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Original Article

Efficient Material Utilization in Truss Structures Using Deterministic and Metaheuristic approach

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Abstract - *When the geometry and connectivity of a truss are fixed, efficient material utilization under strength, serviceability, and stability constraints is addressed as a size optimization problem. This study presents a comparative study of the material minimization of a truss structure by using three optimization algorithms: Sequential Quadratic Programming (SQP), Genetic Algorithm, and Particle Swarm Optimization (PSO). For comparative analysis to keep same framework, these methods are employed to optimize a benchmark 10 Bar truss problem. The minimization of material is achieved by determining optimized area of cross-section of truss members. For comprehensive comparative analysis between optimization methods, statistical key performance indices are evaluated by focusing on optimized area and overall weight of truss, integrating both serviceability (Stress and displacement constraint) and practical sustainability (frequency constraint) criteria. While achieving material minimization, convergence behaviour and computational efficiency are analysed through weight iteration histories and execution time. The results indicate that SQP yields the minimum structural mass of 2486.88 kg and also the lowest Total Structural Area (TSA) of 0.0825 m². The ranking score shows that both SQP and PSO have better performance in convergence and accuracy. In contrast, the GA produces higher structural mass, greater displacement in member, and larger error values. SWOT analysis of all these 3 approaches helps for a better understanding of working mechanism, applicability, accuracy. Which guides for selection of optimization method. The SQP method showed the best accuracy overall. However, study reflects PSO is a good and reliable metaheuristic alternative for optimization of truss.*

Keywords - *Truss material minimization, Metaheuristic, Deterministic approach, 10 bar truss, Penalty function, MATLAB.*

1. Introduction

Material minimization is now an integral part of structural engineering practice, largely because of the growing need to reduce material usage and hence overall construction cost with adhering safety, serviceability and stability of structure. Primarily, the task is to identify a design parameter and constraints, while using the least amount of resources. With growing needs of complex structures and rising emphasis on sustainability, optimization methods have influenced real design decisions, particularly in steel and truss structures, where efficient material utilization is directly affecting both cost and environmental impact.

Improvement in computational techniques over the past few decades has considerably widen the range of problems that can be evaluated through optimization methods. Based on the approach and mechanism, optimization methods mainly classified as metaheuristic and deterministic methods. Metaheuristic methods, including the Genetic Algorithm (GA) [1], Particle Swarm Optimization (PSO) [2], Simulated Annealing (SA) [3], and Artificial Bee Colony (ABC) optimization [4], have been applied extensively to size, shape, and topology optimization [5] of truss structure. These approaches can be employed to problems involving nonlinear behaviour or discrete design variables, where traditional techniques [6] often struggle while achieving size optimization. Recent developments such as the JAYA algorithm [7], differential evolution [8] and teaching learning-based optimization [9] have improved the ability to traverse complex search spaces and found good quality solutions. Another natural phenomenon of flower pollination [1] is also employed for size optimization of truss. This algorithm works efficiently by combining local and global searches, which is inspired by cross-pollination and self-pollination of flowering plants. It had implemented trial designs for constraint handling, which progressively reduce as the investigation reaches the optimum. Further to take advantage of the efficiency of metaheuristic methods, a hybrid approach is developing. To achieve more effective and higher performing algorithm, enhanced hybrid approach [2, 3] is developing, which is increasing winning probability of optimization process.

In spite of these developments, deterministic methods have marked its existence, especially in the case of smooth (a smaller number of objectives and constraints) and mathematically distinct problem formulation. Techniques such as Sequential Quadratic Programming (SQP) and Sequential Linear Programming (SLP) [13, 14] are appreciated for their computational efficiency and fast convergence with gradient information. However, their performance can be degraded in the case of strong nonlinearity or discontinuity, where metaheuristic methods usually play a vital role by achieving best results.

However, the use of optimization in routine structural design is not yet as widespread as one might expect. One of the most important reason is the computational cost, which can lead to increase the design period. Another challenge is of converting optimized designs into formats that are readily compliant with specified design codes and practical construction constraints. Recently, certain changes are have made to solve these problems by including realistic load cases, serviceability constraints, fabrication constraints and code provision is incorporated in the optimization procedure. Mainly, these constraints are distinguished into static and dynamic constraints [15]. A good example is the redesign of the Ghent Market Hall by W. Dillen et al. [16], where optimization led to an approximate 15% material saving and simultaneously fulfilled the requirements of Eurocode. Other researcher has also demonstrated comparable promising applications of optimization techniques in composite columns [17] and bridge structures, suggesting that these approaches can be applied to real-world engineering challenges. Optimization methods widely applicable for numerous Engineering structures. Optimization of transmission tower, space truss, 2D truss [18] such structures were optimized by PSO method. From these examples, it is loud and clear that optimization methods have vast applications in Engineering field. Now, it becomes a very important task to choose a particular method for a particular problem to achieve better results. It is necessary to give emphasis on distinguishing optimization methods for numerous types of problems, it will strengthen Structural Engineering to meet optimum solutions.

On the other hand, in this era, environmental concerns also have become an important factor. The number of construction industry contributes a big share of the global carbon emissions, mainly due to the massive use of steel and concrete. The present study is related to efficient use of material, which results in reducing structural weight, particularly in truss structures, which ultimately offers a direct way to lower embodied carbon [19]. Recent studies have demonstrated that optimization methods have enhanced material efficiency, resulting in substantial reductions in emissions [20], improving the lifecycle without making any compromise in structural performance. Efficient use of material imparts considerable impact on carbon emission hence achieves environment safety as well as reduced cost of construction. To achieve optimization of Engineering design [21], multi-objective methods have been developed. Even though considerable research in truss optimization, most of the researchers concentrate either on existing work to minimize structural weight alone or try to develop new algorithms by employing multiple objectives or by incorporating additional constraints. Individual methods have been employed to solve numerous optimization problem but comparative studies between numerous methods are often limited, either because many researchers adopt different constraints or assumptions, or either they rely on a narrow set of previous results, which enables to make direct comparison. Hence, a prominent research gap is, many researchers had employed a number of optimization methods individually to numerous truss problems, but not employed numerous methods to a single problem with same framework. Also, most of the researchers had chosen only metaheuristic methods for optimization instead of deterministic methods.

The main objective of the present study is to do comprehensive comparative analysis of deterministic (SQP) and metaheuristic (GA and PSO) optimization approaches employed for truss sizing. Deterministic methods such as SQP have been rarely compared with population-based techniques. Ultimately, this comparative analysis may provide a guideline to choose a method for a particular optimization problem. The basic methodology to achieve these objectives is to deploy SQP, GA and PSO to a benchmark 10 bar truss problem with same modelling framework (design variables, loading conditions and constraints). The novelty of this context is that most of the researchers had employed an optimization method to numerous problems, but in this context, a single problem is analysed by 3 different methods. Also, the comparative performance of each method is comprehensively assessed over several criteria, such as the distribution of member areas, overall structural mass, frequency, statistical indicators, error-based indicators and computational efficiency. By jointly considering structural and economical aspect, the study aims at providing clearer guidance for the selection of an appropriate optimization technique for the efficient design and sustainable truss systems. A standard ten-bar truss problem is considered for the purpose of direct comparison with results available in literature.

2. A Benchmark 10 Bar Truss Problem

For a comparative analysis of metaheuristic and deterministic nonlinear programming methods, a basic benchmark 10-bar truss [2] (Figure 1) is employed for size optimization with GA, PSO, and SQP. Several studies have selected the 10-bar problem to validate the applicability of the optimization technique. In the size optimization process, we treat the truss section area as a variable. The optimization methods will generate different sets of areas and check whether the limits on maximum deflection, allowable stress and frequency are satisfied. After several iterations, we find the minimal set of areas in the member's cross-section. The following are the detailed inputs for MATLAB. To construct an appropriate geometry for the ten-bar truss input for MATLAB, as illustrated in Tables 1 and 2.

Table 1. Node coordinates

Node No.	X Coordinate	Y Coordinate
1	18.288	9.144
2	18.288	0
3	9.144	9.144
4	9.144	0
5	0	9.144
6	0	0

Table 2. Connectivity of nodes

Member	Connectivity between nodes
1	3, 5
2	1, 3
3	4, 6
4	2, 4
5	3, 4
6	1, 2
7	4, 5
8	3, 6
9	2, 3
10	1, 4

Modulus of elasticity = 69 GPa
Density = ρ = 2767.99 kg/m^3
Maximum allowable stress = σ_{max} = 172.43 MPa
Allowable maximum deflection = u_{max}= 0.0254 m
Natural frequency = $f_1 \geq 4Hz$
Applied Loads: Force (F1) = Force (F2) = 448.8 x 10^3 N

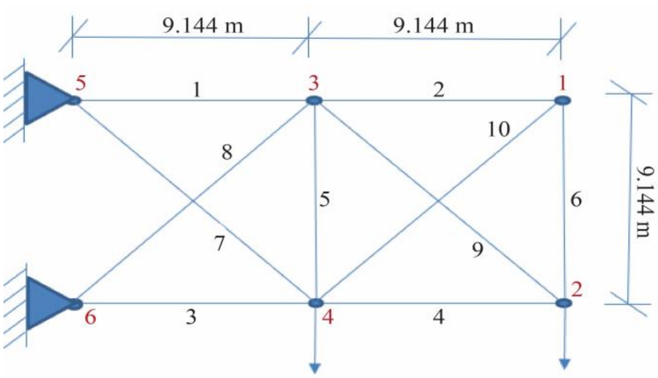

Fig. 1 Basic 10-bar Truss

The objective of this study is to minimize the weight of the 10-bar truss, as illustrated in Equation 1.

