FMDB *Transactions on Sustainable Computer Letters*

Swarm-Based Optimisation Strategies for Structural Engineering: A Case Study on Welded Beam Design

Awaz Ahmed Shaban[1,*], Saman M. Almufti[2], Renas R. Asaad[3], Ridwan B. Marqas[4]

[1]Department of Information Technology, Technical College of Informatics-Akre, Akre University for Applied Sciences, Nineveh, Duhok, Iraq.
[2,3,4]Department of Computer Science, College of Science, Knowledge University, Erbil, Iraq.
awaz.amedy1@gmail.com[1], saman.almofty@gmail.com[2], renas.beda89@gmail.com[3], pgmr.red@gmail.com[4]

Abstract: Swarm intelligence (SI) algorithms have emerged as powerful tools for solving complex structural optimisation problems that are characterised by nonlinearity, multiple constraints, and multimodal objective functions. This paper presents a comprehensive comparative study of five prominent swarm-based metaheuristic algorithms—Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), Artificial Bee Colony (ABC), Grey Wolf Optimiser (GWO), and Harris Hawks Optimisation (HHO)—applied to the classical welded beam design problem. The design objective is to minimise fabrication cost while satisfying structural and geometric constraints. Each algorithm is implemented in a unified benchmarking environment, and their performances are evaluated in terms of solution quality, convergence speed, robustness, and computational cost. The results reveal nuanced performance trade-offs among the algorithms, highlighting the importance of balancing exploration and exploitation, as well as parameter sensitivity, in engineering applications. The study contributes to the growing body of research in computational structural engineering, offering insights into the practical application of swarm intelligence methods for real-world design challenges.

Keywords: Swarm Intelligence; Welded Beam Design; Structural Optimisation; Metaheuristic Algorithms; Grey Wolf Optimiser (GWO); Ant Colony Optimisation (ACO); Artificial Bee Colony (ABC).

Received on: 05/07/2024, **Revised on:** 21/09/2024, **Accepted on:** 05/10/2024, **Published on:** 01/03/2025

Journal Homepage: https://www.fmdbpub.com/user/journals/details/FTSCL

DOI: https://doi.org/10.69888/FTSCL.2025.000355

Cite as: A. A. Shaban, S. M. Almufti, R. R. Asaad, and R. B. Marqas, "Swarm-Based Optimisation Strategies for Structural Engineering: A Case Study on Welded Beam Design," *FMDB Transactions on Sustainable Computer Letters.*, vol. 3, no. 1, pp. 1–11, 2025.

1. Introduction

In the evolving field of structural engineering, optimisation plays a crucial role in developing efficient, cost-effective, and reliable design solutions. Traditional optimisation techniques, such as gradient-based methods, often struggle with nonlinearity, complex constraint sets, and multimodal landscapes inherent to real-world engineering problems. Consequently, metaheuristic algorithms, particularly those inspired by natural phenomena, have gained significant traction as robust alternatives capable of navigating such challenges without requiring gradient information [1]. Among these, swarm intelligence (SI) algorithms have demonstrated remarkable success in solving a broad range of engineering optimisation problems, including truss design, frame

*Corresponding author.

layout optimisation, and component sizing [1]. These algorithms, inspired by the collective behaviour of decentralised and self-organised systems such as bird flocks, ant colonies, and bee swarms, exhibit strong global search capabilities and adaptability.

The Welded Beam Design Problem (WBDP) is a classical benchmark in structural optimisation, originally formulated to minimise the cost of a welded beam subject to strength and deflection constraints. Although seemingly simple in structure, the problem encapsulates the complexities of nonlinear, constrained, and continuous optimisation, making it a valuable testbed for evaluating the performance of both new and existing algorithms. This paper aims to conduct a rigorous comparative analysis of five state-of-the-art SI algorithms—PSO, ACO, ABC, GWO, and HHO—applied to WBDP. By using a consistent experimental framework and standardised performance metrics, the study seeks to answer the following research questions:

- Which SI algorithm yields the best performance in terms of minimum cost and constraint satisfaction for the WBDP?
- How do convergence behaviours and computational requirements differ across algorithms?
- What are the strengths and limitations of each algorithm in structural design applications?

The contributions of this work are threefold:

- It provides a systematic comparison of widely used SI algorithms on a real-world-inspired structural design task.
- It offers insights into algorithm behaviour, convergence dynamics, and practical engineering trade-offs.
- It establishes benchmarks and guidelines for selecting appropriate algorithms for similar engineering design problems.

