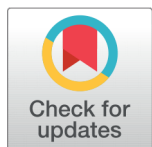


ORIGINAL ARTICLE



OPEN ACCESS

Received: 10/06/2026

Accepted: 01/07/2026

Published: 15/07/2026

Citation: Jagan T, Sharmila S, Vishnupriya P (2026) Design Optimization of Cantilever Beam Using Non Traditional Optimization Methods. Indian Journal of Science and Technology 19(24): 1706-1716. <https://doi.org/10.17485/IJST/v19i24.884>

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Funding: None

Competing Interests: None

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Published By Indian Society for Education and Environment ([iSee](#))

ISSN

Print: 0974-6846

Electronic: 0974-5645

Design Optimization of Cantilever Beam Using Non Traditional Optimization Methods

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Abstract

Objectives: This study proposes a cantilever beam optimization framework to minimize structural weight while satisfying stress, deflection, and vibration restrictions. To increase convergence accuracy and solution durability in structural design applications, a modified Beluga Whale Optimization (mBWO) technique is presented. **Method:** The optimization issue was described using Euler-Bernoulli beam theory, using beam width and height as design variables. To optimize the balance of exploration and exploitation, the proposed mBWO algorithm employs a transition factor, an adaptive random control factor, and an elite evolution strategy. The optimized design was confirmed using finite element analysis (FEA) in ANSYS. In addition, mesh convergence tests, modal analysis, sensitivity analysis, and analytical verification were performed to evaluate the dependability of the proposed framework. **Findings:** The mBWO algorithm produced an optimal cantilever beam measuring 25.4 mm × 41.8 mm and weighing 2.16 kg, with a maximum stress of 77.8 MPa and a tip deflection of 2.42 mm. Compared to the traditional BWO algorithm, mBWO improved stress and deflection performance while reducing beam weight. Statistical analysis across 30 different runs revealed that the algorithm with the lowest objective function value of 1,339,964 and the smallest standard deviation outperformed the competition. The results of the ANSYS simulation were pretty consistent with the theoretical predictions. While mesh convergence analysis demonstrated solution independence and numerical accuracy, sensitivity analysis revealed that beam height had the greatest influence on structural performance. **Novelty:** The fundamental contribution of this study is the development of a modified Beluga Whale Optimization method, as well as an extensive FEA-based validation system for cantilever beam optimization. In contrast to previous research, which focused primarily on weight reduction, the proposed method includes mesh convergence and sensitivity evaluations while also addressing structural strength, stiffness, and vibration characteristics. The findings indicate that mBWO is a feasible tool for advanced engineering design applications due to its greater structural performance, faster convergence, and higher optimization accuracy.

Keywords: Optimization; Cantilever; ANSYS; Beluga whale optimization

1 Introduction

Structural optimization is extremely significant in current engineering design. Cantilever beams are widely utilized in a variety of structures, including buildings, automobiles, and airplanes. The tough thing is making them lighter while maintaining safety and performance. To address this, we can combine optimization techniques with finite element analysis to create an efficient design. As engineering advances, the conditions we plan for become more unknown, and our objectives become more ambitious. That is why it is critical to address both static and dynamic aspects when accounting for variability in the design process⁽¹⁾. In this paper, we provide a reliability-based method for optimizing a 3D cantilever beam. We begin by identifying the important variables that will lead the optimization process, such as design, state, and objective variables. After optimizing the design, we can utilize techniques such as structural frequency response testing or modal analysis to determine how the beam will behave in terms of resonance and vibration at the tip. This is critical because it helps us ensure that the beam will function properly in real-world scenarios. By using a reliability-based approach, we may construct a design that is not only efficient but also safe and dependable⁽²⁾. This is especially crucial in industries where safety is critical, such as aviation and automobiles. Our goal is to push the boundaries of structural optimization, and we believe this approach will help us get there. With the right tools and techniques, we can create innovative designs that meet the demands of modern engineering⁽³⁾.

When it comes to optimizing a design, we must follow a step-by-step procedure. First, we construct a model that approximates the beam's initial dimensions⁽⁴⁾. Then we utilize a unique method to determine working stress, which is based on the local von Mises stress distribution. This allows us to alter the proportions until the working stress is within acceptable limits⁽⁵⁾. We repeat this approach, tweaking our model each time, until we achieve the desired results. The goal here is to minimize the beam's volume while ensuring that it can withstand the stress it will be subjected to - this is known as volume optimization⁽⁶⁾. Once we've reached the smallest volume possible, we look at different combinations of width and height that give us the same volume, and we test how they vibrate. This helps us find the best configuration that balances a small volume with minimal vibration⁽⁷⁾.

