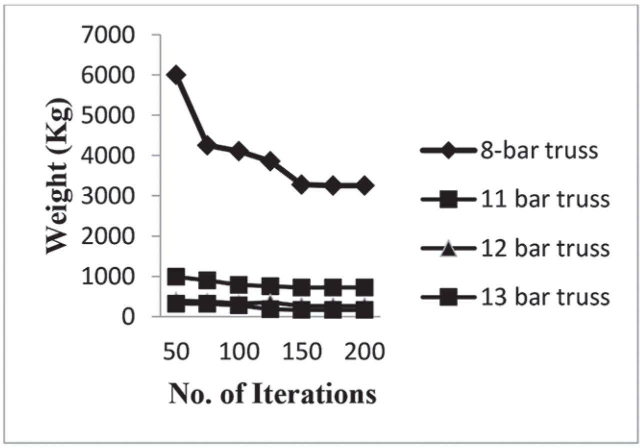

Figure 10: Convergence of total weight

Table 9: Comparison of algorithm complexity metrics

Algorithm	CPU time (sec)	Optimality	NFE
ALO	4.6	0.96	200
ABCO	5.8	0.98	350
ACO	6.2	0.99	300
EBGA	6.5	0.85	100
PSO	4.4	0.97	100

again, among the bio-inspired algorithms, GA, GA variants, and PSO have found extensive application. Further, ALO has shown excellent performance in optimization of space trusses (Masoud Salar and Babak Dizangian, 2019).

The convergence of weights against the number of iterations is presented in Figure 10. It can be seen from this graph that the algorithm has landed in the total weight for lower number of iterations almost 100, for truss 1 and truss 3. But for truss 2 and truss 4, it has taken almost 200 iterations.

To have a prudent comparative metric the complexity of the algorithm is measured and compared to the other algorithms. Generally, the complexity of such meta-heuristic algorithms is made with metrics such as mean best, optimality, CPU time and number of function evaluations or iteration to reach convergence (NFE) (Hayder Kilic, Ugur Yuzgec, 2019). For the sake of impartial comparison of performance among the algorithms, the population size is kept constant at 20. The value indicated refers to the truss with 13 bars. The complexity measures are presented in Table 9. It may be observed that PSO and ALO are placed at same complexity levels in terms of the metric values.

4.0 Conclusions

This paper presented application of Ant Lion meta heuristic algorithm for the optimal weight design of steel planar trusses. Four example trusses of high practical relevance have been considered to study how the algorithm works for different topological trusses. Apart from this the results of four other evolutionary algorithms are also considered. The algorithm converged to the total weight within 100 to 200 iterations. Of course, maximum number iteration was consumed for the 13-bar truss. Following conclusions are drawn that are based on the extensive computational work rendered.

- ALO algorithm behaved in a similar manner as that of PSO in terms of total weight and number of iterations consumed.
- A comparative analysis of the results of ALO with other algorithms, i.e., very small differences in optimized weight values are noticed in optimal weights of individual members and over all weight of the truss. This is owing to constant population size set forth for all the five algorithms.
- ALO converged with in 200 iterations with varied iteration sizes in the range [100-200]. This variation is possible due to differences in number of bars to

be optimized.

- The standard deviation is found to be low across all the algorithms. Low values of standard deviation are indicative of the sizable number of feasible solutions in a particular location of the search space with close neighbourhood. However, ACO and ABCO algorithms have shown higher standard deviation.

5.0 References

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