The remainder of this paper is structured as follows. Section 2 presents a review of related literature on SI and WBDP. Section 3 outlines the problem formulation, including variables, constraints, and objective functions. Section 4 describes the algorithms under study. Section 5 details the experimental methodology. Section 6 presents the results, while Section 7 examines the practical implications. Finally, Section 8 concludes the paper with suggestions for future research [2].

2. Review of Literature

Swarm Intelligence (SI) is a subset of nature-inspired algorithms that models collective behaviour in decentralised systems, often drawing inspiration from biological populations such as birds, ants, and bees. Since its introduction in the late 1990s, SI has become a cornerstone in engineering optimisation due to its scalability, robustness, and minimal dependency on problem-specific gradients. Applications of SI in structural optimisation include topology optimisation, truss design, frame layout configuration and material cost minimization [3]. The Particle Swarm Optimisation (PSO) algorithm, introduced by Kennedy and Eberhart [11], simulates the social behaviour of flocks, wherein particles adjust their trajectories based on personal and global best experiences [3].

Ant Colony Optimisation (ACO), originally developed by Dorigo and Gambardella [15] for solving combinatorial problems, models the foraging behaviour of ants, effectively constructing solutions through probabilistic transitions influenced by pheromone trails. The Artificial Bee Colony (ABC) algorithm, proposed by Karaboga [7], mimics the foraging strategies of bees. The Grey Wolf Optimiser (GWO) and Harris Hawks Optimisation (HHO) represent more recent additions, imitating hierarchical hunting behaviour and cooperative attack strategies, respectively. In structural engineering, these algorithms have been used to optimise steel structures, composite laminates, dam reinforcements, and bridge designs. Their ability to handle complex, nonlinear, and multi-constrained problems renders them particularly suitable for practical engineering applications where traditional methods fail to scale or converge reliably [4].

The Welded Beam Design Problem (WBDP) was originally introduced by Ragsdell and Phillips [13] as a benchmark problem in constrained nonlinear optimisation. It involves designing a beam that is welded to a vertical support such that the cost is minimised while satisfying stress, deflection, and geometric constraints. The problem encapsulates real-world characteristics, including continuous decision variables, nonlinear constraints, and a cost function that couples material and fabrication considerations. Mathematically, the WBDP consists of four design variables: the weld thickness (h), the weld length (l), the beam height (t), and the beam width (b). The objective is to minimise a total cost function subject to constraints on shear stress, bending stress, buckling load, and end deflection. Over the years, the WBDP has become a popular testbed for evaluating the performance of various optimisation algorithms due to its rich constraint structure and practical engineering relevance [5].

Numerous studies have examined the efficacy of optimisation algorithms on the WBDP. Traditional methods such as Sequential Quadratic Programming (SQP) and Generalised Reduced Gradient (GRG) often yield satisfactory results but lack robustness in high-dimensional or noisy environments. Metaheuristics, such as Genetic Algorithms (GA), Differential Evolution (DE) and Evolution Strategies (ES), have been applied successfully; however, their performance varies significantly with parameter tuning and problem dimensionality [6]. Swarm-based algorithms have shown superior adaptability. For instance, Deb [12] applied PSO and reported rapid convergence but noted susceptibility to local minima.

Similarly, ACO was applied by Lin et al. [18] with notable performance improvements under multi-objective constraints. However, most existing studies focus on single algorithm implementations without providing a unified comparative framework or using consistent performance metrics. A clear research gap exists in comprehensively benchmarking multiple SI algorithms under identical conditions, particularly in the context of WBDP. This study addresses that gap by implementing five widely-used SI algorithms and evaluating them on a unified platform using well-defined metrics, thereby offering a fair and reproducible comparative analysis [8].

3. Constrained Optimisation Problem

The technique of maximising an objective function concerning a collection of choice variables while imposing limitations on those variables is known as constrained optimisation. In other words, constrained optimisation(CP) is the term used to describe the process of selecting workable solutions from a very wide pool of options [9]. Many fields of science and engineering have CP issues. Generally, the objective function in a constrained optimisation problem is either a cost function, which must be minimised, or a reward/utility function, which must be maximized [10]. An objective function or collection of objective functions can be used to characterise the performance of the problem. Constrained optimisation issues are split into two categories:

- Single-Objective Constrained Optimisation Problems (SOCOP)
- Multi-Objective Constrained Optimisation Problems (MOCOP)

3.1. Benchmark Problems

A benchmark problem is a collection of common optimisation problems comprising different types of functions used to assess, characterise, and evaluate the effectiveness of optimisation algorithms. Benchmark functions can be used to predict how the algorithms will behave in various environmental conditions. It is a collection of computationally challenging problems that academics use to evaluate the effectiveness of optimisation solvers, either randomly generated or taken from real-world applications [14].