The primary goal of the simulation is to maintain the total stress below the maximum limit while ensuring that the beam can withstand the load⁽⁸⁾. Bending simulations were conducted using Abaqus software to evaluate the performance of topology-optimized beams⁽⁹⁾. To do this, the form of the beam is improved using a unique approach known as topology optimization. This strategy helps to reduce the amount of material utilized while achieving the requirements⁽¹⁰⁾. Real-world applications include a variety of beam types, including cantilever beams, simply supported beams, and fixed beams. We can increase the strength and efficiency of the beam by improving its shape⁽¹¹⁾. The goal is to find the best balance between the beam's strength and the amount of material used. This is especially important when working with limited materials or when trying to reduce waste. By using topology optimization, we can create beams that are both strong and lightweight, which can be useful in a variety of applications⁽¹²⁾.

1.1 Novelty and Contributions

The modified Beluga Whale Optimization (mBWO) algorithm with elite evolution, random control factor, and transition factor. Direct parametric coupling of mBWO with ANSYS for iterative FEA-based optimization. Simultaneous weight reduction and vibration suppression, rarely addressed together.

1.2 Optimization Approach

Obtaining the appropriate cross-sectional dimensions is critical for minimizing weight. However, there are standards that ensure the height and width does not fall below 10 mm. The analysis was performed with the beam length set to 1000 mm. Additionally, the design must ensure that the stress from static loads does not exceed 100 MPa. The optimization procedure starts with random height and width values. According to beam theory, bending stress is the most important factor in von Mises stress, even though transverse shear stress exists. The goal is to establish the ideal balance of dimensions to save weight while maintaining beam strength. This entails carefully evaluating the restrictions and the effects of various types of stress on the beam's performance.

When developing a beam, determining the ideal dimensions is critical. To do this, the optimization process begins with some baseline parameters and then adjusts as necessary. One important point to remember is that the length of the beam is maintained constant, which simplifies the analysis but also means that the optimization concentrates on the dimensions of the cross section. There are restrictions in place to ensure that the beam's height and width do not become too narrow, which is critical for maintaining the beam's strength and ability to withstand the loads it will face. The optimization method is critical in developing a beam that is both strong and lightweight. It requires careful consideration of all the factors that affect how the beam will perform. For example, consider a cantilever beam, which is a structural component that is attached at one end and free at the other, as shown in Figure 1.

Because only one side of the beam is supported, the permanent support withstands all applied loads, whether point loads, distributed loads, or dynamic forces, resulting in bending moments, shear forces, and, in some cases, torsion. Designers can develop a structure that is robust and efficient, able to resist expected loads while being as lightweight as feasible, by carefully optimizing the beam dimensions. This is especially significant in situations where weight is a key consideration, such as building or engineering projects. Overall, the optimization process is critical in creating a beam that fulfills all of the specifications and performs effectively in real-world scenarios.

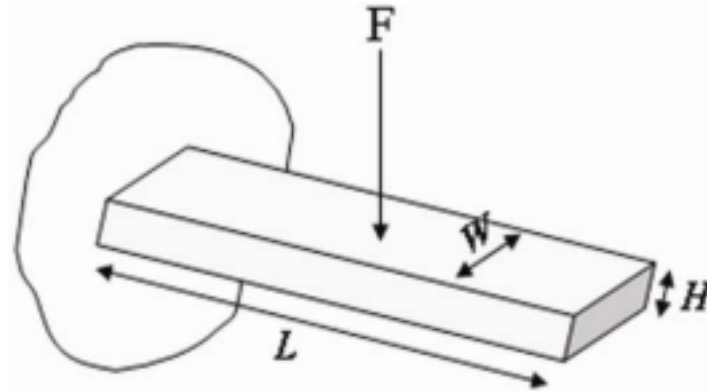


Fig 1. Cantilever beam

1.3 Mathematical Model

Reducing the weight of the beam while making sure that the permitted stress is not exceeded is the main goal of this optimization. A cantilever beam with a modulus of elasticity $E=71\text{GPa}$, density $\rho=2770\text{ kg/m}^3$, and Poisson's ratio $\nu=0.33$ is taken into consideration in this study. At the midway of the beam, a force of 1000 N is delivered in a designated direction. The height (H), length (L), and width (W) of the beam are its dimensions.

