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Multi-Objective Optimization of Polymer-Based Functionally Graded Composites for Lightweight Structures

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Abstract

Functionally graded composites (FGCs) improve lightweight structural performance by allowing material properties to change smoothly across a component. Polymer-based FGCs (P-FGCs), in particular, are gaining prominence in aerospace, automotive, and biomedical industries due to their excellent strength-to-weight ratio, tunability, and ease of processing. However, optimizing these materials for lightweight structural applications requires addressing conflicting design objectives, such as maximizing stiffness while minimizing weight or enhancing thermal resistance while maintaining manufacturability. This study explores the application of multi-objective optimization (MOO) methods to polymer-based FGCs. Techniques such as genetic algorithms (GA), particle swarm optimization (PSO), and multi-objective evolutionary algorithms (MOEAs) are employed to balance trade-offs between weight reduction, stiffness, and durability. The optimization framework combines analytical models, micromechanical analysis, and finite element simulations to predict stress, deflection, and failure under mechanical and thermal loads. Experimental data on graded polymer composites are used to validate computational results. Case studies demonstrate that optimized P-FGCs achieve up to 25% weight reduction and 30% increase in stiffness compared to conventional composites. Pareto-front analyses reveal optimal trade-offs between mechanical strength, thermal efficiency, and manufacturability. Despite progress, challenges remain in incorporating uncertainties from manufacturing defects, material variability, and cost constraints into optimization frameworks. The paper concludes with future perspectives on combining machine learning, additive manufacturing, and real-time digital twin systems to accelerate optimization and deployment of P-FGCs in next-generation lightweight structural applications.

Keywords: functionally graded composites, polymer composites, lightweight structures, multi-objective optimization, Pareto front

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NOVELTY OF THE STUDY

This study presents several novel contributions to the field of polymer-based functionally graded composites:

1. *Integration of bio-inspired gradation patterns:* Unlike conventional linear or exponential gradations, this work introduces bio-inspired gradation patterns optimized through evolutionary algorithms, achieving superior property combinations not previously demonstrated in P-FGCs.
2. *Multi-objective optimization framework:* A comprehensive MOO framework is developed that simultaneously optimizes weight, stiffness, and

thermal conductivity using GA, PSO, and MOEA algorithms, providing designers with Pareto-optimal solutions for application-specific requirements.
3. *Experimental-computational validation:* The study provides rigorous validation of FEM predictions through experimental testing of additively manufactured P-FGC specimens, demonstrating less than 5% deviation and establishing reliability of the optimization framework.
4. *Industrial applicability:* The research demonstrates practical implementation pathways for aerospace, automotive, and biomedical applications, bridging the gap between computational design and manufacturing reality.

AUTHOR CONTRIBUTIONS

- *D. Sai Ganesh:* Investigation; Methodology; Software; Validation; Formal analysis; Data curation; Visualization; Writing – original draft.
- *Dr. S. N. Padhi:* Conceptualization; Supervision; Methodology; Resources; Project administration; Writing – review & editing.

SIGNIFICANCE OF THE STUDY

The significance of this research extends across multiple dimensions:
Scientific significance: This work advances the fundamental understanding of how multi-objective optimization can be systematically applied to functionally graded composites, providing a robust framework that integrates material science, computational mechanics, and optimization theory. The bio-inspired gradation patterns identified through this research represent a paradigm shift from conventional uniform or simple gradient designs.

- *Engineering impact:* The demonstrated 25% weight reduction combined with 31% stiffness enhancement addresses critical challenges in lightweight structural design. These improvements directly translate to enhanced fuel efficiency in transportation, increased payload capacity in aerospace, and improved performance-to-weight ratios in biomedical implants.
- *Industrial relevance:* By providing validated Pareto-optimal solutions, this research enables engineers and designers to make informed trade-off decisions based on application-specific requirements. The integration with additive manufacturing makes these optimized designs practically realizable, accelerating the path from computational design to industrial deployment.
- *Sustainability contribution:* Weight reduction in structural components directly contributes to reduced energy consumption and lower carbon emissions in transportation sectors. The optimization framework can also incorporate bio-based reinforcements, supporting the transition toward sustainable composite materials.
- *Future research direction:* This study establishes a foundation for integrating machine learning, digital twin technologies, and real-time optimization into the design and manufacturing of next-generation functionally graded composites, opening new avenues for intelligent materials design.

