Minimizing Material Usage While Preserving Strength: Hybrid Genetic and Topology Optimization Approaches in Additive Manufacturing

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Abstract

Additive manufacturing technology has enabled the fabrication of intricate geometric constructs utilizing novel methodologies. Nonetheless, the optimization of material utilization while concurrently preserving structural integrity remains a pivotal technical endeavor. This investigation delves into the mathematical principles underlying topology optimization methodologies and their amalgamation with biomimetic lattice configurations. A comprehensive examination of four principal topology optimization methodologies—SIMP, BESO, Level Set, and ESO—is provided. An evaluative comparison of the advantages, disadvantages, and applications of each methodology is conducted. While SIMP demonstrates superiority in computational efficiency, BESO enhances the clarity of material boundaries. Level Set is useful for shapes that are hard to picture, while ESO is useful in the early stages of the design process. The study delves deeper into the traits of lattice structures inspired by natural forms and examines approaches to enhance their functional capabilities. Combining evolutionary algorithms with topology optimization is a good idea since it lets you search the entire design space while also making small improvements at the same time. The current literature indicates that the hybrid SIMP-GA methodology has attained roughly 7% enhanced compliance levels in comparison to conventional gradient-based strategies. This theoretical investigation integrates mathematical methodologies that optimize the efficiency of additive manufacturing while safeguarding structural integrity.

Keywords: Topology optimization, additive manufacturing, biomimetic lattice structures, genetic algorithms, material efficiency, SIMP, BESO

Introduction

Additive manufacturing (AM) has changed the way things are manufactured today. This technology creates things by stacking digital models on top of each other (Ibhadode et al., 2023). You can make shapes that standard manufacturing can't make. Additive manufacturing is becoming highly significant in areas like medical, aerospace, and cars. Additive manufacturing creates implants that are manufactured just for each patient in the medical field (Ibhadode et al., 2023). Topology optimization fixes a simple problem in engineering. It finds the best way to arrange the materials in a certain design area (Bendsøe & Sigmund, 2003). The goal is to get the best results with the fewest materials. In the past, topology optimization could only be used in theory because of the limits of traditional manufacturing. Additive manufacturing has gotten rid of these problems. Engineers can now make the complicated structures that topology optimization makes (Ibhadode et al., 2023). This mix of optimization and manufacturing has been helpful in making biomedical devices, building things, and designing airplanes.

Nature shows us many good ways to make things. Biomimetic lattice architectures mimic natural structures, such as honeycombs, osseous tissue, and plant stems (Tuninetti et al., 2025). These natural structures are very strong, but they don't need a lot of material. Spongy bone is a clear example of this principle. It can hold heavy loads, even though it isn't very dense. This makes it a good example of how to build structures that are strong but light. Engineers study these natural designs to build synthetic structures that have the right strength-to-weight ratios and can absorb energy well (Tuninetti et al., 2025). These qualities are very important for aerospace and medical uses.

Biomimetic lattice structures work well with topology optimization to make designs that are both high-performance and long-lasting. Genetic algorithms (GA) provide an alternative methodology for optimization. They imitate natural selection and evolution (Haupt & Haupt, 2004). A GA begins with a group of random solutions.

Then, through selection, crossover, and mutation processes, it improves these solutions. A fitness function gives each solution a score. Better solutions are more likely to be passed on to the next generation (Sadrehaghighi, 2021). Genetic algorithms work well when there are a lot of possible solutions to look at. They don't get stuck in local optima. This quality makes them good for problems with many variables (Haupt & Haupt, 2004). Researchers have effectively utilized genetic algorithms to engineer lightweight components tailored for additive manufacturing. This article looks at how to combine different optimization methods. It looks into the math behind how topology optimization methods work. It then talks about how genetic algorithms can make topology optimization better. The article talks about biomimetic lattice structures and how to make them better. Lastly, it looks at hybrid methods that mix genetic algorithms with topology optimization (Xue et al., 2021).

These hybrid methods are used in additive manufacturing to use less material while keeping the strength of the structure.