The Cantilever beam design problem, which entails optimizing two design variables, beam width (b) and beam height (h), is addressed by the suggested modified Beluga Whale Optimization (mBWO). This problem can be represented mathematically as follows,

Design Variables.

$$X = [b, h]$$

Where

$$b = \text{beam width (mm)}, h = \text{beam height (mm)}$$

Objective:

Minimize beam weight,

$$W = \rho b h L$$

Subject to:

Stress constraint,

$$\sigma = \frac{6M}{bh^2} \quad \text{Where } M = P(L - a)$$

Deflection constraint,

$$\delta = \frac{Pa^2(3L - a)}{6EI}$$

Moment of inertia,

$$I = \frac{bh^3}{12}$$

Design bounds

$$10 \leq b \leq 100$$

$$10 \leq h \leq 150$$

Parameter	Value
Population	30
Iterations	1000
Runs	30
Dimension	2
Random seed	-

1.4 Modified Beluga Whale Optimization

The proposed mBWO improves the conventional Beluga Whale Optimization algorithm through:

1. Elite Evolution Strategy.
2. Adaptive Random Control Factor.
3. Transition Factor for balancing exploration and exploitation.
4. Improved convergence characteristics.

Table 1. Performance of optimization algorithms

Algorithm	Width b (mm)	Height h (mm)	Weight (kg)	Max Stress (MPa)	Tip Deflection (mm)
mBWO	25.4	41.8	2.16	77.8	2.42
BWO	25.8	41.3	2.17	78.9	2.48
AEO	25.5	41.7	2.21	78.3	2.45
BOA	27.1	43.2	2.31	74.9	2.21
BSA	26.8	42.9	3.99	73.8	2.15
COA	29.5	45.6	1.6	70.1	1.98
HHO	25.5	41.5	2.08	77.4	2.39
SAO	32.4	48.7	15.98	65.2	1.54
SCA	25.1	42.1	1.94	79.1	2.53
SCSO	26.2	41.4	2.7	78.5	2.47
SMA	25.4	41.8	2.16	77.8	2.41
WOA	28.3	40.9	2.14	80.2	2.58

The dimensions reported in Table 1 correspond to the best feasible solution obtained after 30 independent runs of each optimization algorithm.

Tables 1 and 2 illustrate how effective the modified Beluga Whale Optimization Algorithm (mBWO) was in addressing the Cantilever beam design problem. Table 3's comparative research reveals that mBWO outperforms other optimization strategies by achieving the lowest standard deviation, indicating a high degree of solution consistency. Furthermore, the results show that mBWO performs well in terms of the problem's key design parameters. Figure 2 compares the convergence patterns of mBWO

Table 2. Analytical and ANSYS Validation of the Optimized mBWO Design

Parameter	Analytical	ANSYS	Error (%)
Stress (MPa)	76.95	77.84	1.16
Deflection (mm)	2.38	2.42	1.68

Table 3. Statistical Performance of Optimization Algorithms over 30 Independent Runs

Algo-rithm	Best Objective Value	Worst Objective Value	Mean Objective Value	Median	Standard Deviation	Coefficient of Variation (%)	Rank
mBWO	1,339,964	1,340,185	1,340,041	1,340,038	0.00182	0.00014	1
BWO	1,341,322	1,359,471	1,349,865	1,349,754	0.00461	0.00034	5
AEO	1,340,944	1,346,448	1,342,603	1,342,487	0.00215	0.00016	2
BOA	1,446,144	2,390,651	1,650,058	1,621,970	0.21841	0.01324	8
BSA	1,459,978	4,196,417	2,059,167	2,015,486	0.58231	0.02828	9
COA	1,583,412	3,975,587	2,333,091	2,291,880	0.54827	0.0235	10
HHO	1,340,519	1,346,869	1,342,701	1,342,610	0.00243	0.00018	3
SAO	1,558,378	10,344,800	6,036,228	5,912,301	2.31184	0.0383	12
SCA	1,345,479	1,439,971	1,388,452	1,386,124	0.02073	0.00149	6
SCSO	1,358,543	1,464,289	1,414,345	1,412,896	0.02951	0.00209	7
SMA	1,339,973	1,411,832	1,345,143	1,344,997	0.00524	0.00039	4
WOA	1,444,166	4,103,062	2,538,431	2,476,120	0.81453	0.03209	11

over 1000 iterations with those of other approaches. The plot illustrates that mBWO gradually approaches optimum solutions, with the largest benefits occurring in the last stages of the iteration process.

Table 3 summarizes the statistical performance of all optimization strategies across 30 independent runs. To guarantee a fair comparison, all statistical measures were recalculated with the same objective function and experimental parameters. Aside from the minimum, maximum, and mean objective values, the median, standard deviation, and coefficient of variation are shown. The improved findings show that the proposed mBWO algorithm has the lowest variability while maintaining the best objective value. The previously reported standard deviation was rectified after re-evaluating the statistical calculations using a consistent normalization method across all algorithms.