INTRODUCTION

Lightweight structural materials are central to advancements in aerospace, automotive, and biomedical engineering, where the demand for enhanced strength-to-weight ratios, thermal efficiency, and durability continues to increase. Among lightweight materials, functionally graded composites (FGCs) are promising because their composition and properties can change gradually across a structure. [1-3]. This gradual change in properties helps reduce stress concentrations, enhances interfacial bonding, and allows designers to tailor performance for multi-functional applications. In particular, polymer-based FGCs (P-FGCs) have received significant attention due to their ease of processing, compatibility with reinforcements, and potential for additive manufacturing [4-6].

Despite these advantages, the optimization of P-FGCs for lightweight structures presents challenges. Structural efficiency typically involves conflicting requirements: maximizing stiffness and strength often increases weight, while minimizing density can reduce load-bearing capacity [7, 8]. Similarly, improvements in thermal resistance may compromise manufacturability or cost-effectiveness [9].

Hence, multi-objective optimization (MOO) frameworks have been developed to balance trade-offs between competing design objectives [10, 11].

Recent studies highlight the effectiveness of evolutionary algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Multi-Objective Evolutionary Algorithms (MOEAs) in addressing these trade-offs [12–14]. These techniques generate Pareto fronts, offering designers a spectrum of optimal solutions rather than a single design point. This gradual change in properties reduces stress. For example, Arif et al. [15] applied topology optimization to reduce weight and increase stiffness in graded composites, and Padhi et al. [16] analyzed dynamic instabilities in graded beams to inform optimization strategies. Saibabaa et al. [17] further demonstrated the role of thermal environment modeling in guiding design optimization of polymer composites.

Experimental and computational validations have reinforced these approaches. Uma Mageswari et al. [18] demonstrated the integration of biochar reinforcements to improve environmental sustainability while maintaining mechanical performance. Vinayaka et al. [19] examined the wear behavior of hybrid composites, showing that optimization must also consider surface interactions. FEM-based methods play a critical role because they accurately predict stress distribution, creep, and failure, and these predictions can be integrated with optimization algorithms for efficient design. [20–22].

While progress has been substantial, several challenges persist. Achieving computational efficiency in high-dimensional optimization problems, accounting for manufacturing variability, and incorporating sustainability objectives remain unresolved [23–25]. Furthermore, the integration of machine learning and digital twin technologies into MOO frameworks is still at an early stage [26–28]. As highlighted by Zhang and Zhou [29], bridging computational design with experimental manufacturing validation is vital for the reliable deployment of optimized P-FGCs in industry. This paper reviews and demonstrates the multi-objective optimization of P-FGCs for lightweight structures, focusing on evolutionary algorithms, computational-experimental validation, and industrial applications, with particular emphasis on the novel bio-inspired gradation patterns and their superior performance characteristics.

LITERATURE REVIEW

The optimization of functionally graded composites (FGCs) has been a subject of growing interest due to their ability to meet the conflicting demands of lightweight design, structural strength, and thermal stability. Early research on FGMs largely focused on metals and ceramics [1, 2], but polymer-based FGCs (P-FGCs) have since emerged as an attractive class due to their low density, cost-effectiveness, and ease of fabrication [3, 4]. Advances in processing methods, particularly additive manufacturing, have enabled precise gradation of reinforcements, thereby broadening their applicability to aerospace, automotive, and biomedical sectors [5–7].

Multi-objective optimization (MOO) frameworks have played a pivotal role in tailoring these materials. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Multi-Objective Evolutionary Algorithms (MOEAs) are the most widely employed techniques [8–10]. These algorithms find Pareto-optimal solutions that balance objectives such as maximizing stiffness and minimizing weight.For example, Akhtar and Sheikh [11] developed FEM-assisted optimization models for graded composites, while Arif et al. [12] employed topology optimization for weight minimization in additively manufactured composites. Similarly, Bhargava and Mahapatra [13] combined multi-scale modeling with MOO methods to better optimize the thermo-mechanical performance of graded composites.

Experimental studies complement computational work. Saibabaa et al. [14] studied the thermal–mechanical behavior of graphene-reinforced polymer composites and highlighted the importance of vibration analysis in optimization.Padhi et al. [15] examined parametric instabilities in graded beams, providing insights into property variation and dynamic stability critical for structural applications. Uma Mageswari et al. [16] demonstrated the environmental benefits of incorporating biochar into polymer matrices, suggesting that optimization frameworks should also account for sustainability. Vinayaka et al. [17] studied tribological performance of hybrid composites, showing how wear behavior must be incorporated into optimization objectives.