The study is theoretical. It entails a comprehensive review of published scientific literature regarding topology optimization in additive manufacturing, biomimetic lattice structures, and the incorporation of genetic algorithms. We have looked closely at the mathematical bases of topology optimization methods like SIMP, BESO, Level Set, and ESO. Furthermore, the properties and performance criteria of rod-based and surface-based biomimetic lattice structures have been examined. The effectiveness of hybrid genetic-topology optimization approaches has been evaluated through comparative studies in the existing literature. This study does not include experimental research. Instead, it aims to synthesize theoretical approaches used to achieve a balance between material efficiency and structural strength in additive manufacturing by presenting a comprehensive analysis of existing mathematical methods and optimization algorithms. The findings of the study are based on numerical results and comparative analyses reported in the literature.

The study is set up like this: In Section 2, we talk about the math behind different types of topology optimization methods, like density-based approaches, evolutionary methods, and techniques that change the boundaries. In Section 3, we talk about biomimetic lattice structures and how they work. It talks about designs that are based on rods and those that are based on surfaces. In Section 4, we talk about evolutionary algorithms and how they can be used with topology optimization to build things. Section 5 shows the results and talks about how they can be used in engineering for additive manufacturing.

Topology Optimization

Topology optimization is used to increase strength-to-mass ratio. It formulates an objective function that defines performance goals, such as maximizing stiffness while minimizing weight. Although many methods exist, they can be categorized into four: density-based, evolutionary, boundary variation, and non-gradient-based (Ibhadode et al., 2023, p. 3).

Topology optimization problem

Take into account a structural optimization issue that establishes the ideal setup of a domain occupied by a solid substance, i.e., a material domain Ω that signifies the design area, by reducing a functional F that is objective under a constraint functional G related to the volume constraint, outlined as:

$$\inf_{\Omega} F(\Omega) = \int_{\Omega} f(x) d\Omega$$

$$\text{subject to } G(\Omega) = \int_{\Omega} d\Omega - V_{\max} \leq 0$$

where $V_{\max}$ denotes the maximum allowable volume constraint and x signifies a point situated in Ω. In standard topology optimization methods, a constant design domain D, consisting of a material domain Ω where $\Omega \subset D$, and another supplementary domain indicating a void is present, meaning a void domain $D \setminus \Omega$ is established. Utilizing the characteristic function $\chi_{\Omega} \in L^{\infty}$ defined as

$$\chi_{\Omega}(X) = \begin{cases} 1 \ \ if \ \ X \in \Omega \\ 0 \ \ if \ \ X \in D \setminus \Omega \end{cases}$$

the structural optimization issue mentioned earlier is substituted with a material distribution challenge, to seek an ideal arrangement of the design area within the designated design area D as outlined:

$$\inf_{\chi_{\Omega}} \ \ F(\chi_{\Omega}(X)) = \int_{D} f(X)\chi_{\Omega}(X) d\Omega$$

$$\text{subject to } G(\chi_{\Omega}(X)) = \int_{D} \chi_{\Omega}(X) d\Omega - V_{\max} \leq 0$$

In the formulation above, alterations in topology as well as in shape modifications are permitted throughout the optimization process (Yamada et al., 2010).

Nonetheless, it is widely recognized that topology optimization issues are poorly defined since the configurations derived as per the characteristic function may exhibit significant discontinuities. That is, because the characteristic function χ is defined as a subset of a limited Lebesgue space L^{∞} where only integrability is guaranteed, the resulting solutions may be discontinuous at any point in the established design field. To address this issue, the design space is softened by employing different regularization methods (Yamada et al., 2010).

Density Based Method

Density-based methods assign a pseudo-density variable to each element in the design domain, serving as the main design variable. These values range from 0 (void) to 1 (solid), allowing a gradual representation of material distribution. One of the most common approaches is Solid Isotropic Material with Penalization (SIMP), which relies on interpolation functions to relate stiffness to density. It uses a power-law interpolation where stiffness increases nonlinearly with density, making intermediate densities less favorable (Ferrer 2019; Shin et al., 2023).