Objective function:

$$Minimize\ W(A) = \sum_{i=0}^{m} \rho * A * l \tag{1}$$

Where ρ = Density of steel
A = Area of cross-section of members of truss.
l = Length of member.

2.1. Penalty Function used in GA and PSO

If the structure exceeds the predefined constraints of stress, displacement, buckling stress and frequency, then heavy penalty coefficients [22] were applied to infeasible solutions which were violating the constraints, such as stress, displacement, buckling stress and frequency. Penalty function strongly discourages the infeasible solution during the iteration process.

Stress constraint: $|\sigma_i| \leq \sigma_{max}$,
Where, i = 1, 2, 3… 10. As 10 members of the truss.

Penalty function for stress (P_σ)

$$= P_\sigma = \alpha \sum_{i=0}^{m} \max(0, |\sigma_i| - \sigma_{max})^2 \tag{2}$$

Where, α = Penalty coefficient for stress = 10^5
σ_i = Axial stress.

Displacement constraint: $|u_j| \leq u_{max}$
Where, j =1,2,3……………12
As there exist 2 Degrees of freedom for every node.
Penalty function for displacement (P_u)

$$P_u = \beta \sum_{j=0}^{n} \max(0, |u_j| - u_{max})^2 \tag{3}$$

Where, β = Penalty coefficient for displacement = 10^6

Penalty function for buckling stress (P_b)

$$P_b = \gamma \sum_{i=0}^{m} \max(0, |\sigma_{bi}| - \sigma_{bcri})^2 \tag{4}$$

Where critical buckling stress (σ_{bcri})

$$\sigma_{bcri} = \frac{k_i A_i E_i}{L_i^2} \tag{5}$$

Where, γ = Penalty coefficient for buckling stress = 10^7

Penalty function for frequency (P_f)

$$P_f = \varepsilon[\max(0, g_f)]^2 \tag{6}$$

Where,

Normalized frequency = g_f = 1 - $\frac{f_1}{f_{min}} \leq 0$ (7)

ε = Penalty coefficient for frequency = 10^8

From Equation 1, 2, 3, 4 and 6

Penalized fitness function
= F(A) = $W(A) + P_\sigma + P_u + P_f + P_b$ (8)

These structural parameters are calculated through finite element analysis of the truss. Hence, it is necessary to check the truss's static and kinematic stability. Let us consider the calculation of the degree of freedom of a truss.

2.2. Degree of Freedom

The objective function minimizes the structural weight, computed as the sum of all member volumes multiplied by their respective material densities. Constraint functions are employed to enforce the stress, displacement, buckling stress and frequency bounds. As every member has two nodes, if a node is connected to fewer than two members and no external force is applied at that node, then in that member, zero force will exist. If we consider the displacement of nodes and if two nodes move in the same direction with the same magnitude, that is, with no relative displacement, then the members between them undergo no strain. Indeed, this means that there was no generation of stress and no contribution. In addition, we must check the structural contributions of the members.

In the case of a truss, the degree of freedom is referred to as the independent deformations in terms of translation and rotation. These translations and rotations are constrained by the support provided. The truss is checked for static and kinematic stability. As in the case of a truss, all joints are treated as pin joints, and rotation is allowed at the joint. Hence, there was no moment generation at the joint. Therefore, in the case of a truss, while considering the kinematic degree of freedom, only the horizontal and vertical displacements of the peripheral nodes of the structure are considered. The static degree of freedom is verified by using the "Grubler's Criteria" [5].

Degree of freedom = $2 * n - m - r$ (9)

Where n= Number of nodes.
m= Number of members
r= Number of unknown reactive components at support.

3. Optimization Methods

Structural optimization has shifted from an academic exercise to a practical engineering design tool over the past few years, driven by the increasing need for better use of materials and for reducing the environment impact. The basic aim remains simple: to find a structural configuration that is acceptable under all specified conditions and uses the minimum amount of material possible. In the process, the design must satisfy a variety of constraints, including restrictions on axial stresses, buckling resistance, nodal displacements, natural frequencies and the overall kinematic stability. But in real world, while implementation of these technical requirements is complemented by additional practical requirements, such as compliance with the applicable design codes, ease of construction, simplicity of fabrication, consideration of secondary stresses that could come into picture at the time of erection are getting generated. While fulfilling these requirements, a solution is investigated in a nonlinear manner, conventional trial and error approaches rarely meets to efficient designs. Depending on the nature of the design variables, constraints and the allowable changes in the geometry of structure, structural optimization problems are generally classified by focusing on size, shape, and topology separately and also combined size, shape and topology optimization [5].

The present work is focused on efficient material usage that is nothing but size optimization, where only the cross-sectional areas of the members of truss are treated as design variables. In size optimization, the geometry of truss structure is defined by nodal coordinates, and also the connectivity of nodes remains unchanged. This formulation closely meets the practical design situations, where the layout of the structure should lie within upper and lower limits of constraints, loading conditions, and support locations. By adhering to these limitations, only modification can be done in member sizes, which offers an efficient direct way to reduce structural weight without disturbing the load path. For this reason, size optimization has been widely adopted in truss design studies and continues to be one of the most practically relevant approaches. The optimization of the weight of a truss can be achieved using several techniques, which can be broadly categorized into stochastic (metaheuristic) and deterministic approaches, as depicted in Figure 2.

Stochastic methods employ probabilistic search procedures, and are especially useful for dealing with problems exhibiting discrete [23] or continuous variables, high nonlinearity, discontinuities or multiple local optima. These approaches produce a number of candidate solutions, i.e., a set of possible cross-sectional areas, which are then evaluated based on the constraints imposed, such as stress, displacement, buckling stress and frequency limits. These solutions are then enhanced through iterative procedures until no further substantial improvements are possible. A number of metaheuristic techniques have been used in this regard, such as the Genetic Algorithm (GA) [1], Particle Swarm Optimization (PSO) [2, 24], Simulated Annealing [3], Differential Evolution and Artificial Bee Colony optimization [5]. Survey [25] of these methods indicates that their strength lies in their ability to explore complex design spaces and avoid premature convergence, often yielding solutions that are close to the global optimum by drawing inspiration from natural phenomena such as evolution, collective behavior, and thermodynamic processes.

On the other hand, the mathematical path is followed by deterministic methods and do not involve any randomness in the search process. These include techniques of linear and nonlinear programming, including gradient-based as well as gradient-free formulations, as well as techniques based on quadratic and dynamic programming. Such methods are generally more effective when the objective function and constraints are smooth and well-posed, since they tend to converge quickly and provide a high degree of accuracy in the numerical solutions [26]. Among these techniques, Sequential Quadratic Programming (SQP) can be considered as a reliable technique for solving constrained nonlinear problems, as it handles multiple constraints efficiently with fast convergence characteristics. However, deterministic methods may converge at local optima for problems having nonlinear variables and problems with a multi-objective function.