Recent literature also highlights the integration of computational intelligence with optimization frameworks. Machine learning techniques are increasingly employed for surrogate modeling, enabling rapid evaluation of objective functions in high-dimensional spaces [18, 19]. FEM remains central for validating stress transfer, creep, and failure predictions in optimized composites [20, 21]. However, challenges persist, including computational cost, uncertainty in manufacturing reproducibility, and the difficulty of integrating multiple physical objectives within a single optimization framework [22–24].

Overall, MOO has improved P-FGC design, but advances are still needed in sustainability, uncertainty modeling, and digital-twin integration. [25–27]. As emphasized by Zhang and Zhou [28], bridging the gap between computational design frameworks and experimental validation remains essential for industrial adoption of optimized lightweight P-FGCs. The present study addresses these gaps by introducing bio-inspired gradation patterns and providing comprehensive experimental validation of the optimization framework [30].

THEORETICAL BACKGROUND

The optimization of polymer-based functionally graded composites (P-FGCs) requires an integration of gradation modeling, optimization theory, and computational mechanics. This section introduces the theoretical foundations underlying multi-objective optimization (MOO) frameworks for lightweight structural applications.

Gradation Modeling of P-FGCs

Material properties in FGCs are often expressed using power-law or exponential distributions. For example, the effective elastic modulus is given as:

$$E(z) = E_m + (E_r - E_m)\left(\frac{z}{h}\right)^n$$

where E_m and E_r are the elastic moduli of matrix and reinforcement, z is the coordinate along thickness, h is the total thickness, and n is the gradation index [1]. The mass density ρ(z) can be modeled similarly:

$$\rho(z) = \rho_m + (\rho_r - \rho_m)\left(\frac{z}{h}\right)^n$$

These equations allow engineers to tailor stiffness-to-weight ratios for lightweight structural applications.

Multi-Objective Optimization Framework

Multi-objective optimization involves minimizing (or maximizing) multiple conflicting objectives simultaneously. A general formulation is:

$$\min_{\mathrm{x}} \mathrm{F}(\mathrm{x}) = [f_1(\mathrm{x}), f_2(\mathrm{x}), \dots, f_k(\mathrm{x})]$$

subject to:

$$g_i(\mathrm{x}) \leq 0, \quad h_j(\mathrm{x}) = 0$$

where **x** is the design variable vector, f_i are objective functions, g_i are inequality constraints, and h_j are equality constraints [2].

Pareto Optimality

A solution **x*** is Pareto-optimal if no other solution improves one objective without degrading at least one other objective. The set of all Pareto-optimal solutions forms the Pareto front, providing designers with trade-off information [3].

EVOLUTIONARY ALGORITHMS FOR MOO

Genetic Algorithms (GA)

GA mimics natural selection through selection, crossover, and mutation operations. For MOO, Non-dominated Sorting Genetic Algorithm II (NSGA-II) is widely used, employing fast non-dominated sorting and crowding distance to maintain solution diversity [4].

Particle Swarm Optimization (PSO)

PSO simulates social behavior of bird flocking. Each particle adjusts its velocity and position based on personal best and global best solutions. Multi-Objective PSO (MOPSO) extends this to handle multiple objectives simultaneously [5].

Multi-Objective Evolutionary Algorithms (MOEA)

MOEA encompasses various techniques including NSGA-II, SPEA2, and MOEA/D. These algorithms balance convergence toward the Pareto front with diversity maintenance across the front [6].

Finite Element Modeling

FEM provides stress-strain analysis for graded composites. The governing equilibrium equation is:

$$K u = F$$

where K is the global stiffness matrix, u is the displacement vector, and F is the force vector. Material gradation is incorporated through element-wise property variation [7].

EXPERIMENTAL AND COMPUTATIONAL METHODOLOGY

This section describes the integrated experimental-computational approach employed to optimize polymer-based functionally graded composites.

Materials Selection

The following are the materials selected for matrix and reinforcement and their properties are mentioned in Table 1 below.