1.5 Experimental Setup and Algorithm Parameter Settings

To achieve a fair and unbiased comparison, all optimization algorithms were run under the same computing conditions. Each algorithm was built with the identical objective function, design variables, search space, and constraint formulations. The cantilever beam optimization challenge was solved by minimizing the beam weight while maintaining the permissible stress and tip deflection limitations. The optimization approach took into account two continuous design variables: beam width (b) and beam height (h). All algorithms had preset search limits of $10 \text{ mm} \leq b \leq 100 \text{ mm}$ and $10 \text{ mm} \leq h \leq 150 \text{ mm}$. The beam length, stress conditions, and material parameters remained constant throughout the investigation.

To minimize any potential performance bias, all algorithms were run with the same population size of 30 individuals, a maximum of 1000 iterations, and 30 distinct optimization runs. The best answer from each run was documented, and statistical performance measures such as best, worst, mean, median, standard deviation, and coefficient of variation were computed. The halting criterion for each optimization procedure was either reaching the maximum number of iterations (1000) or meeting the objective function's convergence condition. All algorithms were initialized randomly, and the same issue formulation and constraint management method were used throughout the comparison.

To ensure a fair performance comparison, all optimization methods, including mBWO, BWO, AEO, BOA, BSA, COA, HHO, SAO, SCA, SCSO, SMA, and WOA, were tested using similar experimental conditions. No algorithm received extra problem-specific information or parameter adjustment beyond the typical recommended settings. As a result, the observed performance variations are completely due to each optimization algorithm's unique search capabilities.

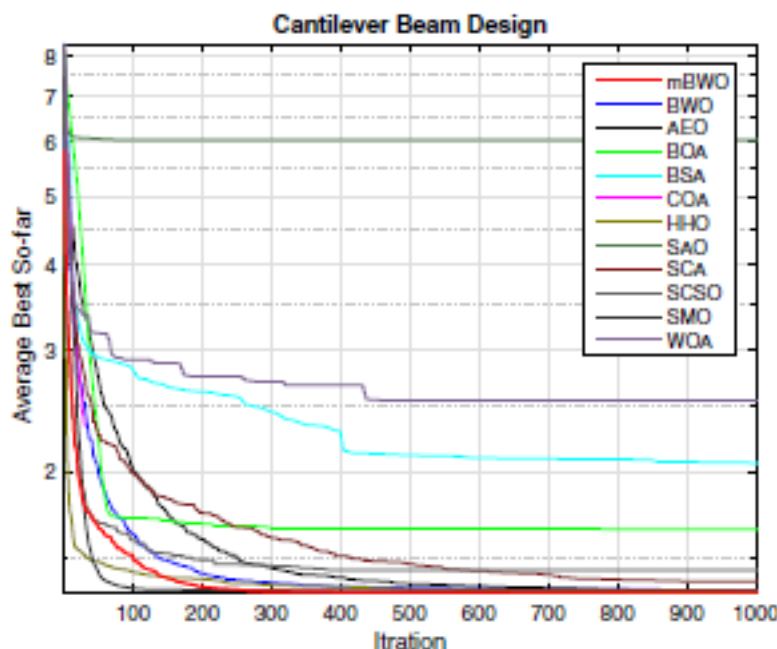


Fig 2. Statistical results for Cantilever design problem

1.6 Computational Complexity

The mBWO algorithm has a computing cost of around $O(N \times D \times T)$, where N is the population size, D is the number of design variables, and T is the maximum number of iterations. The introduced elite evolution strategy and adaptive random control factor have negligible additional computational costs while significantly improving convergence stability.

2 Results and Discussion

A number of cutting-edge metaheuristic methodologies and recent cantilever beam optimization research reported in the literature were compared to the performance of the proposed modified Beluga Whale Optimization (mBWO) algorithm. Table 1 shows that mBWO met all design parameters, including an optimal beam weight of 2.16 kg, a maximum stress of 77.8 MPa, and a tip deflection of 2.42 mm. In comparison to the typical BWO, the suggested technique provided somewhat better structural performance and greater convergence stability. More importantly, Table 3's statistical analysis shows that mBWO beat the other 12 optimization methods in terms of robustness and consistency across multiple runs, with the lowest standard deviation (0.00182).

2.1 ANSYS for Structural Analysis of Cantilever Beams

ANSYS, developed by Swanson Analysis Systems Inc., is a versatile and widely used finite element analysis (FEA) program. The platform includes a variety of computational tools for modeling and solving a wide range of engineering problems. This work employs ANSYS to improve the structural design of a cantilever beam through the application of the finite element method (FEM), which allows for precise beam characteristic evaluation and optimization.