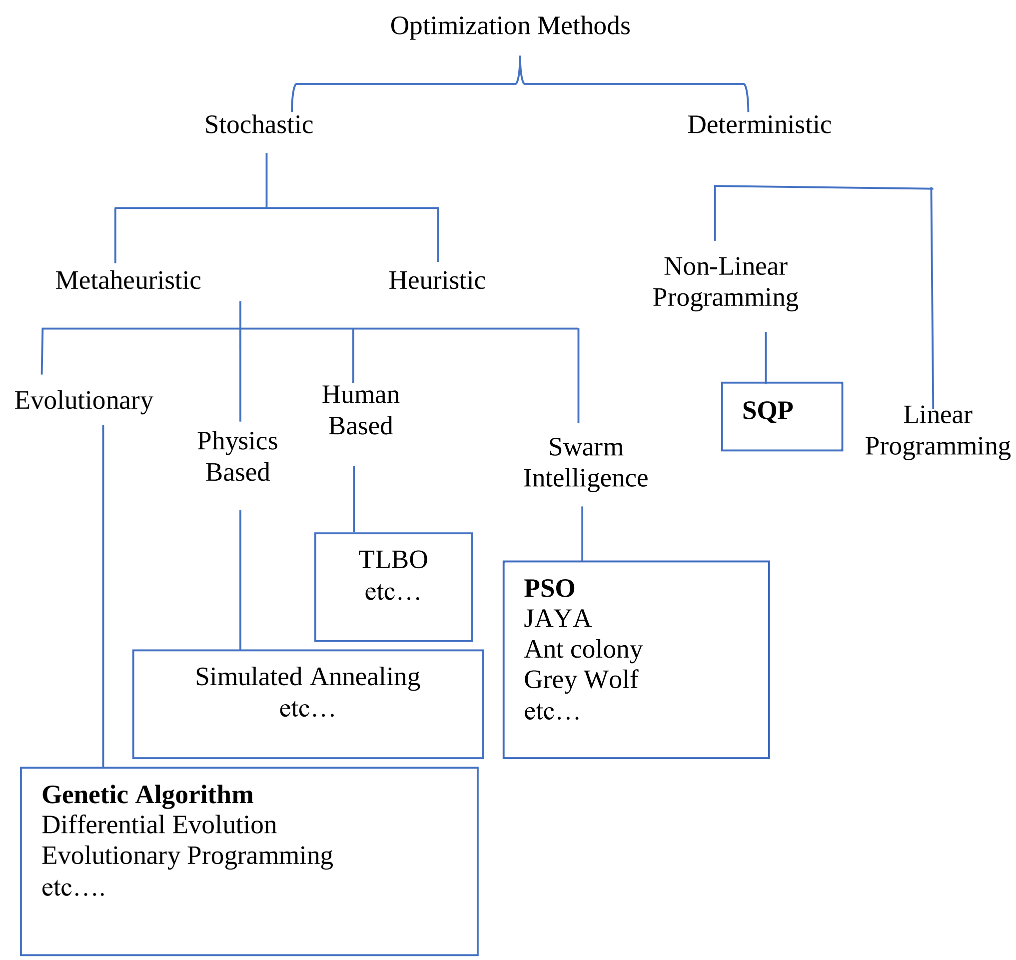

Fig. 2 Optimization methods

Due to the above advantages and limitations of deterministic and stochastic methods, it is necessary to compare these approaches in a common framework, especially for complex structural optimization problems. In this study, SQP, belonging to the deterministic approach, GA and PSO, belonging to the metaheuristic approach, are employed to the benchmark 10-bar truss problem. GA and PSO both are population-based and inspired by natural phenomenon of selection and collective swarm behavior, respectively. The aim of the study is to compare the behavior of these techniques in terms of quality of solutions, convergence behavior and applicability to real-world truss size optimization problems by evaluating them under consistent modelling assumptions.

3.1. Sequential Quadratic Programming (SQP)

Sequential Quadratic Programming (SQP) is a deterministic method that is widely used for solving constrained nonlinear optimization problems in structural engineering [27]. It is attractive because of its good convergence properties and the capacity of satisfying the equality and inequality constraints with high accuracy during the solution process. SQP does not solve the nonlinear problem [28] directly, but solves iteratively a sequence of Quadratic Programming (QP) subproblems. Formulation of each subproblem is done by linear approximations for the constraints, and a Lagrangian is employed in terms of quadratic representation, which enables to handle constraint violations in a systematic and numerical stable manner. The accuracy of SQP is totally dependent on the availability of gradient and Hessian information [29]. If the objective function is belonging to a smaller number of variables, then this information will lead to faster and reliable convergence. For smaller problems with minimum variables and constraints, Hessian matrices are useful, but for medium-sized problems belonging to a multi-objective function. Quasi-Newton approximations are preferred to achieve better accuracy and also help to reduce computation time. For large structures having a number of variables and constraints, sparse matrix techniques are applicable to such problems. To increase accuracy and robustness, a line search strategy and favorable region methods are incorporated, which help the algorithm to remain stable even in the nonlinear variation.

The present study aims to size optimization of members of the 10-bar truss problem treated as a nonlinear programming problem, subjected to constraints such as maximum axial stress and deflection. In this problem cross-sectional areas of members of the truss are treated as design variables. The objective is to utilize efficient material by reducing total structural weight. On the other hand, the design must satisfy the upper bound and lower bound of variables, allowable maximum nodal displacements, allowable axial stresses in tension and compression, and Euler buckling capacity. The SQP starts its investigation that lies within, or close to, the prescribed upper and lower bounds. At every iteration, the degree of constraint violation is evaluated and based on it future search direction is fixed by solving the associated QP subproblem. After every interaction, the design is updated, with a prescribed step size, so that the solution leans towards objective function by achieving a lesser weigh of structure for subsequent iterations. SQP tries for next iteration until the best solution for the objective function is achieved with satisfying the constraint lying within prescribed limits. Once the acceptable solution under given constraints is obtained, still additional iterations are employed to achieve a refined design. As SQP is having deterministic approach that produces repeatable results and with fast convergence, it is further compared with stochastic methods.

3.2. Genetic Algorithm (GA)

Genetic Algorithm (GA) is belonging to the stochastic optimization method, which is based on the principle of natural phenomenon of Darwin's Law "Fittest is the survival" [30]. Rather than a single search path, the GA works on a population-based candidate solution, which evolves through subsequent generations. Because of this perspective, more GA explores a larger design space, which is suitable for problems with nonlinear response surfaces or problems having multiple local optima. In the context of truss size optimization, each generation's solution is encoded as a chromosome [31, 32] in binary format, which usually represents the variable cross-sectional areas of the structural members. The iteration starts with the generation of a random population within the allowed design limits. Each iteration is evaluated using a fitness function, which evaluates the structural weight and also checks whether design constraints are satisfied. In every iteration, the population is updated and better performing solutions are promoted to generate the next generation.

The population-based evolution is performed by three main operations: selection, crossover, and mutation [33]. From every generation, a candidate is selected having better fitness and is allowed to carry forward their significant characteristics to the upcoming next generation. Crossover merges data from selected two fit parent solutions to create new designs which will possess useful properties from both. Mutation helps to avoid early convergence at local minima by adding small random changes.

As for every iteration, the quality of the solution increases, this process is revised until the best possible solution is achieved. While going through a number of iterations, constraints are violated, which is handled by using an adaptive penalty approach [22]. A violation of constraints such as stress, displacement, buckling or frequency limits is getting reflected in the fitness value by adding a heavy penalty function. This approach does not discard the solution completely but discourages the impossible designs, which allows the algorithm to explore the solution near the boundary of the solution region. Application of the penalty function converts the constrained problem into the evolutionary framework, guiding it to lean towards a valid solution. The algorithm converges at the best fitness value assessed across generations. As Figure 5 illustrates, the fitness value converges and stabilizes after a certain number of iterations, it reflects that further enhancement in the solution is minor. The MATLAB implementation [34] of GA demonstrates that, though it is a stochastic method aligned with a natural phenomenon can achieve efficient material utilization with subsequently satisfying the constraints.

Input for MATLAB:

Population Size = 30
Number of Generation = 500
Mutation Rate = 0.2
Crossover Rate= 0.8

3.3. Particle Swarm Optimizer (PSO)

Particle Swarm Optimization (PSO) is belonging to metaheuristic swarm intelligence, this algorithm is based on a population search. Where each candidate of a population is treated as a particle moving within the solution space

This concept is motivated by natural swarms coordinated motion, where individuals adjust their path and motion by considering both personal acceleration and group acceleration. In the present context, cross-sectional areas of the truss members are treated as particle, and its variable movement across each iteration reflects successive improvements in achieving the objective function. At every iteration, the coordinates of a particle are updated using data from two reference points: particles own best location as compared to earlier location and also identifies the best location by considering the swarm as a whole. This mechanism reflects a perfect balance between independent search and collective guidance, which facilitates the algorithm to explore the design space in subsequent iterations with updated, improved position and motion, along with satisfying the constraints limit.

Unlike evolutionary methods based on crossover and mutation, PSO directly updates the velocity and coordinates of a particle, which reduces the required number of control parameters, thus it simplifies the algorithm structure. The enhancement of velocity of a particle is controlled by three terms: inertia, cognitive influence and social influence [35]. The inertia term retains a fraction of characteristics from the previous motion, thus it maintains the continuity in the search path. The cognitive term represents the characteristics of a particle to revert back to its historical prominent solution, while the social term attracts these particles towards the optimized solution investigated by the swarm. The combination of all these three terms helps to investigate overall search behavior, and hence choosing an appropriate parameter is critical by maintaining a balance between exploration and convergence. The decentralized nature of this process makes the PSO more robust, particularly in problems where occurs multiple local optima or if the response surface is highly nonlinear. To improve stability and constraint handling, modified frameworks of standard PSO is incorporated in this study. An inertia weight strategy is introduced to control the transition from global exploration of the solution within early iterations to refinement of the local solution in subsequent stages. Moreover, a fly-back mechanism is used to treat boundary violations, where the particles moving outside the permissible values of design variables are relocated in the feasible domain, thus avoiding the divergence of the search process. Constraint enforcement is carried out through a penalty-based formulation, in which violations of stress, displacement, buckling, and frequency limits are incorporated into the objective function [36]. This approach assures systematic penalization of infeasible solutions, while at the same time it allows the algorithm to investigate the solution near to the constraint boundaries.