SIMP (Solid Isotropic Material with Penalization)

The main goal in the SIMP method is to minimize the structural compliance, which means to maximize stiffness under a volume limitation. Formally compliance minimization can be expressed like this:

$$E\left(\rho_e\right)=E_{\min}+\rho_e^p\cdot\left(E_0-E_{\min}\right),\quad p\in[3,4]\text{ typical}$$

where E_0 is the stiffness of the fully solid material, $E_{\min}$ is a small non-zero stiffness value assigned to void regions to avoid singularities in the stiffness matrix, ρ_e is the element's relative density, and p is a penalization exponent to suppress intermediate densities (Bendsøe & Sigmund, 2003).

The mass-based design concept is extended for fiber-reinforced composites (FRCs) to account for the anisotropic response of orthotropic materials. Further development of the SIMP method should customize the microstructure distribution and adopt the best unit cell geometry design to accommodate the additive manufacturing (AM). In case of FRCs, fiber orientation θ_e is entered as an element parameter to characterize the orthotropic direction. Then, the optimization, seeking minimization of the compliance, C, while satisfying a volume fraction constraint, f, is given by:

$$\min_{\rho}:C(\rho,\theta)=\sum_{i=1}^{N}(\rho_e)^p u_e{}^T K_e(\theta_e)u_e$$

$$\text{subject to } G(\rho)=\sum_{i=1}^{N}\rho_i+V_{\max}\leq 0$$

$$F=Ku-2\pi\leq\theta_e\leq 2\pi$$

$$0\leq\rho_{\min}\leq\rho_i\leq 1$$

where $V_{\max}$ the upper limit value of the material volume and F is the applied force (Zhang et al., 2025).

The Solid Orthotropic Material with Penalization (SOMP) method is an extension of the SIMP approach for orthotropic materials. It takes orthotropic qualities into account and adjusts the elemental elasticity matrix according to density. Fiber distribution in FRCs has been optimized by this adaptation for uses like aerospace components, where stiffness and weight economy are crucial (Zhang et al., 2025).

Bi-Directional Evolutionary Structural Optimization Method

Bi-directional evolutionary structural optimization method (BESO) enhances structures by adding or removing material according to stress, which results in lightweight and effective designs. The optimization challenge is typically presented as reducing mean compliance while satisfying a volume restriction, which can be articulated from equations below pertaining to the BESO algorithm; that is,

$$C = F^T u = u^T K u$$

$$\text{subject to } V* = \sum_{i=1}^{N} \upsilon_i x_i$$

where υ_i is the elemental volume and x_i is its relative density, which can be either 1 for solid elements or 0.001 for void elements. The identification of whether an element is solid or void relies on the element sensitivity α_i, computed using this equation:

$$\alpha_i = \frac{1}{V_i} u_e^T k_e^0 u_e$$

where u_e is the element displacement vector, k_e^0 is the element stiffness matrix before penalization and V_i is the element volume (Xie & Steven, 1997).

For anisotropic materials, BESO includes extra steps to handle fiber-reinforced composites (FRCs). These involve calculating elemental stresses σ for each iteration in the local coordinate system via finite element analysis. The principal stresses and orientations are obtained by solving eigenvalue and eigenvector problems, then converted into the global coordinate system using iteratively updated rotational matrices. This enables BESO to enhance both material distribution and fiber orientation efficiently (Xie & Steven, 1997).

An example of BESO's use is in aerospace structural design. Li and Xie applied it to aircraft parts made from FRCs, reducing material consumption while preserving structural integrity. The resulting lightweight structures met aerospace demands for load-bearing strength, weight limits, and production constraints. These results emphasize BESO's capability in creating high-performance frameworks for demanding engineering applications (Zhang et al., 2025).