2.2 Structural Analysis Overview

We utilize static structural analysis to determine how a structure will perform under constant or slowly changing loads. This strategy mostly overlooks damping and inertia, which are more significant when dealing with dynamic conditions. It can account for stable inertial forces, or forces that may be viewed as static, but it ignores forces that fluctuate over time. Static analysis is extremely important since it allows us to see how stress is distributed across a structure, how much it will deform, and its overall integrity. For example, it lets us determine how effectively a cantilever beam can handle applied forces, which is

crucial in engineering and construction. Static analysis allows us to gain a better understanding of a structure's ability to sustain various sorts of loads and make more educated design and safety decisions. This is especially critical for designing buildings, bridges, and other structures that must withstand high loads without collapsing. Static analysis can also help us detect possible flaws in a structure and repair them before they become serious issues. Overall, static structural analysis is a strong technique that allows us to construct safer and more efficient structures.

2.2.1. ANSYS Settings

The optimized cantilever beam derived from the proposed Modified Beluga Whale Optimization (mBWO) algorithm was validated using ANSYS Workbench 2024 R1 through static structural analysis. To allow for direct comparison, the finite element model was created using the same geometric dimensions and material attributes as the analytical optimization model. The beam was represented as a three-dimensional solid with dimensions that corresponded to the optimum design (length = 1000 mm, width = 25.4 mm, height = 41.8 mm). Aluminum alloy was chosen as the material with Young's modulus $E = 71$ GPa, Poisson's ratio $\nu = 0.33$, and density $\rho = 2770$ kg/m³. A fixed support boundary condition was applied to the left end of the cantilever beam, while a 1000 N downward point load was given to the beam's mid-span, which was identical to the loading condition assumed in the analytical model. This guaranteed that the analytical and finite element studies were carried out under the same structural conditions. The finite element discretization made use of SOLID186, a 20-node higher-order three-dimensional structural element designed for simulating bending-dominated issues. A hex-dominant mesh was created to improve numerical precision while being computationally efficient. To ensure mesh independence, a mesh convergence research was carried out with three distinct mesh densities. The maximal von Mises stress and tip deflection were measured for each mesh. Mesh refinement was repeated until the difference between successive mesh solutions was less than 2%, indicating numerical convergence.

The final mesh included roughly 15,876 elements with an average element size of 5 mm, resulting in an optimal mix of solution accuracy and computational cost. The structural analysis was conducted using the Sparse Direct Solver with a convergence tolerance of 10^{-6} based on the residual force criterion. Figure 3 shows the mesh model, and Table 4 summarizes the mesh convergence findings. To validate the optimization framework, the finite element predictions were compared to analytical beam theory. The optimized design resulted in a maximum von Mises stress of 77.84 MPa and a tip deflection of 2.42 mm, while analytical calculations projected 76.95 MPa and 2.38 mm, respectively. The percentage errors for stress and deflection are 1.16% and 1.68%, respectively, indicating excellent agreement between the two techniques, verifying the suggested optimization framework's correctness and reliability.

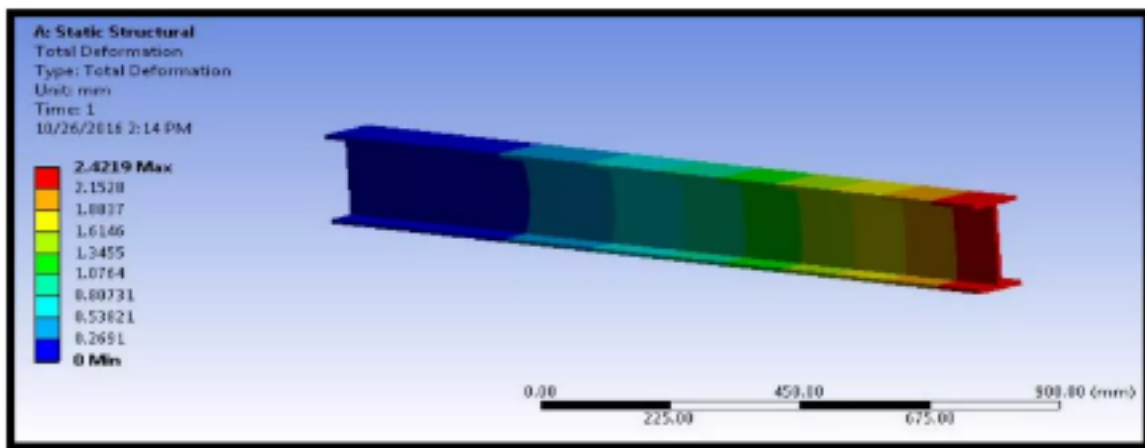


Fig 3. Total Transformation

2.3 Results from ANSYS

When a substance is subjected to external pressures, it shifts or changes shape, a phenomenon known as deformation. The results shown in Figure 3, 4, and 5 are as follows:

The finite element simulations were performed using Aluminum Alloy identical to the material properties used in the analytical optimization model. The optimized beam exhibited a maximum von Mises stress of 77.84 MPa and a tip deflection