The performance of the adopted PSO formulation is tested on the 10-bar truss optimization problem [2], which is a benchmark problem, with multiple interacting constraints. This benchmark problem provides a consistent basis for testing the algorithm in the presence of multiple interacting constraints with discrete variables [37]. Emphasis is given to the selection of the cognitive and social acceleration coefficients, as these parameters have a significant impact on the convergence properties. Higher cognitive weight tends to promote broader exploration, whereas stronger social influence speeds up convergence to the prominent solution. Improved PSO [38] has demonstrated that the appropriate calibration of these parameters improves both the convergence rate and solution quality. The convergence pattern illustrated in Figure 7 indicates a steady minimization in structural weight with successive iterations. As the objective function does not include any oscillatory variable, it gives a stable search. The rate of convergence denotes the computational efficiency of the method. On this basis, PSO is considered as an effective tool for truss size optimization, particularly in problems where gradient information is not available and subjected to multiple constraints.

Input for MATLAB code:

Swarm Population size = 10
Maximum iterations = 100
Inertia weight = w = 0.72
Personal acceleration = c_1 = 1.5
Social acceleration = c_2 = 1.2

Particle velocity and position is updated by using;

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (p_i - x_i^t) + c_2 \cdot r_2 \cdot (g - x_i^t) \qquad (10)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \qquad (11)$$

where: v_i^t *and* x_i^t Are the velocity and location of the i^{th} particle at iteration t.

"p_i" denotes the particle's personal best position.
"g" represents the global best position found by the swarm.
"r_1" and "r_2" are random numbers varying from 0 to 1.

Social velocity represents the average velocity of bird flocks or fish, and personal velocity represents the velocity of an individual bird. Flocks and individual birds fly to reach their goal as efficiently by finding possible shortest path with maintaining a safe distance between them.

4. Results and Discussion

4.1. Size Optimization by SQP

Figure 3 shows the evolution of the SQP algorithm during the weight optimization of the truss. A steep drop in the structural weight can be observed during the first few iterations, which is an indication that the method rapidly finds a much better design from the initial configuration. The weight decreases from a relatively high initial value to below 2000 kg in a few steps, which reflects the effectiveness of the gradient based search directions in guiding the solution while still respecting stress, displacement and stability constraints.

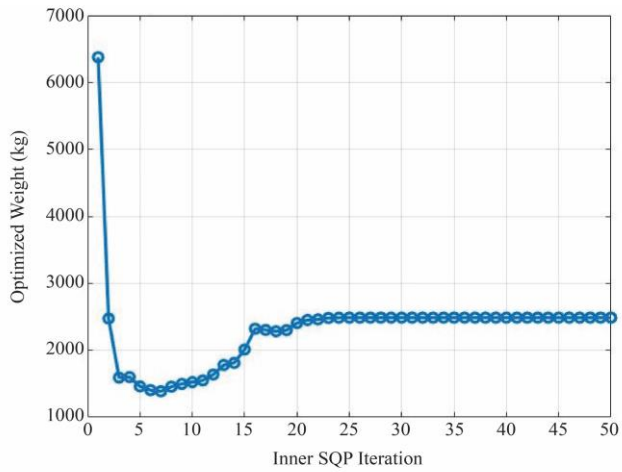

Fig. 3 Convergence plot by SQP

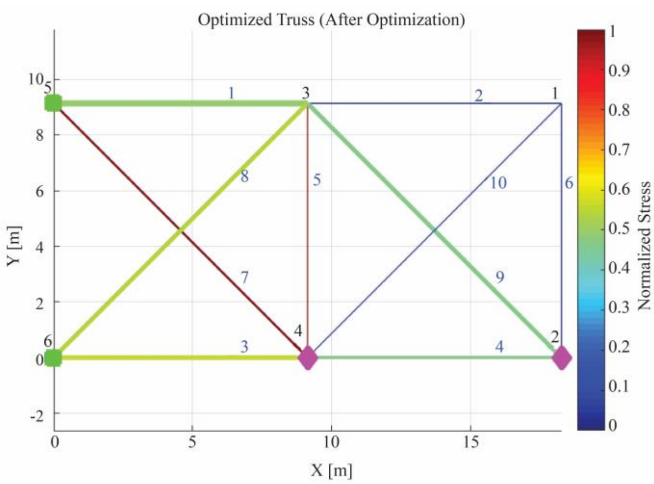

Fig. 4 Post optimized truss geometry by SQP

It can be observed that a slight oscillation between iteration 5 to 15 as we iterate. The main reason for this is the activation/deactivation of penalty functions applied to constraints during the optimization, in particular, the stress limits and the nodal displacements. When SQP solves the quadratic subproblems and updates the corresponding Lagrange multipliers, the solution moves a little bit around the boundaries of the constraints. Such small oscillations are common in constrained nonlinear optimization and do not indicate instability. The small size of these oscillations, on the other hand, indicates that the algorithm is robust and well-behaved throughout. After about twenty iterations, the solution converges to a structural weight of 2486.88 kg without noticeable improvement in the following iterations. This plateau shows that the algorithm has reached a feasible and locally optimal design that meets the imposed constraints. The global convergence pattern, i.e. the initial fast improvement, small adjustment and finally stable behavior, confirms the efficiency and reliability of SQP. These results demonstrate that SQP is well-suited for truss size optimization, where consistent performance and relatively fast convergence are important.

4.2. Size optimization by GA

Figure 5 shows the convergence pattern of the Genetic Algorithm (GA) for the problem of minimizing the weight of the truss, where the structural weight and the penalties for the violations of the constraints are incorporated into the fitness function. The best fitness value decreases sharply, with a remarkable improvement in the early generations. Starting from a value above 3400 kg, the solution improves significantly and approaches 2500.82 kg in about the first 80 to 100 generations. This early trend reflects the ability of the GA to explore the design space broadly, with the help of the numerous solutions comprised together to form of the population and the stochastic nature of the crossover and mutation operations. The decrease in the rate of improvement as the algorithm proceeds signals the transition of the algorithm from the exploration phase to the refinement phase. In this phase, the population is still evolving and slowly better solutions are found. When the fitness value becomes 2500.82 kg, the algorithm converges to an optimal region. This reflects a perfect balance between the exploration of new configurations and the refinement of existing configurations, with satisfying the constraints of stress, displacement, buckling stress and frequency.

The convergence curve begins to smoothen after about 100 generations, and further for 500 generations the fitness value remains constant. This flattening of a curve depicts that the converged solution is stable, along with satisfying the given constraints. The subsequent enhancement in the later generations reduces the diversity and tries to investigate minima in a particular region of the design space. Although GA requires more iterations compared to the deterministic approach (SQP), it marks its uniqueness by navigating the complex problems having multimodal design spaces. Overall, the observed convergence behavior indicates that GA is well-suited for truss optimization problems by considering the robustness and global search capability rather than focusing on rapid convergence.

4.3. Size Optimization by PSO

Figure 7 shows the convergence behavior of the PSO method for the minimization of the truss weight. The objective function is the sum of the structural weight and penalties for constraint violations. The objective value is seen to decrease significantly in the first iterations. The best cost drops significantly from about 3300 kg to almost 2600 kg in the first 10 to15 iterations. This initial behavior is due to the strong searching ability of PSO, where the exchange of information by their own best location and global best solution enables the swarm to quickly move to the promising region.

The first phase concludes after roughly 40 to 60 iterations, the rate of improvement decreases, and optimization enters a refinement stage. In this period of time, the weight reduction becomes more gradual, and finally achieves about 2489.94 kg with constraints of stress, displacement, and stability satisfied.

The steady and smooth decrease of the objective function shows stable behavior of the swarm and a good balance of investigation of new solutions and utilization of established solutions.

The convergence curve is almost flat after about 40 iterations, and the objective value is unchanged up to 100 iterations. This flattened curve indicates that the algorithm has reached to a stable solution, and further enhancement will not lead to any significant improvement. It has been observed that PSO converges and achieves optimum weight in a lesser number of iterations as compared to GA, which denotes that PSO is having better computational efficiency to search the solution in the favorable region of the design space with faster convergence. In addition to this, the method avoids premature convergence in the early phases and tries to obtain an optimum solution along with satisfying imposed constraints. These properties suggest that PSO is a good trade-off between the computation time and the reliability of the solution and can be useful for engineering applications where efficiency and reliability are important.