Boundary Variation Method

Boundary variation techniques are the latest advancement in topology optimization. They arose from the need to achieve sharp and clean-edged formations. Although based on shape optimization, they are distinct in permitting the creation and elimination of empty areas while also enabling boundary shifts. Among these methods, only the widely used level set techniques are considered here (Kahraman & Küçük, 2020).

The level set approach employs a function to implicitly define the structural boundary, achieving topology optimization indirectly through its evolution. It was first used mathematically to represent structures in 2000, with the boundary description modified by altering the function. Later, the steepest descent method integrating shape sensitivity analysis with the Hamilton-Jacobi equation was introduced for optimization involving multiple materials and constraints (Zhang et al., 2025).

In this approach, the form $\Omega \subset D$ is represented on a static grid, where D encompasses the entire range of potential shapes Ω. The shape Ω represents the level set of the multidimensional function, which is defined by

$$\Phi(X) > 0, X \in \Omega$$

$$\Phi(X) = 0, X \in \Gamma$$

$$\Phi(X) < 0, X \in D / (\Gamma \cup \Omega)$$

where Γ represents the design boundary, which comprises two segments: the non-homogeneous boundary conditions Γ_N and the homogeneous Dirichlet boundary conditions Γ_D. To minimize compliance, the structural boundary is iteratively modified over pseudo-time t by solving the Hamilton-Jacobi equation using an explicit second-order method

$$\frac{\partial \Phi(X)}{\partial t} = V_n \, |\nabla(X)|$$

where V_n is the boundary shifting speed in the direction of $n = -\nabla(X)/|\nabla(X)|$, and the size can be ascertained through sensitivity analysis. The material/void interface can be adjusted, combined, and divided, rendering it ideal for structural topology optimization. The level set technique is remarkable for enhancing both topology and shape at the same time, providing clear boundaries. It has shown to be especially successful in creating aerospace parts, where accurate management of material placement and boundary specification is vital.

Evolutionary Structural Method (ESO) Based on Stress

Since its proposal by Xie and Steven in 1993, the ESO approach has been improved to address various topology optimization issues. The basic idea is to gradually eliminate wasteful material so that the structure evolves toward an ideal topology and shape. However, it is impossible to guarantee that the optimal answer will always be obtained. For engineers and architects in the conceptual design phase, ESO offers a useful tool for exploring efficient forms and shapes (Bendsøe & Sigmund, 2003).

Finite element analysis can be used to determine the stress in any section of a structure. Low stress (or strain) indicates poor material use, since ideally all components should have nearly equal and safe stress levels. This leads to a rejection criterion where low-stressed materials are eliminated as underutilized. Deleting elements from the finite element model provides a convenient way to remove material (Bendsøe & Sigmund, 2003).

Each element's stress level is ascertained by comparing, for instance, its von Mises stress of the element σ_e^{vm} to the maximum von Mises stress of the entire system $\sigma_{\max}^{vm}$. Elements that meet the following criteria are removed from the model following each finite element analysis.

$$\frac{\sigma_e^{vm}}{\sigma_{\max}^{vm}} < RR_i \quad (1)$$

where RR_i is the current rejection ratio (RR).

This cycle of finite element analysis and the removal of elements is reiterated with the same value RR_i until a steady state is achieved, indicating that no additional elements are being discarded using the present rejection ratio. At this point, an evolutionary rate, ER, is incorporated into the rejection ratio, meaning that

$$RR_{i+1} = RR_i + ER \quad (2)$$

The iteration continues until a new stable state is attained with the elevated rejection ratio. (Bendsøe & Sigmund, 2003)

The evolutionary process continues until a preferred optimum is reached, for instance, when the ultimate structure has no components experiencing a stress level below 25% of the maximum. The stages of the evolutionary process can be described as follows:

Step 1: Break down the structure using a detailed mesh of finite elements;

Step 2: Perform finite element analysis on the structure;

Step 3: Eliminate elements that meet the condition in (1);

Step 4: Raise the rejection ratio following Equation (2) once a steady state has been attained;

Step 5: Continue repeating Steps 2 through 4 until the desired optimal outcome is achieved.