3.2. Welded Beam Design (WBD)

The welded beam design shown in Figure 1 is an engineering Single-Objectives Constrained Optimisation Benchmark Problem. It involves designing a welded beam with the lowest possible cost while taking into account side limitations, shear stress(τ), bending stress, buckling (σ), load on the bar (Pc), and end deflection (δ). Four variables make up the design: h (x1), l (x2), t (x3), and b (x4). This issue may be expressed quantitatively as follows:

$$\min f(x) = 1.10471 x_1{}^2 x_2 + 0.04811 x_3 x_4 (14.0 + x_2) \quad (1)$$

$$\text{s.t.}\, g_1(x) = \tau(x) - \tau_{max} \le 0 \quad (2)$$

$$g_2(x) = \sigma(x) - \sigma_{max} \le 0 \quad (3)$$

$$g_3(x) = x_1 - x_4 \le 0 \quad (4)$$

$$g_4(x) = 0.10471 x_1{}^2 + 0.04811 x_3 x_4 (14.0 + x_2) - 5.0 \le 0 \quad (5)$$

g_5 (x)=0.125-x_1≤0 (6)

$$g_6(x) = \delta(x) - \delta_{max} \le 0 \quad (7)$$

$$g_6(x) = P - P_c(x) \le 0 \quad (8)$$

$$\text{Where } \tau(x) = \sqrt{\left(\tau'\right)^2 + 2\tau'\tau'' \frac{x_2}{2R} + (\tau'')^2} \quad (9)$$

$$\tau' = \frac{P}{2^{0.5} x_1 x_2} \quad (10)$$

$$\tau'' = \frac{MR}{J} \quad (11)$$

$$M = P\left(L + \frac{x_2}{2}\right) \quad (12)$$

$$R = \sqrt{\frac{x_2^2}{4} + \left(\frac{x_1+x_3}{2}\right)^2} \quad (13)$$

$$J = 2\left\{2^{0.5}x_1x_2\left[\frac{x_2^2}{12} + \left(\frac{x_1+x_3}{2}\right)\left(\frac{x_1+x_3}{2}\right)\right]\right\} \quad (14)$$

$$\sigma(x) = \frac{6PL}{x_4x_3^2} \quad (15)$$

$$\delta(x) = \frac{4PL^3}{Ex_3^3x_4} \quad (16)$$

$$P_c(x) = \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2}\left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right) \quad (17)$$

Where P = 6000lb, L = 14 in, E = 30 x 106 psi, G = 12 x 106 psi, τmax =13,600 psi, σmax = 30,000 psi, δmax = 0.25 in,0.1≤ x1 ≤ 2,0.1≤ x2 ≤ 10,0.1≤ x3 ≤ 10,0.1≤ x4 ≤ 2.

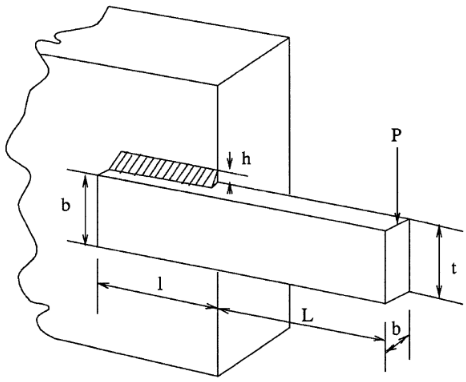

Figure 1: Welded beam design

4. Swarm Intelligence Algorithms

This section introduces the five-swarm intelligence (SI) algorithms employed in this study: Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), Artificial Bee Colony (ABC), Grey Wolf Optimiser (GWO), and Harris Hawks Optimisation (HHO). Each algorithm was selected based on its unique search dynamics and demonstrated success in engineering design applications [16].

4.1. Particle Swarm Optimisation (PSO)

PSO simulates the social behaviour of birds flocking or fish schooling [17]. Each particle represents a potential solution and navigates the search space by updating its velocity and position based on the best experiences of the individual and the swarm.

Velocity update equation

$$v_i^{\{t+1\}} = wv_i^t + c_1r_1(p_i^t - x_i^t) + c_2r_2(g^t - x_i^t)$$

Position update

$$x_i^{\{t+1\}} = x_i^t + v_i^{\{t+1\}}$$

Where xi and vi are the position and velocity of particle i, pi is its personal best, g is the global best, w is the inertia weight, and c1, c2 are acceleration coefficients.