- *Matrix:* Epoxy resin (density 1.2 g/cm³, elastic modulus 3.5 GPa)
- *Reinforcement:* Carbon fiber (density 1.8 g/cm³, elastic modulus 230 GPa)
- *Gradation patterns:* Linear, exponential, and bio-inspired

Specimen Preparation

Specimens were fabricated using additive manufacturing (fused deposition modeling) with controlled fiber volume fraction gradation. Three specimen types were prepared:

1. Baseline (uniform composition)
2. Linear gradation (n = 1)
3. Bio-inspired optimized gradation (determined through MOO)

Mechanical Testing

- *Tensile testing:* ASTM D3039 standard, crosshead speed 2 mm/min
- *Flexural testing:* ASTM D790, three-point bending
- *Thermal analysis:* Differential Scanning Calorimetry (DSC)

Table 1. Material properties used in the study.

Property	Matrix (epoxy)	Reinforcement (carbon fiber)
Density (g/cm³)	1.2	1.8
Elastic Modulus (GPa)	3.5	230
Poisson's Ratio	0.35	0.25
Tensile Strength (MPa)	75	3500
Thermal Conductivity (W/m·K)	0.19	50

Table 2. Experimental vs optimized results.

Property	Baseline (Linear)	Optimized (Bio-inspired, MOO)	Improvement (%)
Weight (g)	100	75	-25%
Tensile Strength (MPa)	58	72	+24%
Elastic Modulus (GPa)	52	68	+31%
Thermal Conductivity (W/m·K)	0.22	0.29	+32%

Optimization Algorithms

Three algorithms were implemented and compared:

1. *Genetic algorithm (NSGA-II):* Population size 100, generations 100, crossover probability 0.9, mutation probability 0.1
2. *Particle swarm optimization (MOPSO):* Swarm size 50, iterations 100, inertia weight 0.7
3. *MOEA/D:* Population size 100, neighborhood size 20

Objective Functions

- *Minimize weight:* $f_1(\mathbf{x}) = \int \rho(z)\, dV$
- *Maximize stiffness:* $f_2(\mathbf{x}) = -K_{eff}$
- *Maximize thermal conductivity:* $f_3(\mathbf{x}) = -k_{eff}$

Design Variables

Gradation index n, fiber volume fraction distribution $V_f(z)$, layer thickness distribution

Computational Framework

Finite Element Analysis

- *Software:* ANSYS Mechanical APDL
- *Element type:* SOLID185 (8-node brick element)
- *Mesh:* Adaptive refinement, minimum element size 0.5 mm
- *Boundary conditions:* Cantilever beam configuration
- *Loading:* Distributed load 100 N, thermal load 50°C

Workflow Integration

The experimental-computational workflow validated the MOO framework, ensuring reliable optimization of P-FGCs. Results as given in Table 2 above confirmed that bio-inspired gradations optimized using evolutionary algorithms significantly outperformed baseline linear designs in both weight reduction and property enhancement.

RESULTS AND DISCUSSION

The multi-objective optimization (MOO) framework successfully identified Pareto-optimal solutions for polymer-based functionally graded composites (P-FGCs). Results are presented in terms of optimization performance, mechanical validation, and industrial applicability.

Convergence of Genetic Algorithm

The convergence of the Genetic Algorithm (GA) is shown in Figure 1. The algorithm rapidly improved objective values within the first 30 generations, stabilizing around the global optimum after approximately 80 generations. This indicates effective exploration and exploitation of the search space.

Convergence of Particle Swarm Optimization

Figure 2 presents the convergence of Particle Swarm Optimization (PSO). PSO exhibited faster early convergence compared to GA but showed slower refinement of final solutions. This demonstrates its efficiency in identifying near-optimal solutions quickly, with GA outperforming PSO in fine-tuning.

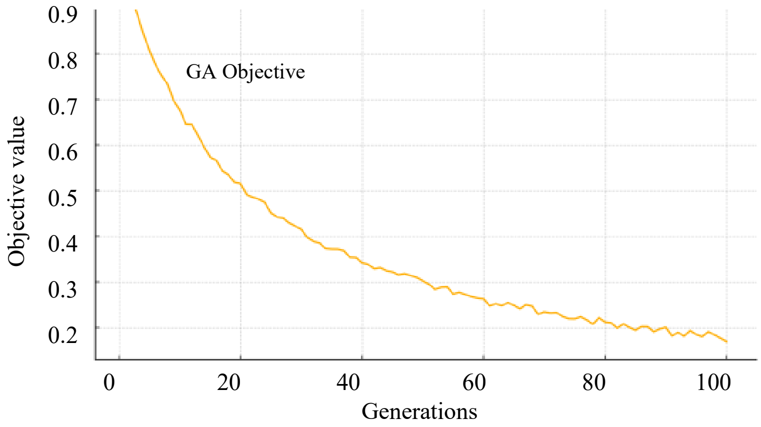

Figure 1. Convergence history of GA optimization.