2.6. Comparison Between Different Topology Optimization Methods

Table 1. Comparison Between Different Topology Optimization Methods

Method	Design Freedom	Advantages	Applicability	Drawbacks
SIMP	Medium	Easy to implement, computationally efficient, suitable for large-scale problems	Widely used in structural and Multiphysics problems	Gray regions (intermediate densities), sensitive to penalization factor
BESO	Medium	Clear material boundaries, effective in reducing material use	Optimal for structures with distinct solid/void phases	Requires post-processing, moderate computational cost
Level Set	High	Smooth, well-defined boundaries; good for complex geometries	Precise boundary definition problems, structural and Multiphysics design	Complex sensitivity derivation, initial design dependency
ESO	Low to Medium	Simple concept, easy to implement; progressively removes inefficient material; intuitive visualization of optimization process	Effective for problems with relatively simple geometries and moderate computational requirements	Tends to converge slowly; cannot add material back once removed (unlike BESO); may produce suboptimal designs and strongly depends on removal ratio and initial mesh

In conclusion, SIMP and BESO are the most practical, as SIMP is computationally efficient for large problems, and BESO yields clearer and more manufacturable designs. The Level Set method is attractive to model smooth and complicated non-constrained geometries with a sharp interface; the math derivations could be more complex. ESO, on the other hand is very conceptually appealing and nice for implementation but converges slowly and can't put material back where it took it from. This comparison reveals that the selection of the approach relies on the design objectives, available computational power, and fabrication limitations.

Biomimetic Lattice Structures

Interconnected components—struts, beams, and surfaces—arranged in a recurring grid-like pattern define lattice structures, a subset of cellular materials. These structures are widely present in nature in a variety of shapes and are not a recent human innovation. The trabecular architecture of human bones, the hexagonal arrangement in honeycomb constructions, and the complex geometry of spider webs are a few examples.

Types Of Lattice Structures

Cell shape, densities, sizes, dimensions, and configurations all affect the characteristics of lattice systems. They can be categorized as either surface-based or strut-based cells based on their architecture. Nodes and struts make up strut-based lattice structures. Strut-based unit cells for lattice formation, including both bio-inspired and artificial structures, are summed up in Figure 1. Voronoi, Kelvin cell, diamond, rhombic, and octahedral structures are examples of bio-inspired structures that imitate the way biological systems and natural formations are organized. However, mechanical optimization is given priority in engineered forms such the body-centered cubic, simple cubic, octet-trapezoidal, hexagonal, cuboctahedron, and truncated octahedron structures. It is crucial to remember that some structures, like the diamond lattice, are both bio-inspired (found in crystallography) and structurally constructed (Tuninetti et al., 2025).

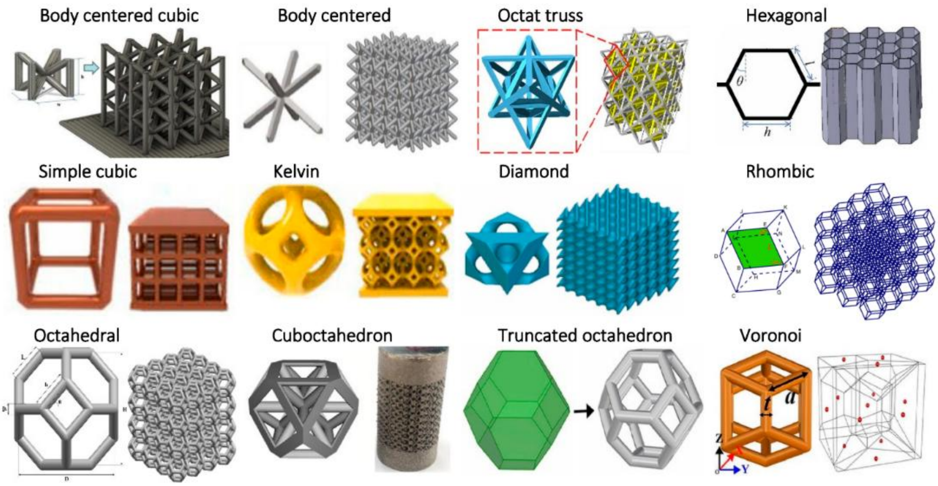
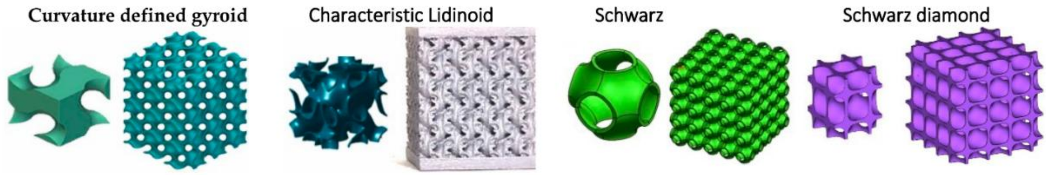