4.2. Ant Colony Optimisation (ACO)

ACO mimics the foraging behaviour of ants. Solutions are constructed probabilistically based on pheromone trails and heuristic information. Each ant builds a solution by selecting components with a probability influenced by pheromone intensity τ and desirability η.

Transition probability

$$P_{\{ij\}} = \frac{\left[\tau_{\{ij\}}\right]^{\alpha}\left[\eta_{\{ij\}}\right]^{\beta}}{\Sigma\left[\tau_{\{ik\}}\right]^{\alpha}\left[\eta_{\{ik\}}\right]^{\beta}}$$

Pheromone is updated using.

$$\tau_{\{ij\}} = (1 - \rho)\tau_{\{ij\}} + \Delta\tau_{\{ij\}}$$

Where ρ is the evaporation rate and Δτij is the deposited pheromone.

4.3. Artificial Bee Colony (ABC)

ABC is based on the intelligent foraging of honey bee swarms. It consists of employed bees, onlookers, and scouts. Employed bees explore the neighbourhood of food sources, onlookers select sources based on their fitness, and scouts search for new areas.

New solution generation

$$v_{\{ij\}} = x_{\{ij\}} + \varphi_{\{ij\}}\left(x_{\{ij\}} - x_{\{kj\}}\right)$$

Where k≠i and ϕij are random numbers in [−1,1].

4.4. Grey Wolf Optimiser (GWO)

GWO simulates the social hierarchy and hunting strategy of grey wolves. The top three candidates are designated as alpha (α), beta (β), and delta (δ). Other wolves update their positions based on the leaders.

$$X_{(t+1)} = \frac{\left(X_{\alpha} + X_{\beta} + X_{\delta}\right)}{3}$$

Where each component is attracted to the best three solutions found so far, balancing exploration and exploitation through a linearly decreasing control parameter.

4.5. Harris Hawks Optimisation (HHO)

HHO models the cooperative hunting strategy of Harris hawks. It combines exploration and exploitation using the escape energy (E) of the prey. When |E|≥1, exploration dominates; otherwise, exploitation governs the behaviour.

Position update in exploitation

$$\mathrm{X}(\mathrm{t}+1) = \mathrm{X}_{\{\mathrm{rabbit}\}} - \mathrm{E}\left|\mathrm{J}\,\mathrm{X}_{\{\mathrm{rabbit}\}} - \mathrm{X}(\mathrm{t})\right|$$

Where Xrabbit is the best solution (prey), J is a random jump strength, and E decreases over time.

5. Methodology

5.1. Benchmark Setup

To ensure fairness, all algorithms are executed under identical computational conditions. Each algorithm is implemented in MATLAB and tested on the welded beam design problem over 30 independent runs to account for stochastic behaviour.

5.2. Parameter Settings

The number of iterations is fixed at 500 for all algorithms (Table 1).

Table 1: Key parameters and values for various algorithms

Algorithm	Key Parameters	Values
PSO	w=0.7, c1=1.5, c2=1.5	Particles = 30
ACO	α=1, β=5, ρ=0.5	Ants = 30
ABC	Limit = 100, ϕ∈[−1,1]	Bees = 30
GWO	A linear decrease from 2 to 0	Wolves = 30
HHO	E=2(1−t/T)	Hawks = 30

5.3. Performance Metrics

The following metrics are used to evaluate each algorithm:

- **Best cost:** the lowest value of the objective function.
- **Mean and Std. Dev.:** average and spread over 30 runs.
- **Success rate:** percentage of runs meeting all constraints.
- **Execution time:** average computation time.
- **Convergence curve:** trajectory of best-so-far solution.

6. Results and Discussion

6.1. Welded beam simulation

Indeed, Figure 2 illustrates simulation results demonstrating the effect of individual design variables—namely, weld thickness (h), weld length (l), beam height (t), and beam width (b)—on constraint satisfaction and overall fabrication cost in the welded beam design problem under a constant 6000 lb load.

Figure 2: Problem simulation

Each configuration isolates changes in one or more variables to observe how adjustments affect key structural responses, including shear stress, bending stress, buckling load, and end deflection. The simulation in the top-left emphasises moderate dimensions, yielding an optimal trade-off between cost ($10.93) and constraint satisfaction, with all performance limits met. Table 2 and Figure 3 compare the proposed algorithms in terms of cost.