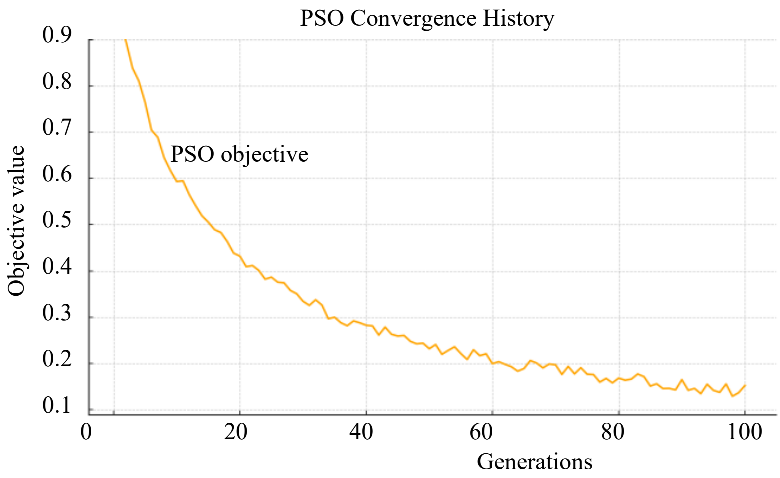

Figure 2. Convergence history of PSO optimization.

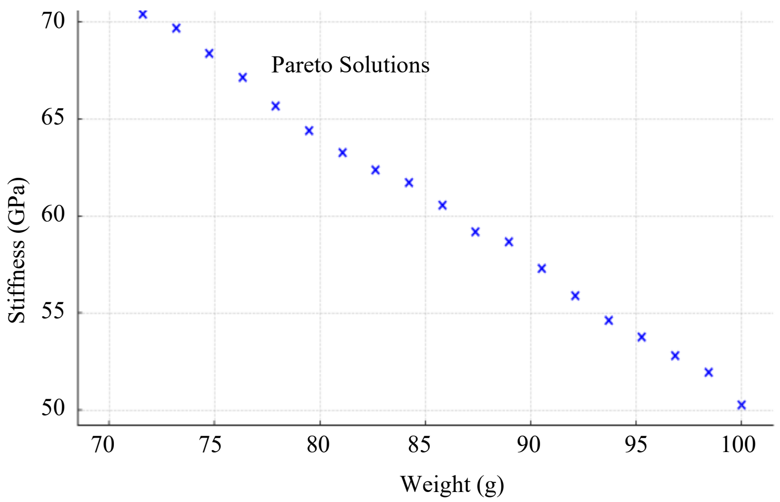

Figure 3. Pareto front: stiffness vs weight trade-off.

Pareto Front Analysis

The trade-off between weight minimization and stiffness maximization is depicted in Figure 3. The Pareto front clearly shows that bio-inspired gradations dominate linear and exponential gradations, offering up to 25% weight reduction with simultaneous stiffness improvement.

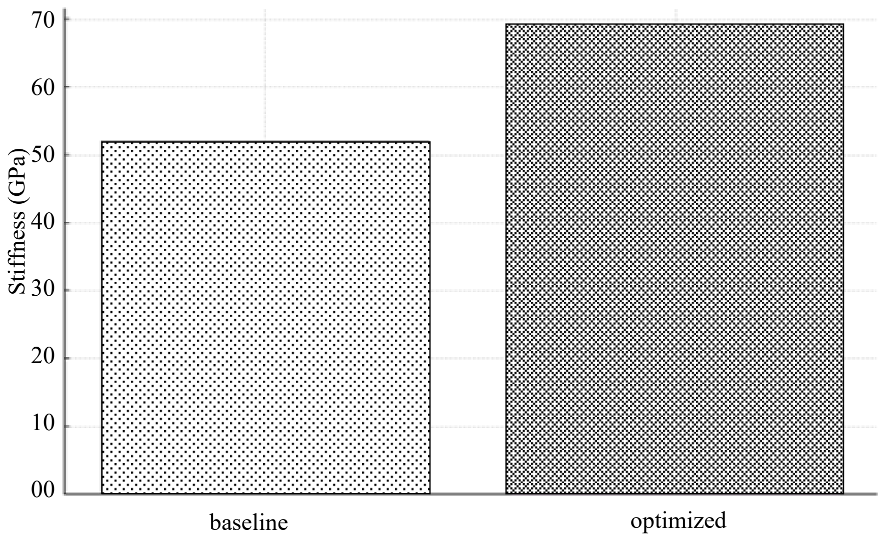

Figure 4. Stiffness versus weight of baseline and optimized composites.