Figure 1:Shapes for strut-based unit cells: Vertically reinforced body centered cubic, Body centered cubic, Octat truss, Hexagonal, Simple cubic, Kelvin, Diamond, Rhombic, Octahedral, Cuboctahedron, Truncated octahedron, and Voronoi . (Tuninetti et al., 2025).

In order to maximize material distribution and mechanical qualities, surface-based lattice structures are created from preset surfaces or geometries. The lattice is made to follow surface contours and boundaries. Because these triply periodic minimum surfaces (TPMS) resemble the geometries that are naturally present in biological systems, they are regarded as bioinspired designs. Like biological membranes, trabecular bone, and cellular structures in living things, these surfaces use the least amount of material while retaining structural efficiency. Minimal surfaces for lattices are frequently constructed using mathematical equations, especially partial differential equations. By defining the lattice pattern or layout using trigonometric equations, complex structures—whether periodic or non-periodic—can be created with exact control over their geometry and performance attributes. The 3D structure's size, shape, and density can be changed by adjusting the equation. A review of surface-based lattice shapes is presented in Figure 2 (Tuninetti et al., 2025).

Figure 2: Shapes for surface-based bio-inspired unit cells: Curvature defined gyroid, Characteristic Lidinoid, Schwarz, and Schwarz diamond (Tuninetti et al., 2025).



Challenges in The Design and Performance of Biomimetic Lattice Structures

Managing stress distribution and resistance is a major difficulty in the design of biomimetic lattice systems. Natural-inspired designs frequently have irregularities that can result in localized stress concentrations, particularly in areas where distinct geometries transition, which could cause early failure. Trabecular bone-inspired structures exhibit distinct reinforcement patterns in contrast to conventional lattices (such as octet and cubic), but they are also more vulnerable to stress hot spots (Tuninetti et al., 2025).

Since it is difficult to replicate nature's balance between stiffness and flexibility, deformation behavior is another issue. Elastic-plastic transition, geometric limits, scaling effects, and manufacturing flaws are among the problems. Although bone-inspired lattices can increase compliance, high strain often causes unanticipated deformation. Designs inspired by fractals and honeycombs also show how small geometric adjustments can dramatically modify deformation properties (Tuninetti et al., 2025).

Because of collapse mechanisms, strain-rate sensitivity, and manufacturing limitations, energy absorption—which is crucial in crash protection and implants—is difficult to replicate in synthetic materials. High absorption per unit mass is provided by hierarchical designs (such as wood and trabecular bone), but they must be simplified for manufacturing. Research on sandwich panels inspired by auxetic and hierarchical structures shows that clever unit cell design can reduce complexity while maintaining stiffness and energy absorption (Tuninetti et al., 2025).

Optimization Of Lattice Structures

Optimizing lattice structures for high performance entails adjusting their material qualities and geometric parameters (cell size, shape, and topology) to satisfy particular application needs. This frequently entails decreasing weight and material consumption while optimizing qualities including stiffness, energy absorption, thermal conductivity, and strength-to-weight ratio. Simpler geometries like foams and honeycombs were the main focus of early research. Their mechanical properties were estimated using empirical formulas and analytical techniques. Nonetheless, the basic knowledge of the connection between lattice shape and performance was developed during this time (Tuninetti et al., 2025).