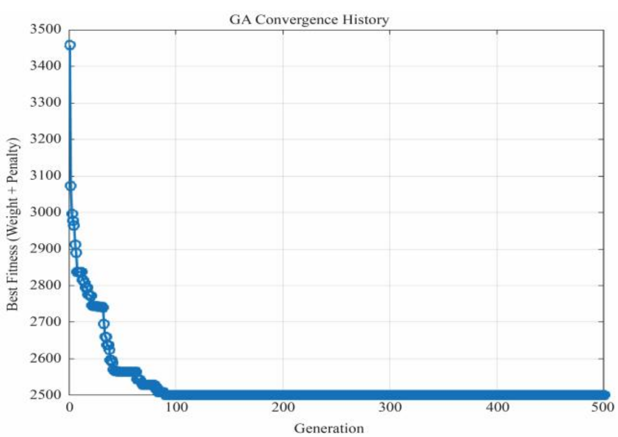

Fig. 5 Convergence plot by GA

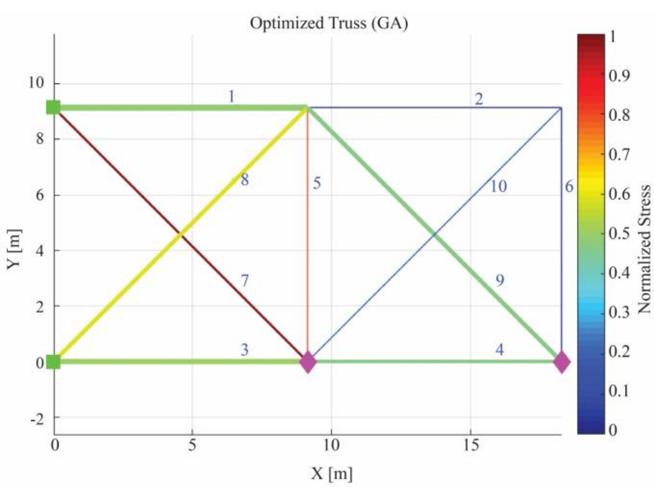

Fig. 6 Post-optimized truss geometry by GA

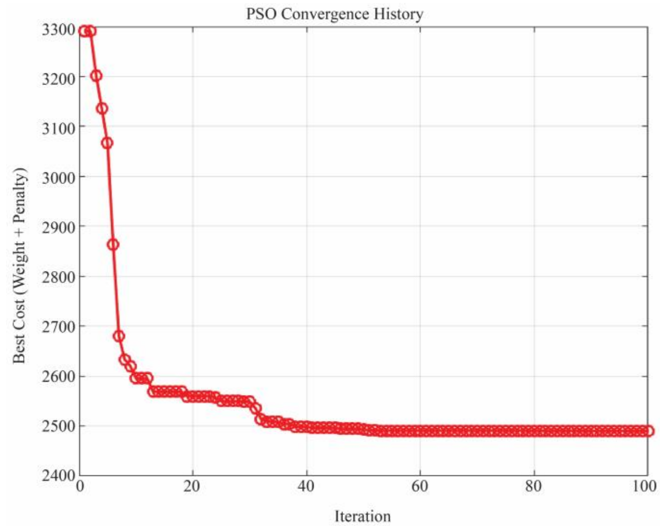

Fig. 7 Convergence plot by PSO

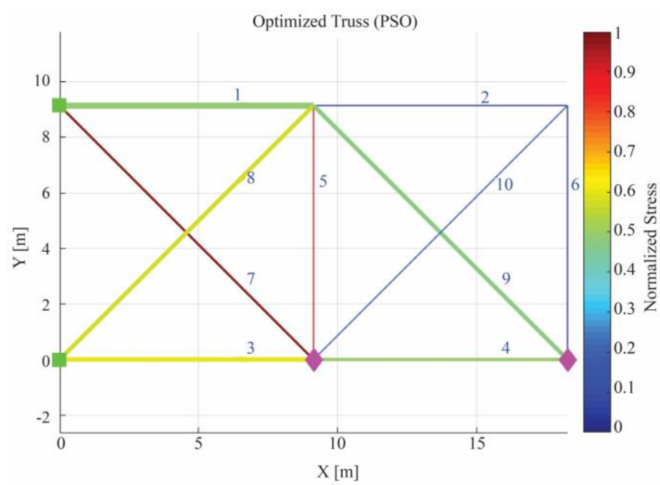

Fig. 8 Post optimized truss geometry by PSO

The assessment of an objective function and the interpretation of the fitness function in relation to iteration graphs, as shown in Figures 3, 5, and 7, indicate that SQP attains the optimized weight of the truss more rapidly than GA and PSO. Figures 4, 6, and 8 show the truss's shape after its size has been optimized. The thickness of a line represented in Figures 4, 6, and 8 corresponds to an optimized cross-sectional area. The thicker the line, the larger the cross-sectional area, so it helps compare among all members of the truss. The scale on the right-hand side, ranging from 0 to 1, denotes normalized stress. It illustrates the stress variation, which helps interpret that the contribution of certain members is negligible; therefore, they may be removed if we extend this study to topology optimization. Color variation illustrates induced normalized stresses, and the member's thickness represents the minimum area required to sustain within the limits of allowable stresses and deflection. From this color variation, we can observe that members 2, 5, 6, and 10 are subjected to less stress and require the least cross-sectional area as compared with other members. These observations help to interpret certain insights into topology optimization, help to identify the load path and thereby can identify critical members. The analysis of the load path and stress variation helps in the topology optimization process. Furthermore, this context can be considered as a prerequisite for the simultaneous employment of topology and shape optimization.

4.4. Results based on Optimized Area of Cross-Section

Following rigorous application of optimization methods, the cross-sectional areas obtained using SQP, GA, and PSO are presented in Figure 9.

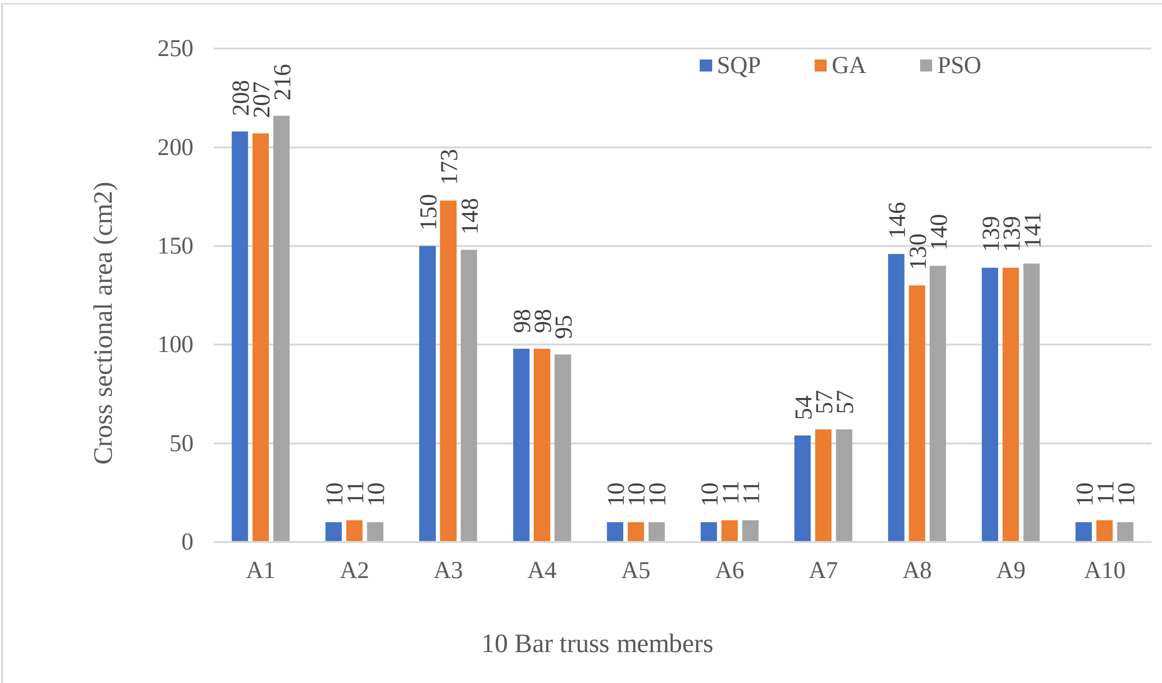

Fig. 9 Optimized cross-sectional area by SQP, GA, and PSO

The minimum weight of the truss was obtained by employing SQP; hence, the performance of the metaheuristic approaches is measured relative to SQP. The percentage deviation in area for GA and PSO is computed for each member. Table 3 shows the difference in the optimized cross-sectional area achieved by GA and PSO compared to SQP.

Percentage deviation of area

$$\%\ \Delta A = \frac{A_{method} - A_{SQP}}{A_{SQP}}\ X\ 100 \qquad (12)$$

The comparative analysis of the optimized cross-sectional areas reveals distinct behavioral patterns among the three optimization strategies. SQP, a method that uses gradients and is deterministic, produces the smallest total structural area. Hence, the method provides a strong benchmark to benchmark the performance of metaheuristic approaches. The solutions obtained by this approach exhibit small variation and satisfy the given structural constraints well. However, the search process is inherently local and thus its ability to explore highly nonconvex regions of the design space may be a disadvantage in nonlinear truss optimization problems.

The results of the GA indicate a wider exploration of the design domain. The major change in the member areas is evident from the fact that the maximum change is recorded in A3 (15.33%). This diversity is helpful for the algorithm to not converge too early. However, there are also relatively large cross-sectional areas in some members, which indicates that the algorithm is not refined enough near the optimal area under the parameter settings. However, some improvements are noticed. For example, on A8, the decrease is 10.96%. However, the total area of the structure is still about 8.73% larger than that obtained by SQP. This means that more trial and error analysis (such as checking the population size or investigating a compatible combination of mutation and crossover rate) is needed for GA to outperform as compared to SQP or PSO.