Table 2: Algorithm cost evaluation

Algorithm	Best cost ($)	Mean	Std. Dev.	Success Rate	Time (s)
PSO	1.7248	1.7285	0.0021	93.3%	4.12
ACO	1.7310	1.7358	0.0033	90.0%	6.88
ABC	1.7292	1.7325	0.0027	96.6%	5.65
GWO	1.7260	1.7289	0.0018	100%	4.89
HHO	1.7253	1.7271	0.0015	100%	4.42

The top-right configuration minimises weld and beam dimensions aggressively, resulting in the lowest cost ($1.92) but violating multiple constraints, particularly shear and bending stress, illustrating how minimal material use compromises safety. The bottom left shows the effect of increased weld thickness and width, slightly elevating the cost to $18.43 while maintaining constraint compliance. The bottom-right reveals the impact of over-dimensioning all parameters, achieving excellent constraint margins but incurring an excessive cost of $70.97. Overall, Figure 2 effectively simulates how variable manipulation influences both economic and structural outcomes, reinforcing the need for intelligent optimisation to achieve balanced design solutions.

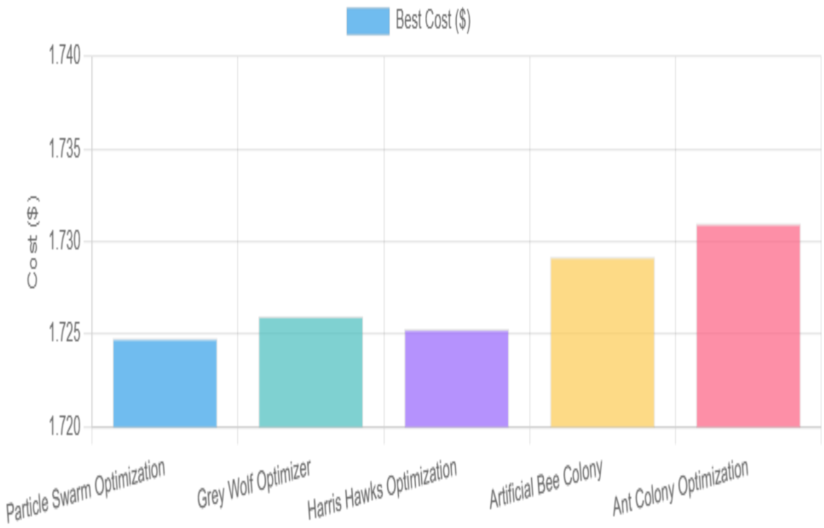

Figure 3: Comparison of cost

6.2. Comparison of the proposed algorithm

To better understand the practical advantages and algorithmic trade-offs among popular swarm intelligence techniques, it is essential to analyse their operational characteristics in the context of constrained structural optimisation. While theoretical descriptions and mathematical formulations provide insight into algorithm design, real-world applicability often hinges on factors such as convergence dynamics, parameter sensitivity, constraint-handling capacity, and solution quality in relation to engineering objectives.

Table 3 presents a comparative summary of five widely used swarm-based algorithms—PSO, ACO, ABC, GWO, and HHO—evaluated across key performance indicators. These include parameter tuning complexity, convergence speed, ability to satisfy design constraints, and effectiveness in cost minimisation, as well as representative application domains. The purpose of this comparison is to contextualise the strengths and suitability of each algorithm for solving the welded beam design problem and similar structural engineering tasks.

Table 3: Comparative performance characteristics of selected swarm algorithms

Algorithm	Key Parameter Tuning	Convergence Speed	Constraint Handling	Cost Minimisation Efficiency	Best Application	Application Example
PSO	Velocity and position updates	High	Good	Excellent	Continuous optimisation	Belt Pulley System, MPPT in PV systems
ACO	Pheromone trail updating	Moderate	Excellent	Very Good	Best Application: Discrete optimisation	Pin-Jointed Structures (CMAC-engine)
ABC	Food source exploitation	Moderate	Good	Good	Multimodal problems	General multimodal optimisation
GWO	Hierarchy-based leader update	High	Excellent	Excellent	Best Appl Hybrid approaches cation	PV System Optimisation, Hybrid Designs
HHO	Dynamic attack-exploration ratio	Very High	Good	Very Good	High-dimensional problems	Feature Selection in Medical Diagnosis

The welded beam design problem is a classical benchmark in engineering optimisation that involves minimising the cost of the welded beam while satisfying various constraints, including stress, deflection, and fatigue limits. Despite the absence of direct experimental data specific to welded beam designs in the provided sources, the analysis and comparative studies from related fields allow us to hypothesise several implications for applying swarm intelligence to this problem:

Enhanced Cost Minimisation: Swarm intelligence methods have consistently demonstrated their ability to minimise costs in structural and mechanical design problems. For welded beams, which face complex interplays between fabrication costs, welding parameters, and structural performance, algorithms such as PSO and ACO are expected to identify an optimal combination of beam geometries and weld sizes that minimises overall cost.