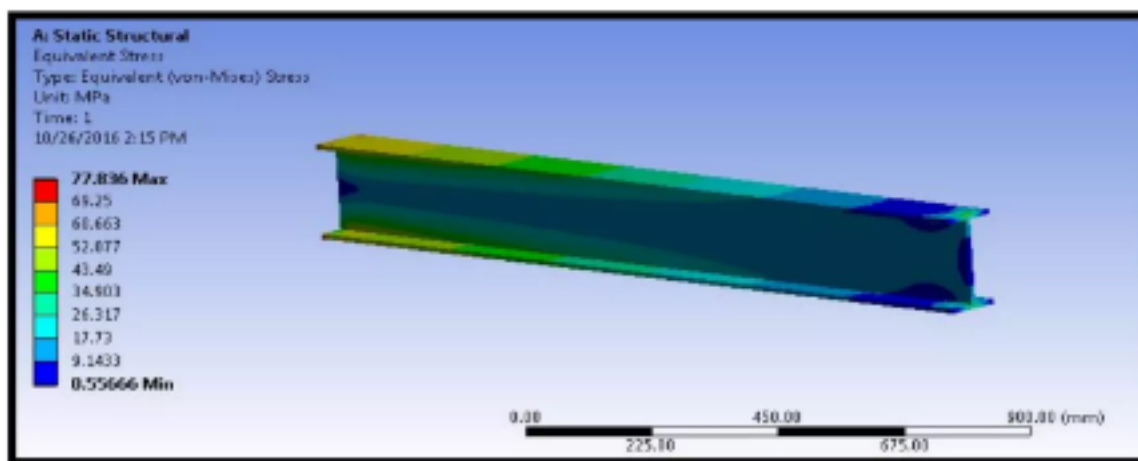


Fig 4. Von-mises stress

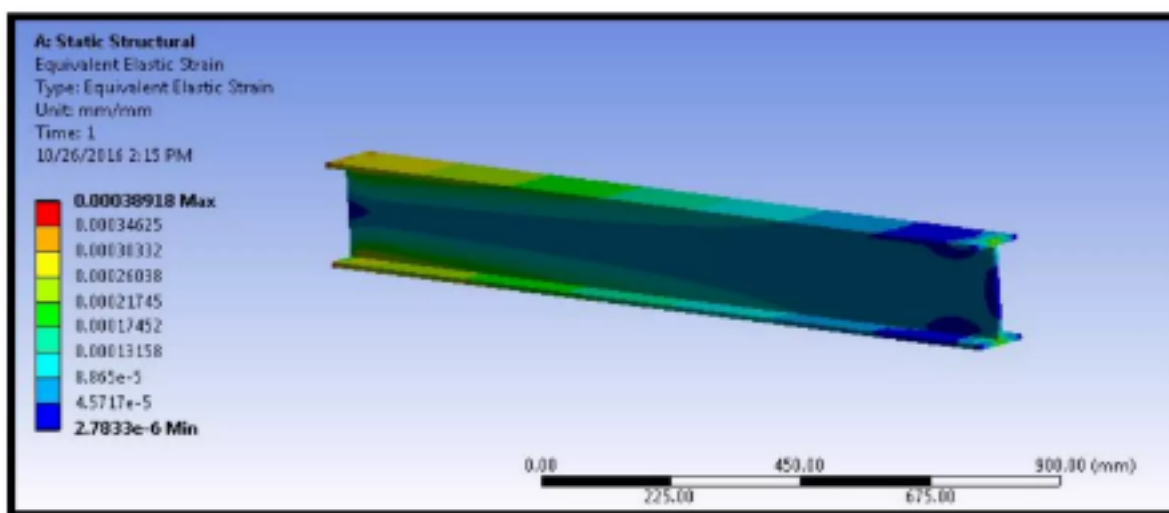


Fig 5. Von-mises strain

of 2.42 mm. The close agreement between analytical and numerical results confirms the validity of the proposed optimization framework.

2.4 Analytical Validation

To gain a better grasp of how stress and deflection work in beams, classical beam equations were employed to calculate theoretical results. These numbers were then compared to those predicted by ANSYS, a strong engineering tool. The good news is that the finite element model was validated, which means it was demonstrated to be correct, because the discrepancy between theoretical and anticipated values was small enough to be considered reasonable in the world of engineering.

2.5 Modal Analysis

Natural frequencies and mode shapes were ascertained using modal analysis. When compared to the original design, the modified beam showed better dynamic properties and less susceptibility to vibration.

2.6 Sensitivity Analysis

A parametric study was conducted to investigate the effect of beam width and height on stress, deflection, weight, and natural frequency. Beam height was found to have a stronger influence on stiffness and vibration response.