Table 3. Deviation relative to SQP

Member	SQP	GA	PSO	%Δ GA vs SQP	%Δ PSO vs SQP
A1	0.0208	0.0207	0.0216	–0.48%	3.85%
A2	0.001	0.0011	0.001	10.00%	0.00%
A3	0.015	0.0173	0.0148	15.33%	–1.33%

A4	0.0098	0.0098	0.0095	0.00%	–3.06%
A5	0.001	0.001	0.001	0.00%	0.00%
A6	0.001	0.0011	0.0011	10.00%	10.00%
A7	0.0054	0.0057	0.0057	5.56%	5.56%
A8	0.0146	0.013	0.014	–10.96%	–4.11%
A9	0.0139	0.0139	0.0141	0.00%	1.44%
A10	0.001	0.0011	0.001	10.00%	0.00%

On the other hand, PSO explores a solution with shows better convergence. Results shows that remarkable reductions (around 1% to 4 %) in area of several members of truss, relative to SQP, especially for A1, A3, A4 and A8. The total optimized area obtained by PSO is only 7.64% higher as compared with SQP, which is less than the deviation observed with GA. It can be observed that PSO achieves a better refinement with balancing exploration and convergence. This phenomenon of velocity and coordinate update mechanism seems to work well for the nonlinear constraint space of truss optimization problems.

The overall comparison shows that SQP achieves the most optimum solution among the compared methods. However, PSO achieves a perfect trade-off between reliable convergence and an acceptable global search capacity.

On the contrary, GA exhibits a strong exploration and weak exploitation, hence it explores heavier design solution. PSO is the best metaheuristic approach for the minimization of weight of the 10-bar truss size, considering the solution quality, robustness and search characteristics. Its stable convergence behavior and good agreement with the SQP based solution provide its appropriateness for practical structural design applications.

4.4.1. Statistical Key Performance Indices Emphasizing the Area of Cross-Section

To quantify the comparative performance of the three optimization methods (SQP, GA, and PSO), several statistical indicators and Key Performance Indices (KPIs) is computed using the member area data, as illustrated in Table 4.

Let $A_i^{SQP}, A_i^{GA}, A_i^{PSO}$ Be the optimized area of the member

(i = 1……10) received after going through iterations.

Let n = 10.

$$\text{Mean member area (MMA)} = \frac{1}{n}\sum_{i=i}^{n} A_i \quad (13)$$

$$\text{Total structural area (TSA)} = \sum_{i=i}^{n} A_i \quad (14)$$

Mean absolute percentage deviation (MAPD)vs SQP

$$MAPD = \frac{1}{n}\sum_{i=i}^{n}\left|\frac{A_i^{method} - A_i^{SQP}}{A_i^{SQP}}\right| X\,100 \quad (15)$$

Standard deviation (SD) of the cross-sectional area of truss members

$$SD = \sqrt{\frac{1}{n}\sum_{i}^{n}(A_i - A_{MMA})^2} \quad (16)$$

The statistical indicators reveal clear behavioral differences among the optimization methods. SQP, as expected from a gradient-based deterministic framework, delivers the minimum total area and thus sets a baseline with high performance. However, because SQP relies on local gradients, it may converge to local minima in nonconvex truss problems. It makes SQP primarily suitable as a reference rather than as a globally robust search strategy. The small standard deviation indicates a very consistent distribution of areas among the members.

Statistical key performance indices applied to the optimized area of cross-section indicate that PSO has yielded a more optimized area of cross-section as compared with the results of GA. Results show that PSO achieves a Mean Absolute Percentage Deviation (MAPD) of 3.73%, which is significantly lower than 6.13% for GA. This means that the sizes of the members found by PSO are closer to the reference solution by Sequential Quadratic Programming (SQP) in average. For the maximum percentage deviation, a similar trend is observed, where PSO is limited to 10%, and GA reaches 15.33%. This shows that PSO is more capable to handle extreme variations in member sizes. This behavior can be explained as the velocity position update mechanism in PSO fine-tunes solutions in a gradual and coordinated way, unlike the more stochastic changes introduced by mutation in GA. Therefore, PSO tends to converge more smoothly and stably, meanwhile retaining enough exploration ability.

On the contrary, the GA results are more diverse among the members. Some of the cases show reductions, but several of them show increases, the most notable of which is member A3, in which the deviation is above 15%. This trend suggests that the later stages of the investigation may not be able to sufficiently refine the solution, a limitation that is often associated with the choice of crossover and mutation parameters.

This is also supported by additional indicators such as the deviation of the Total Structural Area (TSA) for GA (+8.73%), which is the highest, and the standard deviation (0.00716), which is also the highest among the methods studied. The results show that GA converges to a solution which is less robust and slightly less efficient in material distribution. For complex search problems, GA explores a good solution, but due to random selection of the population it may vary final design solution. Also, if constraint parameters are not properly tuned with objective function, then it may lead to a heavier design solution.

Considering the combined statistical analysis of key performance indices (MMA, TSA deviation, MAPD, maximum percentage deviation and standard deviation), PSO gives a more favorable solution as compared to GA. Also, PSO achieves a comparable accuracy level. The perfect balance between exploration of solution and convergence is achieved, which makes it a more reliable tool to determine suitable member sizes of truss, and hence PSO algorithm is recognized as a promising method for truss size optimization problems. Consequently, these advantages position PSO as the optimal optimization technique for nonlinear truss systems, where the fulfilment of constraints and the minimization of material usage are paramount for achieving optimal structural performance.

Table 4. Statistical key performance indices applied to the optimized area of the section

Statistical key performance indices	SQP	GA	PSO
Mean Member Area (MMA)	0.0083	0.00897	0.00888
Total Structural Area (TSA)	0.0825	0.0897	0.0888
% Increase in TSA vs SQP	–	8.73%	7.64%
MAPD vs SQP	–	6.13%	3.73%
Max Percentage Deviation (MaxPD)	–	15.33%	10.00%
Standard Deviation (SD) of Areas	0.0068	0.00716	0.00694
Members with Reduced Area vs SQP	–	2 members	4 members
Members with Increased Area vs SQP	–	5 members	4 members

4.5. Results based on the overall Optimized Weight of the Truss

A 10-bar truss problem was set as a benchmark problem for employing optimization methods. As illustrated in Figure 10, the current study achieved a more optimized weight than previous researchers [39] assumed that a single design variable can take only 16 possible values. This assumption reduced the chromosome length to only 4 bits, thereby making the search space small enough to find reasonable solutions with populations of 20, 30, and 40 individuals, running for no more than 20 generations. However, even without employing those assumptions, dealing with a larger search space [40] found superior results, with larger population sizes and generations.

Camp et al. [41] achieved better optimality with the lightest historical design at 2463 kg, a benchmark for optimality. For optimization, some modifications to the genetic algorithm method are implemented by incorporating a penalty function [42]. When constraints such as deflection and axial stress are violated, a heavy penalty function is applied, and the optimization algorithm attempts the next interaction. [43] It had also employed a genetic algorithm and achieved an optimized weight of 2486 kg. In this work, the 10-bar truss benchmark problem is solved using SQP, GA and PSO. The solutions from SQP (2486.88 kg) and PSO (2489.94 kg) are within approximately 1% of the reference benchmark, which indicates good convergence and high accuracy. Furthermore, the results are similar to and sometimes better than those found in previous research. On the contrary, the GA gives a weight of 2500.82 kg, which is a little higher. In practice, this solution is still acceptable, but the larger weight is indicative of the relatively larger variability and slower convergence of the method. In general, the results obtained from both SQP and PSO are very similar to the most prominent methods discussed in the literature, showing the feasibility of the methods for minimizing the truss weight.

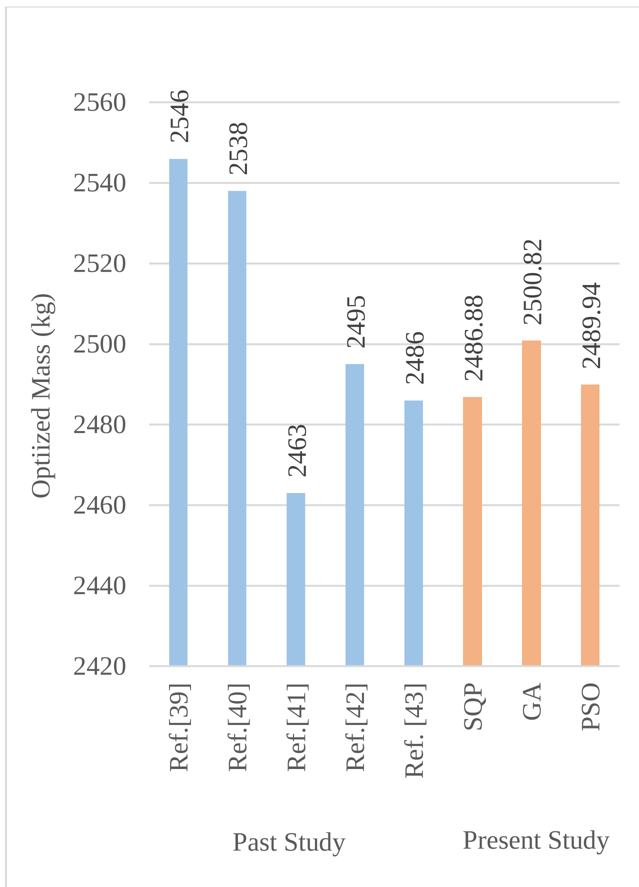

Fig. 10 Comparative study of weight optimization by SQP, GA and PSO

4.5.1. Statistical Key performance Indices for optimized Weight of Truss

GA and PSO belong to population-based phenomenon, Population is comprised of number of solutions which were randomly generated. Amongst it a most optimised feasible solution is chosen and taken as a benchmark solution to develop another better solution. After a certain number of generations, an optimised best solution was obtained. As GA and PSO are stochastic in nature, results obtained by them will always vary for every run.