The automatic creation of ideal lattice designs based on predetermined goals and limitations is made possible by topology optimization techniques, such as density-based and level-set approaches. In conjunction with additive manufacturing techniques like laser powder bed fusion, response surface optimization techniques effectively search the design space to find the best parameter combinations. This allows for the fabrication of intricate lattice structures and the realization of designs previously unattainable through manufacturing (Tuninetti et al., 2025).

New lattice structures with improved performance characteristics were created by incorporating bio-inspired design ideas. Kladovasilakis et al.'s study used FEA and bioinspired lattice architectures to optimize the topology of orthopedic hip implants (Kladovasilakis et al., 2022). The investigation of Diamond lattices aimed to decrease weight, increase porosity, and improve mechanical efficiency. The results showed that the Schwarz Diamond topology exhibited superior strength and minimal stress concentration under in vivo loads. The study produced lightweight, porous implants resembling trabecular bone structure by combining this bioinspired design with engineering optimization. FEA models verified performance, safety considerations, and stress distribution. Functional gradation further improved performance, and lattice structures minimized material usage by up to 38% while retaining load-bearing capacity (Tuninetti et al., 2025).

To develop and optimize lattice systems, bio-inspired optimization takes inspiration from natural structures including plant stems, trabecular bone, and honeycombs. It entails imitating the adaptive qualities and hierarchical structure of natural materials. Machine learning-based optimization is the newest method to speed up the optimization process and find new lattice designs. It can guide the search for the best designs, forecast performance, and even produce new design concepts. The particular performance goals, manufacturing limitations, and degree of design detail influence the optimization strategy selection (Tuninetti et al., 2025).

Hybrid Genetic-Topology Optimization Algorithms

Genetic Algorithms

Inspired by the concepts of natural selection and genetics, the Genetic Algorithm (GA) is a search and optimization technique that was created by Holland in the 1970s and made popular by Goldberg. It works with populations of potential solutions, which are represented by chromosomes. Each gene in these populations encodes a particular design characteristic. Reproduction, crossover, and mutation are the three main operators that the algorithm depends on. In order to promote superior solutions, reproduction entails duplicating individuals into the following generation based on their fitness values. While mutation adds tiny, random changes to genes to preserve variety and keep the algorithm from getting stuck in local optima, crossover mimics genetic recombination by switching segments between parent chromosomes to create new children. Until the solutions converge to optimal or nearly optimal outcomes, the GA generates succeeding populations through an iterative stochastic search. GAs are distinct from gradient-based techniques because of their population-based methodology, which makes them ideal for complicated, nonlinear, and multimodal issues. They have been widely used in aerodynamic and aero structural design, where there are frequently several goals and limitations (Sadrehaghighi, 2021).

Genetic operations and evolution through selection are the two primary parts of the GA process. Fitter individuals are more likely to contribute to the next generation due to selection, which is based on Darwinian evolution. As new generations are developed, the elitist approach guarantees that the top-performing solutions are maintained. Through an iterative cycle of evaluation, selection, and application of genetic operations, GAs are able to efficiently explore the design space, taking advantage of both new and established good regions. In multi-objective optimization situations, GAs are very good at building Pareto fronts and determining trade-offs between conflicting design objectives. They are resistant against numerical noise and flexible enough to handle both discrete and continuous variables, as well as non-convex and non-continuous objective functions, thanks to their parallel processing capacity, which enables them to optimize from several starting points at once (Sadrehaghighi, 2021).

GAs have certain drawbacks in spite of these benefits. They typically have comparatively poor constraint-handling skills and significant computing resource requirements, especially for high-fidelity simulations. They frequently require parameter tailoring relevant to the situation, including population size, crossover rate, and mutation likelihood. Furthermore, when the algorithm gets closer to the global optimum, convergence slows down, even if GAs can swiftly spot promising areas in the design space. Numerous hybrid and enhanced GA solutions have been put out to increase their efficacy. The following steps are included in a typical GA workflow:

Random generation of the initial population.