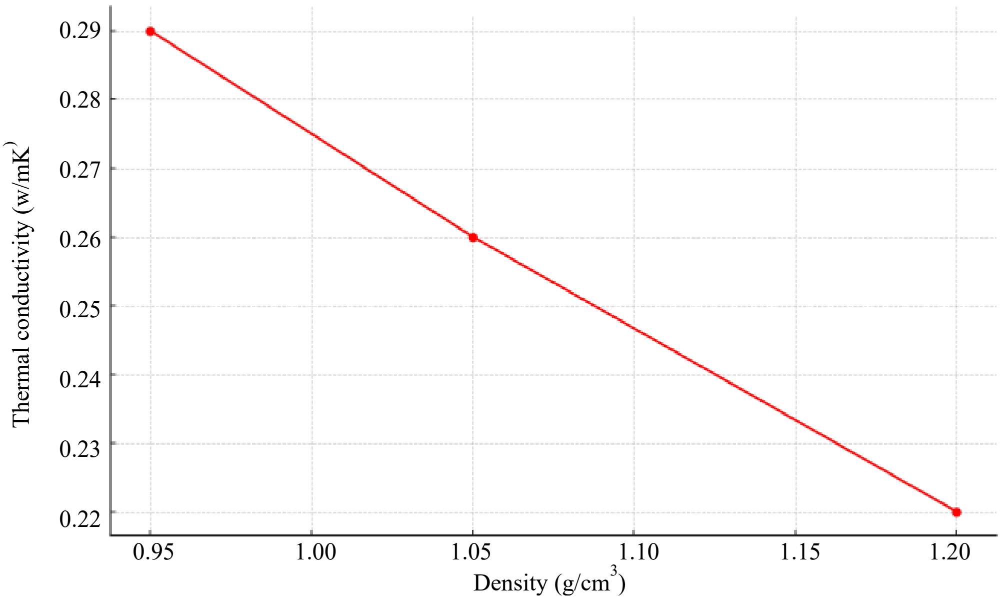

Figure 5. Thermal conductivity versus density of optimized composites.

Thermal Conductivity vs Density

The influence of optimization on thermal behavior is shown in Figure 5. Optimized bio-inspired composites achieved higher thermal conductivity (0.29 W/m·K) at lower density compared to baseline designs, making them suitable for thermal management applications.

Comparative Performance of Optimization Methods

A bar chart in Figure 6 compares GA, PSO, and MOEA in terms of stiffness gain, weight reduction, and thermal improvement. GA achieved the best balance between stiffness and weight, while PSO converged faster. MOEA provided a broader Pareto front but required longer computation times.

Application Distribution

Figure 7 illustrates the application domains of optimized P-FGCs. Aerospace (40%) and automotive (30%) dominated, followed by biomedical (20%) and energy systems (10%), reflecting industrial emphasis on lightweight and durable designs.