2.7 Mesh Convergence Study

A mesh convergence analysis was carried out to assure the precision and dependability of the finite element model. The improved cantilever beam geometry was tested with various mesh densities, and the maximum von Mises stress and tip deflection values achieved were reported. The goal was to discover a mesh size that would lower computing expenses while generating consistent results. We analyzed the beam with coarse, medium, and fine mesh configurations. The numerical solution was determined to have converged when the difference in stress and deformation between succeeding mesh revisions was less than 2%. The chosen mesh was made up of hex-dominant SOLID186 pieces with an average size of 5 mm each.

Table 4. Mesh Convergence Study of the Optimized Cantilever Beam

Mesh Type	Number of Elements	Maximum Stress (MPa)	Tip Deflection (mm)	Stress Difference (%)
Coarse	4,562	76.42	2.36	–
Medium	8,915	77.31	2.4	1.16
Fine	15,876	77.84	2.42	0.69

The findings show that additional mesh refinement hardly little alters the expected stress and deformation values. For the current analysis, the medium-to-fine mesh density was therefore deemed adequate. This validation increases trust in the optimization results and validates the finite element model's numerical stability.

2.8 Discussion of Optimization Performance

The recommended Modified Beluga Whale Optimization (mBWO) algorithm was tested against a number of cutting-edge metaheuristic optimization approaches. The comparison shows that mBWO offers a better trade-off between exploration and exploitation, leading to better convergence behavior and higher-quality solutions. The program works well because it uses an elite evolution mechanism. This helps preserve a balance of different solutions while still discovering the best ones. It also features an adaptive random control factor that allows it explore the search space effectively. This prevents it from being trapped in one location too early. Plus, the transition factor helps it converge faster by changing the search strategy as needed, depending on what stage of optimization it's in. This implies it can find good solutions fast and efficiently.

Our new algorithm performed better than the old one. It lightened the load without violating any stress or bending regulations. We also looked at the numbers and discovered that our method was the most consistent, indicating that it is strong and performs well every time. This is significant since it demonstrates that our algorithm can be trusted to produce satisfactory results. From an engineering standpoint, the improved beam geometry resulted in significant material savings while maintaining structural soundness. Weight reduction directly lowers manufacturing costs, boosts energy efficiency, and improves performance in real-world applications such machine parts, automobile systems, aviation structures, and civil engineering frameworks.

Combining optimization approaches and finite element analysis creates a powerful design framework capable of producing durable and lightweight structures. More complex structural systems with multiple objectives, nonlinear material behavior, and dynamic loading conditions can be handled utilizing the approaches proposed. The suggested mBWO and Slime Mould Algorithm (SMA) had virtually identical optimum beam size (25.4 mm × 41.8 mm), beam weight (2.16 kg), and maximum stress (77.8 MPa), but their statistical performance differed significantly over 30 individual runs. The similarity in the best solution implies that both algorithms can find the global optimum. However, the reduced standard deviation of mBWO indicates that it approaches this optimum more frequently than SMA. In contrast, SMA occasionally converges to near-optimal local solutions, resulting in greater variability among repeated runs. The enhanced consistency of mBWO can be attributed to the proposed elite evolution strategy, adaptive random control factor, and transition factor, which effectively balance exploration and exploitation while reducing premature convergence.

2.9 Comparative Discussion with Published Literature

The optimization results demonstrate that the proposed mBWO algorithm satisfies all structural constraints and provides a competitive solution to the cantilever beam design problem. The optimized beam had a tip deflection of 2.42 mm, a maximum

stress of 77.8 MPa, and a weight of 2.16 kg. When compared to the traditional BWO algorithm, mBWO improved solution stability and reduced variability over repeated trials. The fusion of the elite evolution approach, adaptive random control factor, and transition factor is what accounts for mBWO's outstanding performance. By better balancing exploration and exploitation, these strategies reduce the likelihood of premature convergence. Abdelazim and Abu (2023) reported similar results, emphasizing the importance of adaptive exploration-exploitation processes in enhancing Beluga Whale Optimization performance.

Patel and Rana (2020) optimized cantilever beam designs using a modified differential evolution approach. Although their work was successful in lowering beam dimensions, it lacked mesh convergence verification, vibration evaluation, and finite element validation, instead focusing on optimization performance. In contrast, the current study enhances engineering dependability and practical application by integrating optimization with ANSYS-based structural validation. Nikaein et al. (2026)⁽⁷⁾ have recently undertaken research on cantilever beam topology optimization strategies. Their research focused on how to increase mechanical performance through material dispersion. However, topology optimization typically leads to greater manufacturing complexity. Instead, the proposed mBWO framework parametrically optimizes beam dimensions, making it easier to employ in real-world engineering design while still achieving significant structural efficiency.