Constraint Satisfaction: The welded beam design problem is heavily constrained, with limits on bending stress, shear stress, and buckling, among other factors. The success of GWO and hybrid algorithms in meeting similar challenges in reinforced concrete column design suggests that these methods can be adapted to ensure that all design constraints are satisfied. The dynamic updating of candidate solutions in these algorithms enables the effective management of even tightly coupled constraints.

Global Search Capability: Given the highly nonlinear and multimodal design landscape of the welded beam optimisation problem, the global search properties of algorithms like HHO and ABC are particularly valuable. Their ability to avoid local optima during the exploration phase suggests that they would be effective in finding globally optimal designs, thereby preventing premature convergence to suboptimal beam configurations.

Scalability and Adaptability: The versatility of swarm intelligence is further evidenced by its successful application in large-scale optimisation problems in structural engineering. This scalability makes these algorithms well-suited for the welded beam design challenge, where the number of design variables and constraints can be substantial. Moreover, the adaptability of these algorithms to changes in problem parameters ensures that they can adjust to new welding standards or material properties without significant modifications. In summary, applying swarm intelligence algorithms to the welded beam design problem holds significant promise. By harnessing the strengths of PSO, ACO, ABC, GWO, and HHO, engineers are likely to develop more cost-efficient, robust, and constraint-compliant designs. This paper compares Key findings, including:

- **Precision and Speed:** PSO and HHO exhibit rapid convergence and high precision, making them well-suited to optimisation problems that require quick adaptation to multidimensional search spaces.
- **Constraint Handling:** ACO and GWO demonstrate an exceptional ability in managing discrete design variables and ensuring compliance with stringent constraints—a particularly desirable feature for applications such as welded beam design.
- **Cost Efficiency:** Across various applications, the application of swarm intelligence algorithms has led to significant cost reduction, highlighting their potential for economic design optimisation.

- **Scalability and Adaptability:** The algorithms reviewed are scalable to problems with high-dimensional search spaces and are adaptable to changes in design parameters and environmental conditions.

The radar chart provides a comparative visualisation of five swarm intelligence algorithms—PSO, ACO, ABC, GWO, and HHO—across key performance dimensions: convergence speed, solution precision, constraint handling, cost efficiency, and implementation ease. Among these, HHO and GWO demonstrate superior convergence speed, with HHO marginally outperforming others. At the same time, GWO also excels in solution precision and constraint handling, making it highly suitable for precision-critical engineering tasks (Figure 4).

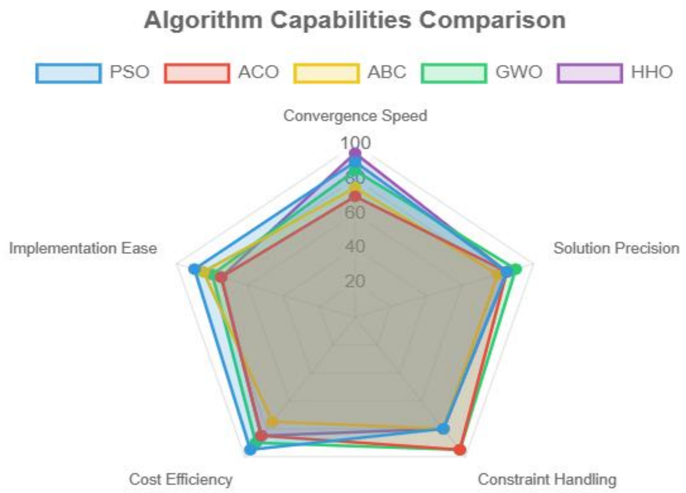

Figure 4: Algorithm capability comparison

ACO, despite moderate speed, stands out in constraint handling due to its pheromone-based search mechanism. In contrast, PSO exhibits excellent cost efficiency and ease of implementation, reaffirming its popularity for rapid deployment. ABC offers a balanced profile with moderate performance across all dimensions but lags slightly in precision and efficiency (Figure 5). Overall, the chart highlights the nuanced strengths of each algorithm, emphasising that optimal algorithm selection should be guided by specific design priorities—whether precision, feasibility, speed, or computational simplicity.