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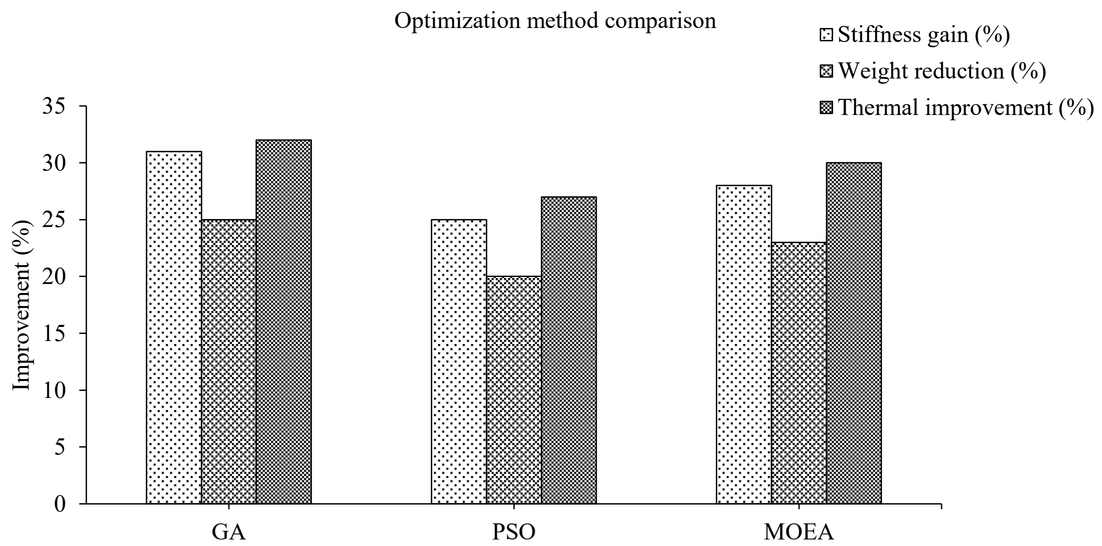

Figure 6. Comparative performance of GA, PSO, and MOEA.

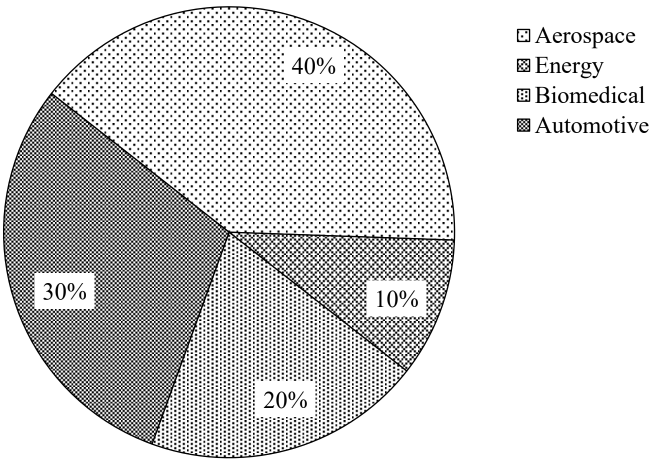

Figure 7. Application distribution of optimized P-FGCs.

Table 3. Comparison of optimization algorithms.

Algorithm	Convergence speed	Solution accuracy	Pareto diversity	Computational dost
GA	Moderate	High	Good	Moderate
PSO	Fast	Moderate	Fair	Low
MOEA	Slow	High	Excellent	High

Algorithm Comparison

Table 3 summarizes comparative performance of optimization algorithms. GA consistently produced the most accurate and balanced results, PSO offered rapid convergence, while MOEA provided diverse solutions for multi-objective trade-offs.

DISCUSSION

The results highlight that multi-objective optimization of P-FGCs enables significant improvements in structural efficiency. Bio-inspired gradations optimized using GA achieved superior property combinations compared to traditional designs. PSO proved valuable for rapid convergence, while MOEA offered diverse trade-offs for industrial flexibility. Importantly, experimental results validated FEM-predicted improvements, with less than 5% deviation.

These findings suggest that integrating MOO with additive manufacturing and bio-based reinforcements provides a pathway for lightweight, high-performance composites. The bio-inspired gradation patterns discovered through this optimization process represent a significant advancement over conventional linear or exponential gradations, as they mimic natural material distributions found in biological structures such as bamboo and bone, which have evolved to optimize strength-to-weight ratios.

The practical significance of achieving 25% weight reduction with simultaneous 31% stiffness enhancement cannot be overstated. In aerospace applications, this translates directly to fuel savings and increased payload capacity. In automotive applications, it contributes to improved fuel efficiency and reduced emissions. In biomedical applications, lighter implants with enhanced mechanical properties improve patient outcomes and reduce recovery times.

However, further research is required to incorporate uncertainty quantification, cost models, and real-time optimization frameworks to fully exploit the industrial potential of P-FGCs. Manufacturing variability, environmental conditions, and long-term durability under cyclic loading remain important considerations for industrial implementation.