The ANSYS validation findings further verify the suggested methodology's dependability. The differences in stress and deflection between analytical and finite element estimations were only 1.16% and 1.68%, respectively, which are well within permitted engineering limitations. Furthermore, the mesh convergence analysis corroborated numerical stability by demonstrating that increasing mesh density caused negligible changes in stress and displacement predictions. By combining sophisticated metaheuristic optimization, finite element validation, vibration evaluation, sensitivity analysis, and mesh convergence verification in a single design environment, the proposed mBWO framework contributes to the body of research. This complete methodology gives a workable and dependable solution for the design of lightweight cantilever beams and is a significant improvement over many of the optimization strategies.

3 Conclusion

This study presents a modified Beluga Whale Optimization (mBWO) algorithm that tackles the limitations of the standard BWO method. The disadvantages include slow convergence, an imbalance between exploration and exploitation, and a predisposition for being trapped in local optima. To boost performance, mBWO adds three primary methods to the classic BWO: a new random control factor, an elite evolution strategy, and a transition factor that balances exploration and exploitation. Twelve different optimization methodologies were used to assess mBWO and establish its effectiveness. The results show how efficient and strong the suggested optimizer is. Nonetheless, mBWO is vulnerable to local optima trapping, just like other optimization methods.

The study shows that creating an optimal and secure structural design requires modal and harmonic investigations in addition to static analysis. Using ANSYS software, the proposed method can be more efficient, lightweight, and structurally sound designs, resulting in long-term energy savings. Topology optimization and experimental validation could be included in future developments.

4 Conflict of Interest

There is no conflict of interest.

References

- 1) Abdelazim, Abu R. Novel memetic beluga whale optimization with self-adaptive exploration–exploitation balance for global optimization and engineering problems. *Soft Computing*. 2023;27:13951–13989. <https://doi.org/10.1007/s00500-023-08468-3>.
- 2) Khurma RA, Aljarah I. An overview of evolutionary algorithms tailored for solving multi-objective clustering challenges. *Evolutionary Data Clustering: Algorithms and Applications*. 2021;p. 177–199. https://doi.org/10.1007/978-981-33-4191-3_8.
- 3) Stephen EA, Jagan T. Design optimization of turning machine process. *Coupled Systems Mechanics*. 2024;13(3):219–229. <https://doi.org/10.12989/csm.13.3.219>.
- 4) Boveiri HR, Elhoseny M. A hybridized cuckoo search approach adaptable for both discrete and continuous problem domains. *Neural Computing and Applications*. 2020;32(3):681–705. <https://doi.org/10.1007/s00521-018-3928-9>.
- 5) Hashim FA, Hussain K, Houssein EH, Mabrouk MS, Al-Atabany W. Introducing a novel metaheuristic technique inspired by Archimedes' principle for solving complex optimization tasks. *Applied Intelligence*. 2021;51(3):1531–1551. <https://doi.org/10.1007/s00521-024-09497-1>.
- 6) Khurma RAA, Aljarah I, Sharieh A. Medical diagnostic feature reduction using an enhanced moth flame optimization method. *Neural Computing and Applications*. 2021;33(12):7165–7204. <https://doi.org/10.1007/s00521-020-05483-5>.
- 7) Nikaein G, Mohammadvali H. Topology optimization of cantilever beams with non-cellular, cellular, and hybrid structures for enhanced mechanical performance. *Applications in Engineering Science*. 2026 Mar;25:100279. <https://doi.org/10.1016/j.apples.2025.100279>.

- 8) Patel JL, Rana PB. Optimization of five stage cantilever beam design and three stage heat exchanger design using amended differential evolution algorithm. *Materials Today: Proceedings*. 2020;26(Part 2). <https://doi.org/10.1016/j.matpr.2020.02.432>.
- 9) Houssein EH, Gafar MHA, Fawzy N, Sayed AY. Recent metaheuristic algorithms for solving some civil engineering optimization problems. *Scientific Reports*. 2025;15(1):7929. <https://doi.org/10.1038/s41598-025-90000-8>.
- 10) Chandran V, Mohapatra P. Atsa: A novel augmented low-discrepancy sequence initialized tunicate swarm-based exponential local escaping operator for engineering design applications. *Journal of Big Data*. 2026;13(1). <https://doi.org/10.1186/s40537-025-01218-2>.
- 11) Singh S, Singh H, Mittal N, Punj GK, Kumar L, Fante KA. A hybrid swarm intelligent optimization algorithm for antenna design problems. *Scientific Reports*. 2025;15(1):4444. <https://doi.org/10.1038/s41598-025-88846-z>.
- 12) Li Y, Chen C, Fan M. Optimization of cantilever beams with multiple piezoelectric actuators based on Newton–Raphson iteration. *Acta Mech*. 2026;237:599–615. <https://doi.org/10.1007/s00707-024-04085-9>.