These stochastic methods (GA and PSO) were employed with ten runs (as shown in Table 5), to check the robustness and consistency. Best minimum and also mean weight is obtained by PSO, which indicates that PSO is capable of investigating a lighter weight by maintaining consistency in converging better quality solution amongst multiple independent runs.

Table 5. Comparison of stochastic method with same runs

Algorithm	GA	PSO
Run (n)	10	10
Best (kg)	2500.82	2489.94
Mean (kg)	2541.339	2518.871
Worst (kg)	2601.67	2561.67
Standard deviation (SD)	34.09	22.72

In the worst case of investigation of the solution, PSO had obtained a better solution than GA, which indicates that PSO had maintained its robustness. PSO had exhibited with less standard deviation, which indicates that the solutions produced by PSO were more stable and variation between subsequent developed solutions was also minimum, denoting the consistency of PSO over GA.

Standard deviation (SD)

$$\text{SD} = \sqrt{\frac{\sum(m_i - m_m)^2}{n-1}} \quad (17)$$

Where; m_i = Optimized mass for ith run.
m_m = Mean mass of total "n" runs.
n = Number of runs.

Table 6 presents a summary of the results distinguishing the feasibility of the traditional and modern optimization techniques for truss weight minimization using statistical Key Performance Indicators (KPIs). For comparison, we use a solution provided by Camp et al. [36] with a minimum mass of 2463 kg. It has a Consistency Index (CI) of 1.000. It serves as a benchmark for the evaluation of other methods due to its zero Root Mean Square Error (RMSE) and zero Mean Absolute Percentage Error (MAPE). On the other hand, the RMSE and MAPE values reported in previous studies [39], [40] are much higher, indicating less accuracy and less convergence to the global optimum. The researcher [42, 43] have shown higher CI scores, lower RMSE and MAPE values, which indicates that they have maintained a better balance between exploration and subsequent enhancement for every iteration. Also, these are having comparatively small value of MSE and RMSE values, which denotes a slight variation with respect to the reference mass. These results reveal that nonlinear and multimodal problems like material minimization can be solved better by the application of heuristic methods.

Table 6. Statistical key performance indices for weight, with respect to Camp et al. [41]

Method	Mass (kg)	MSE	RMSE	MAPE (%)	CI	DMM	PRS
Rajeev et al. [39]	2546	6889	83	3.37	0.967	51.6	5
Coello et al. [40]	2538	5625	75	3.04	0.971	43.6	4
Camp et al. [41]	2463	0	0	0	1	–30.4	1
Nanakorn et al. [42]	2495	1024	32	1.29	0.987	9.6	3
Azad et al. [43]	2486	529	23	0.93	0.991	0.6	2
Present – SQP	2486.88	570.05	23.88	0.97	0.991	1.48	2
Present – GA	2500.82	1429.74	37.82	1.54	0.984	15.4	4
Present – PSO	2489.94	725.6	26.94	1.09	0.989	4.5	2

The present work has shown a comprehensive comparative analysis between SQP, GA and PSO in a common modelling framework. The SQP results are slightly deviated from the reference solution with an RMSE of 23.88 kg and a MAPE of about 0.97 %, which indicates a high numerical accuracy for problems with smooth and precise constraints. Moreover, the low values of MSE and RMSE demonstrate a stable convergence with very low variance over the iterations. PSO also gives good results with MAPE around 1.09% and RMSE of 26.94 kg. These numbers show that PSO can achieve near optimal solutions with consistent convergence. Moreover, the good performance of SQP and PSO in this investigation is justified by their relatively low values of the Distance Metric Method (DMM) and Prediction Residual Sum (PRS).

M_{method} = Optimized mass got by using GA and PSO

M_{ref} = Reference minimum weight Camp et al. [41]

= 2463 Kg.

Mean Square Error = MSE = $(M_{method} - M_{ref})^2$ (18)

Root Mean Square Error (RMSE)

RMSE = $\sqrt{(M_{method} - M_{ref})^2} = |M_{method} - M_{ref}|$ (19)

Mean Absolute Percentage Error (MAPE)

MAPE (%) = $\left(\frac{|M_{method} - M_{ref}|}{M_{ref}}\right) * 100$ (20)

Convergence Index = CI = $1 - \left(\frac{|M_{method} - M_{ref}|}{M_{ref}}\right)$ (21)

Deviation from Mean Mass (Indicating relative deviation) (DMM)

DMM = $M_{method} - \overline{M_{-1}}$ (22)

$\overline{M_{-1}} = \frac{1}{N-1} \sum_{k=1}^{n} M_k$ (23)

Where N = Number of methods = 8

k = Employed method

Performance ranking score = PRS = Rank (M_{method})
Where 1 Denotes best and a higher rank leans towards worst.

While GA results are still competitive, error metrics like MAPE, MSE and RMSE are relatively higher. This is due to the stochastic nature of the algorithm, i.e. the effects of crossover and mutation, which introduce randomness into the search process. However, GA is better than the previous classical approaches, showing the capability of exploring complex design spaces, but with lower accuracy than SQP and PSO.

In general, the statistical indicators give a good basis to conclude that SQP and PSO are the most reliable approaches in this investigation, with a good trade-off between correctness, stability and convergence behavior. The results presented here offer further evidence for the use of advanced optimization methods in structural weight minimization problems, particularly metaheuristic and hybrid approaches.

This study illustrates a marginal improvement in the result as compared with earlier study. This happens because the results obtained by GA and PSO are totally based on population search employed with randomization. GA solution search quality depends upon the appropriate selection of parameters like population size, number of generations, crossover and mutation rate.

Likewise, PSO had explored a solution by considering social and personal acceleration values. In addition to these parameters, a penalty function is employed to enhance the solution.

4.6. Performance based on Frequency

In practice, the frequency constraint [5] is employed to avoid resonance and controlling the structure against vibrations. Frequency denotes the stiffness of the structure and hence the resistance to the dynamic excitation. Frequency of the 10-bar truss obtained by SQP, GA and PSO is illustrated in Table 7. The maximum difference in the frequency is 1.11%, which is so minor.

The results indicate that GA has yielded the highest frequency, representing higher stiffness and explores a structurally better distribution of cross-sectional area of members, with achieving structural feasibility by satisfying the frequency constraint. However, the close agreement between PSO and SQP illustrates the robustness of the optimization framework.

Table 7. Frequency of 10-bar truss

Method	Frequency (Hz)
SQP	5.4143
GA	5.4732
PSO	5.4187

4.7. Performance based on Time for Iteration

The elapsed time is the main parameter to study the computational efficiency of the SQP, GA and PSO with the iteration counts of 50, 100, 150 and 200. The results shown in Figure 11 indicate the significant differences in the time requirements of the three methods. SQP requires least computational time of all the techniques studied. As a deterministic formulation is applied to problems having smooth, distinct properties, hence faster convergence is achieved. When computational time is limited, then SQP is best suitable for such problems, which allows gradient based methods. The GA works good at dealing with irregular and complex search problems, but it requires more time for computation. This stochastic method is based on selection of the best candidate from the generated population for every iteration, followed by crossover and mutation, which results in longer processing times. In spite of this still GA can be considered the best choice for nonlinear and discontinuous problems. The computation time of PSO is moderate in comparison with SQP and GA. It converges faster than GA but still maintains the stability while searching the solution over the entire design space. PSO has become a good choice for situations where both efficiency and time of computation are desirable, as it emerges with a good trade-off between convergence speed and exploration. In summary, this study brings a spotlight on the criteria of selection of a suitable optimization technique for a particular type of problem. Selection can be done by focusing on both solution quality and computational time along with consideration of available resources. This study could be a benchmark for the selection of appropriate optimization methods. One may develop certain criteria of selection of method by considering the trade-offs between the assessment of scalability and the accuracy of solutions.