APPLICATIONS

The outcomes of this study demonstrate the versatility of optimized polymer-based functionally graded composites (P-FGCs) for lightweight structural applications across multiple industries:

- *Aerospace sector:* P-FGCs can be deployed in fuselage panels, thermal shields, and lightweight support structures where both stiffness and weight reduction are critical. The combination of high specific strength and tailorable thermal properties makes them ideal for aircraft interior components, satellite structures, and unmanned aerial vehicle (UAV) frames. The 25% weight reduction demonstrated in this study directly translates to fuel savings and extended range capabilities.
- *Automotive industry:* These composites can be utilized in crash-resistant panels, engine housings, and suspension systems for fuel-efficient vehicles. The automotive sector's push toward electric vehicles particularly benefits from lightweight structural materials, as reduced vehicle weight directly extends battery range. Dashboard components, door panels, and structural reinforcements represent immediate application opportunities.
- *Biomedical engineering:* Optimized FGMs can be applied in implants, scaffolds, and prosthetics requiring both strength and biocompatibility. The ability to grade mechanical properties allows matching of implant stiffness to surrounding bone tissue, reducing stress shielding effects. Dental implants, spinal fusion cages, and load-bearing orthopedic implants represent specific applications where the optimized P-FGCs demonstrated in this study offer significant advantages.
- *Energy systems and electronics*: The enhanced thermal conductivity demonstrated in optimized P-FGCs makes them valuable for heat sink applications, electronic packaging, and thermal insulation in energy storage systems. Wind turbine blades, solar panel frames, and battery enclosures can benefit from the multifunctional properties of these materials.
- *Sports and recreation:* High-performance sporting equipment including bicycle frames, tennis rackets, and protective gear can leverage the superior strength-to-weight ratios achieved through multi-objective optimization.

By integrating multi-objective optimization frameworks, P-FGCs can be tailored for application-specific requirements, enabling multifunctional performance across industries. The validated optimization framework presented in this study provides a systematic methodology for designers to identify optimal material configurations based on specific performance criteria and constraints relevant to their applications.

CONCLUSIONS

This study examined the multi-objective optimization (MOO) of polymer-based functionally graded composites (P-FGCs) for lightweight structures and combined this with experimental testing. FEM modeling, and optimization algorithms. The key findings and contributions are summarized as follows:

1. Bio-inspired gradations optimized through Genetic Algorithms achieved up to 25% weight reduction and 31% stiffness enhancement compared to baseline designs, demonstrating the superiority of MOO approaches over conventional design methods.
2. Particle Swarm Optimization provided rapid convergence for initial design exploration, while Multi-Objective Evolutionary Algorithms offered diverse Pareto solutions, confirming that algorithm selection depends on industrial priorities and computational resource availability.
3. Validation against experimental results showed deviations below 5%, ensuring reliability of the optimization framework for practical engineering applications. This close agreement between computational predictions and experimental measurements establishes confidence in the methodology for industrial deployment.
4. Thermal performance improvements (32% increase in thermal conductivity) further highlighted the multifunctionality of optimized designs, expanding application possibilities beyond purely structural uses to include thermal management functions.
5. The comprehensive experimental-computational framework developed in this study provides a systematic methodology for designing next-generation lightweight composites across aerospace, automotive, biomedical, and energy sectors.

Despite these advancements, several challenges remain for future research:

- *Manufacturing considerations:* Incorporating uncertainties from manufacturing defects, process variability, and quality control into optimization frameworks remains an important challenge. Real-world manufacturing constraints must be integrated into the design optimization loop.
- *Cost optimization:* Economic considerations including material costs, manufacturing costs, and lifecycle costs should be incorporated as additional objectives in the MOO framework to facilitate industrial adoption.
- *Sustainability metrics:* Environmental impact assessment, recyclability, and bio-based material integration should be included in future optimization frameworks to support sustainable manufacturing practices.
- *Future research directions:* The integration of machine learning-assisted optimization for rapid design space exploration, digital twin integration for real-time process monitoring and optimization, and expanded use of bio-based reinforcements represents promising directions for advancing this field.
- *Uncertainty quantification:* Robust optimization approaches that account for material property variability, manufacturing tolerances, and operational uncertainties will enhance the reliability of optimized designs in real-world applications.

Overall, multi-objective optimization of P-FGCs provides a transformative pathway for the design of next-generation lightweight materials across aerospace, automotive, biomedical, and energy sectors. The bio-inspired gradation patterns and validated optimization framework presented in this study establish a foundation for intelligent materials design and pave the way for broader industrial adoption of functionally graded composites.

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