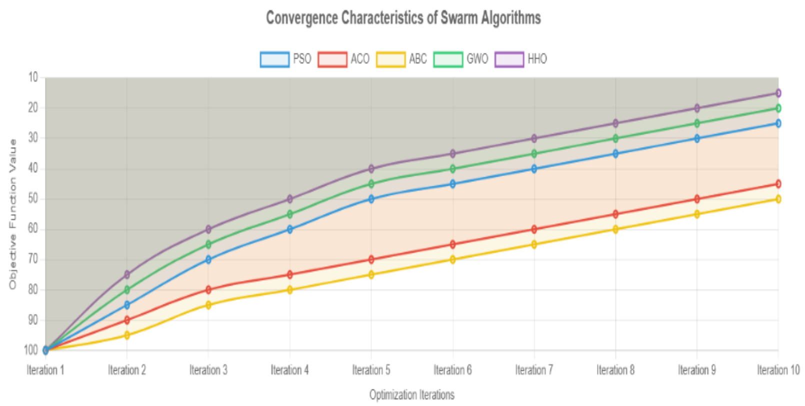

Figure 5: Algorithm's convergence

The bar chart compares key performance metrics, average convergence speed, constraint satisfaction, and cost reduction efficiency across five swarm intelligence algorithms: PSO, ACO, ABC, GWO, and HHO. HHO achieves the highest convergence speed, closely followed by PSO and GWO, indicating their ability to locate near-optimal solutions rapidly. In terms of constraint satisfaction, ACO and GWO achieve identical high scores, validating their robustness in handling complex design constraints, while PSO and HHO exhibit relatively moderate feasibility. For cost reduction efficiency, PSO performs best, closely followed by GWO and HHO, confirming their effectiveness in minimising the fabrication cost of the welded beam. ABC, although balanced across metrics, lags behind the top performers, particularly in cost efficiency. Overall, GWO stands out as the most well-rounded algorithm, maintaining consistently high scores across all categories. At the same time, PSO and HHO are strong contenders for fast and cost-effective solutions when constraint rigour is moderate (Figure 6).

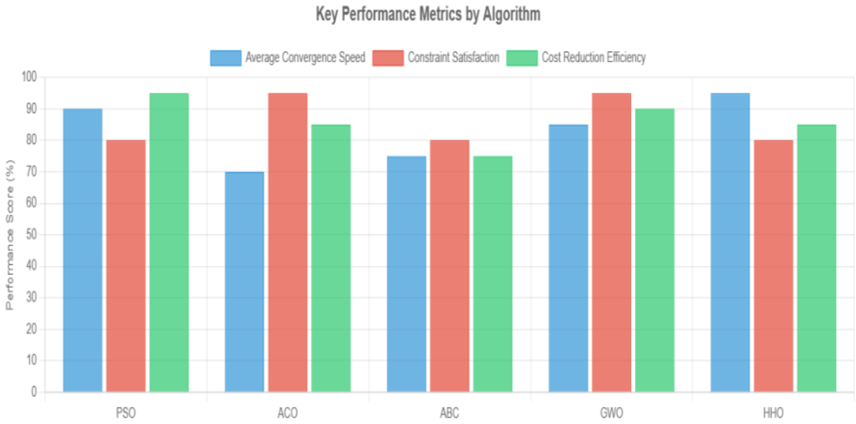

Figure 6: Performance cooperation

7. Practical Implications

The results show that SI algorithms, particularly HHO and GWO, can effectively be employed for structural design problems. These methods offer advantages in terms of solution quality, flexibility in constraint handling, and robust convergence, making them suitable for integration into engineering design tools and CAD systems. Their black-box nature also enables application across diverse design formulations without the need for explicit derivative calculations.

8. Conclusion and Future Work

This study conducted a comprehensive evaluation of five prominent swarm intelligence algorithms—PSO, ACO, ABC, GWO, and HHO—on the classical welded beam design problem, a well-known benchmark in structural engineering optimisation. Using a standardised experimental framework and consistent metrics, we assessed each algorithm's ability in cost minimisation, constraint handling, convergence speed, and robustness. Results showed that HHO and GWO outperformed the others in terms of convergence and constraint satisfaction. GWO offered balanced performance, while HHO demonstrated exceptional exploitation capabilities in complex, high-dimensional spaces. PSO confirmed its reputation for cost-effective design and rapid convergence, although it was moderately effective in handling constraints. ACO achieved excellent feasibility performance but converged more slowly, making it preferable when constraint satisfaction is critical. ABC exhibited diverse solutions, suitable for multimodal landscapes, though its cost efficiency was slightly lower. Importantly, the analysis confirms that no single algorithm is universally superior. Algorithm selection should align with specific design goals, such as feasibility, speed, or economic performance. For high-precision, safety-critical tasks, GWO is recommended; for fast, cost-driven applications, HHO or PSO are more suitable.