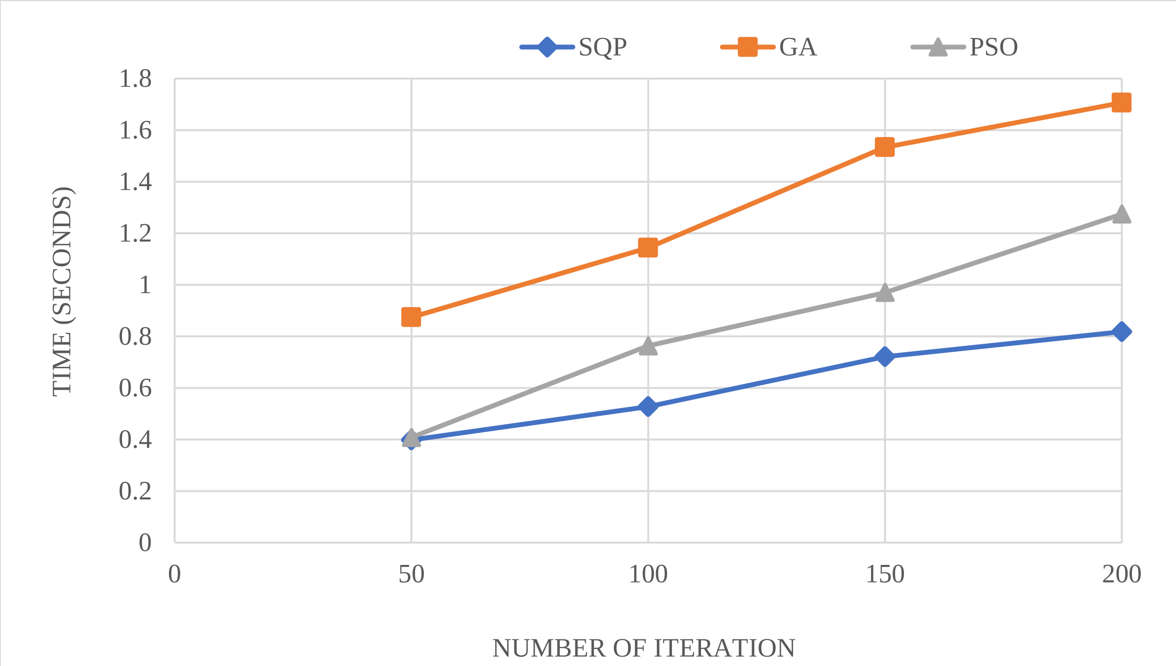

Fig. 11 Computation time for number iterations by SQP, GA, and PSO

4.8. Swot Analysis

SQP has illustrated significant advantages from the perspective of computational speed, efficient material utilization and, at utmost priority a numerical accuracy. It has achieved the overall smallest structural area (0.0825 m^2) and the smallest mean member area (0.0083 m^2) amongst the approaches considered, which illustrates a more efficient utilization and distribution of material over the truss members. As compared with the best result obtained by earlier researchers, SQP has achieved an extremely close matching design solution. It denotes a structural weight of 2486.88 kg with a low percentage error (0.97%) and a high consistency index (CI = 0.991). One of the best features of SQP is the fast convergence. Though we got a design solution at about 25th iteration, to extent the comparative study amongst 3 approaches, computation time (0.82 Seconds) required for 200 iterations is evaluated. It denotes that this approach is best suitable for problems subjected to limited computational time. However, the faster convergence for nonlinear problems may arise ambiguity in the solution. Hence, convergence to a local optimum is still possible, in particular for systems with strong nonlinear behavior. Large topological changes can be a scalability problem, but when the objective function and constraints are smooth and distinct, SQP is a reliable and effective option.

However, the Genetic Algorithm is better suited for global exploration, because of its population-based and stochastic nature. This reduces the probability of being trapped in local minima and allows for the exploration of a larger design option space. But this more extensive search comes at a price. The GA solution obtains the maximum structural weight (2500.82 kg) and maximum overall structural area (0.0897 m^2), and the increase in the overall structural area over the SQP is about 8.73%. These results are also shown by relatively larger error measures, namely a Mean Squared Error (MSE) of 1429.74, a Root Mean Squared Error (RMSE) of 37.82 and a Mean Absolute Percentage Error (MAPE) of 1.54%. Slightly lower Consistency Index (CI = 0.984) further indicates reduced accuracy than SQP and PSO. Moreover, the GA takes about 1.71 seconds for the longest computation for 200 iterations. It is sensitive to the choice of parameters and can require a lot of computational effort, but it can be useful for exploration, especially for complex or discontinuous design spaces. These elements can reduce its effectiveness for large-scale or time-critical applications.

The PSO is a middle ground between the two strategies, in terms of convergence stability and exploration. The mean member area (0.00888 m^2) and total structural area (0.0888 m^2) obtained are very much closer to the results by SQP as compared to GA. Also, it shows better enhancement. Error metrics reflect that PSO works with stable convergence behavior, along with a maximum percentage deviation of 10% and a moderate mean absolute percentage deviation (MAPD = 3.73%). After the perfect material utilization approach, optimized weight (2489.94 kg) is near as compared with the earlier researcher [36], denoting a variation about 1.1% with low MAPE (1.09%) and relatively high consistency index (CI = 0.989). PSO also shows that it is able to successfully change every member area, reducing the number of members while still feasible. It is computationally fast, taking about 1.27 s for 200 iterations, faster than GA and close to SQP. The main drawback is the sensitivity to the parameter settings (particularly inertia and acceleration coefficients) that can affect the convergence behavior. However, PSO is still a good fit for nonlinear and multimodal problems where both accuracy and flexibility are required.

The comparative analysis shows distinct advantages of each approach in combination. SQP is good choice for deterministic problems that require reliable and quick solutions because of its excellent precision, stable and fast solutions. However, PSO is very useful for complex design spaces, providing a good tradeoff of performance with near-optimum solutions, reliable convergence, and low computing cost. The powerful exploratory ability of GA makes it effective, but it is less efficient in convergence and precision, especially for problems in which the variety of solutions is important. Thus, the nature of the problem should determine the best approach: SQP for accuracy and efficiency, PSO for a balanced performance, and GA for a thorough investigation of difficult design spaces.

5. Conclusion

From the comparison of SQP, GA and PSO for the minimization of truss weight by size optimization, the following conclusions can be drawn.

1. Efficient material utilization can be explored by employing SQP, GA and PSO methods of optimization.
2. The SQP technique provided the most consistent distribution of member sizes and the least total structural area (0.0825 m^2), as shown by the low measures of variability. The results obtained using PSO were very similar to those of SQP, with only a small increment in the total area (around 7.64%), while still satisfying all the specified limits. GA, on the other hand, showed more dispersion both in the overall mass and the member regions. The higher deviation measures, such as MAPD (6.13%), MaxPD (15.33%) and higher optimized mass (2500.82 kg) indicates less accurate convergence.
3. Optimized weight investigated by SQP (2486.88 kg) and PSO (2489.94 kg), which is near to the reference benchmark [36] and also associated with lower MSE and RMSE, while GA has explored higher optimized mass and overstated error indices.
4. SQP obtained optimized solution in fewer iterations, but for complex problems, it may require relatively larger computing power for consideration of nonlinearity and multiple constraints. PSO has explored a design solution with a reasonable amount of computing time and number of iterations. On the contrary, the GA requires more generations and longer computation time.
5. The results show that SQP is the most accurate but only applicable to only smooth problems subjected to less constraint and a single objective. PSO has a good and reliable solution with a balancing solution quality and computational time. GA is good at exploration of design space, but certain improvement is necessary to enhance efficiency and stability.

5.1. Study Limitations and Future Research Direction

While interpreting the results, it is also equivalently important to recognize the limitations of this study. A limitation of this work is that it has focused on only on size optimization. Where only cross-sectional areas of the truss members are taken as design variables, subjected to fixed nodal coordinates and their connections. Although only size optimization covers many real-world design cases, it limits the solution space for the problems where size, shape and topology optimization are to be considered together. It may lead to an additional reduction in structural weight. As shape optimization allows to update the position of node and topology optimization allows to remove the unnecessary truss members carrying insignificant stresses.

All these 3 optimization approaches, if applied together, then a more flexible redistribution of material by considering a load path can be achieved. From the methodological point of view, the comparison is limited to two metaheuristic approaches (GA and PSO) and one deterministic methodology (SQP). However, the application of SQP is limited to problems with strong nonlinearity, discontinuity or a large number of conflicting objectives due to the dependency on gradient information, although it has better accuracy and computational efficiency. However, GA and PSO are stochastic methods; they can explore complex design spaces but cannot guarantee perfect optimality and may produce inconsistent results. This highlights the need for alternative or hybrid strategies that take advantage of both metaheuristic and deterministic approaches.

Future studies may therefore investigate the integration of data-driven methods, such as artificial neural networks and machine learning, into the optimization framework. These techniques can be used to guide the search process, approximate complex goal functions or reduce the computational cost by surrogate modelling. These approaches are very promising for large-scale or multi-objective optimization problems, when the standard approaches might be less efficient or computationally expensive.

In summary, further developments of the present work to include additional performance constraints, the implementation of a unified size, shape and topology optimization framework, and the use of hybrid or learning-based optimization techniques may offer a more reliable and adaptable approach to structural design. Implementation of such things can significantly enhance the efficiency and accuracy of optimization techniques.

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Credit Authorship Contribution Statement

Dr. R. J. Fernandes: Review, editing, and supervision. Mr. Amit A. Kusanale: Conceptualization, formal analysis and writing original draft.

Data Availability

The supporting data to the findings of this study can be made available by the authors upon reasonable request.

Conflict of Interest

The authors confirm that there are no any known conflicts of interest associated with this publication. No conflict.

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Ethics Statement

This work does not involve any sensitive data. Therefore, ethical approval and informed consent were not required.

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