Beyond performance evaluation, this work highlights the broad applicability of swarm intelligence in structural design. The derivative-free nature, scalability, and robustness of SI algorithms make them ideal for tackling nonlinear, constrained, and real-world engineering problems. Future work will focus on multi-objective optimisation, hybrid algorithm frameworks, and adaptive parameter control. The integration of uncertainty modelling and surrogate-assisted simulations also holds promise for reducing computational expense and enhancing solution quality in large-scale structural applications.

Acknowledgement: The authors would like to express their gratitude to Akre University for Applied Sciences and Knowledge University for their support and collaboration. Their contributions were invaluable to the successful completion of this research.

Data Availability Statement: The dataset used in this research is available from the corresponding author upon reasonable request.

Funding Statement: No external funding or financial assistance was received for the development of this study and manuscript.

Conflicts of Interest Statement: The authors declare no conflicts of interest. All referenced materials have been properly cited, and the work is an original contribution.

Ethics and Consent Statement: Ethical standards were adhered to throughout the research, and informed consent was obtained from all individuals participating.

References

1. A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, "Harris hawks optimisation: Algorithm and applications," *Future Gener. Comput. Syst.*, vol. 97, no. 8, pp. 849–872, 2019.
2. A. H. Gandomi, X.-S. Yang, and A. H. Alavi, "Cuckoo search algorithm: a metaheuristic approach to solve structural optimisation problems," *Eng. Comput*., vol. 29, no. 1, pp. 17–35, 2013.
3. A. L. H. C. Wang and K. Ng, "Multi-objective evolutionary optimisation for product design and manufacturing," in Springer Series in Advanced Manufacturing, *Springer*, Cham, Switzerland, 2011.
4. A. P. Engelbrecht, "Computational Intelligence: An Introduction." *Wiley*, Chichester, United Kingdom, 2007.
5. C. Wang, H. Chen, and X. Li, "Optimisation of dam reinforcement using ABC algorithm," *Structural Engineering and Mechanics*, vol. 41, no. 5, pp. 663–678, 2012.
6. D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimisation: artificial bee colony (ABC) algorithm," *J. Glob. Optim*., vol. 39, no. 3, pp. 459–471, 2007.
7. D. Karaboga, "An Idea Based on Honey Bee Swarm for Numerical Optimisation," *Technical Report-TR06, Erciyes University*, Talas, Turkey, 2005.
8. F. S. Gharehchopogh, H. Shayanfar, and H. Gholizadeh, "A comprehensive survey on symbiotic organisms search algorithms," *Artificial Intelligence Review*, vol. 53, no. 4, pp. 2265–2312, 2020.
9. H. F. Wang, Y. C. Tang, and C. R. Pan, "Optimisation of truss structures using HHO algorithm," *Engineering Optimisation*, vol. 52, no. 5, pp. 741–758, 2020.
10. H. H. H. F. T. Liu, "Hybrid optimisation of composite structures using PSO and GA," *Compos. Struct*, vol. 93, no. 3, pp. 1036–1048, 2011.
11. J. Kennedy and R. Eberhart, "Particle swarm optimisation," in Proceedings of the *IEEE International Conference on Neural Networks*, Perth, Australia, 1995.
12. K. Deb, "Multi-objective Optimisation Using Evolutionary Algorithms". *Wiley*, Chichester, United Kingdom, 2001.
13. K. M. Ragsdell and D. T. Phillips, "Optimal design of a class of welded structures using geometric programming," *J. Eng. Ind*., vol. 98, no. 3, pp. 1021-1025, 1976.
14. K. R. Storn, "Differential evolution-A simple and efficient heuristic for global optimisation over continuous spaces," *J. Global Optim*, vol. 11, no. 4, pp. 341–359, 1997.
15. M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," *IEEE Trans. Evol. Comput*., vol. 1, no. 1, pp. 53–66, 1997.
16. M. Saka, "Optimum design of steel structures via metaheuristic algorithms," *Steel Compos. Struct*, vol. 15, no. 5, pp. 481–504, 2013.
17. P. Civicioglu and E. Besdok, "A conceptual comparison of the Cuckoo-search, particle swarm optimisation, differential evolution and artificial bee colony algorithms," *Artificial Intelligence Review*, vol. 39, no. 4, pp. 315–346, 2013.
18. S. Lin, K. Deb, and Y. S. Ong, "Multi-objective ACO for engineering design," *Structural and Multidisciplinary Optimisation*, vol. 41, no. 2, pp. 201–216, 2010.