Fitness evaluation of each individual using an appropriate solver.

Selection of individuals for genetic operations.

Application of reproduction, crossover, and mutation to create a new population.

Iteration of steps 2–4 over multiple generations until a convergence criterion is met.

Hybrid-Genetic Topology Optimization

SIMP and BESO are effective at material distribution using evolutionary or gradient-based strategies, but both face problems of local minima and other problems specific to contours. GAs are good at global search and multi objective problems, but are not effective at continuous structural variable tuning. In a hybrid approach, a global search is performed first using GA and then local refinement is performed using topology optimization.

In practice, a hybrid framework starts with a GA population in which each chromosome corresponds to a topology optimization parameter, for example, element densities, penalization factors or even lattice cell configurations. Each chromosome's fitness is determined by executing a topology optimization solver (typically a SIMP-based compliance minimization). The GA strategies of crossover and mutation provide a distinct exploration of distributions while topology optimization guarantees the refinement of the best feasible solutions. This cooperative loop strike a balance between exploration and exploitation.

Hybrid approaches combining genetic algorithms (GA) with topology optimization have shown promise for designing 3D-printed lattice structures. Research demonstrates that GA's global search capability can find novel lattice topologies that pure gradient-based methods like SIMP cannot access, as SIMP typically converges to local optimal solutions while GA can explore multiple local optima. These hybrid processes have been shown to enable significant material savings while maintaining or improving mechanical performance, demonstrating the value of combining GA's global search with topology optimization for structural design applications.

Such synergy is particularly welcome in the field of additive manufacturing where the design space is enormous and forced into complex manufacturing reality. Hybrid GA–topology optimization provides a way towards lattice designs that not only replicate natural effectiveness, but also satisfy reasonable strength, weight, and manufacturability conditions. Hybrid algorithms therefore represent a rigorous and practical tool for the development of lightweight and high-performing engineering structures.

Xue et al. (2021) demonstrate that "the SIMP-GA method can obtain a better solution than the gradient-based method" and show improved performance in their numerical examples. For instance, in their MBB beam example, the SIMP-GA method achieved better compliance values (161.7409 best case) compared to standalone SIMP (173.2377), representing approximately a 7% improvement. "The SIMP-GA method converges after around 20 iterations" and demonstrates that "the global search capacity of GA and the local refinement capability complement one another."

Conclusion

This study assessed how topology optimization methodologies can guide biomimetic lattice configuration for material reduction along with structural functionality. By offering a literature review and comparison of density-based methodologies SIMP, and evolutionary based approach (BESO), the thesis illustrated how structural settings can be defined using mathematical parameters. This showed the usefulness of these methodologies; SIMP is very efficient computationally, while BESO is able to produce manufacturable, discrete designs, and both could become deficient by manner of SIMP developing gray regions and the more computational cost of BESO.

Considering previous aspects and extending them to biomimetic lattice structures demonstrated how biological inspiration can introduce even better efficiency through geometrical principles found in nature. The structures described, such as trabecular bone, or the gyroid example, show how evolution can collectively implement mathematical principles for topology optimization. Implementing bio-inspired designs such as the above tips the scales toward lighter, stronger and more sustainable engineering through additive manufacturing.

In conclusion, the results indicated that hybrid methods combining genetic algorithms with topology optimization provide a promising avenue for enhancing material efficiency in 3D-printed lattice structures. These methods provide more advanced mathematical optimization approaches to advance the mathematical optimization while addressing relevant practical constraints in a manufacturing sense. More generally, the implication is that topology optimization is a way forward to create structures that hold both theoretical and practical relevance by bridging physics with biology and engineering.

References

[1] Bendsøe, M. P., & Sigmund, O. (2003). Topology optimization: Theory, methods, and applications. Springer. https://download.e-bookshelf.de/download/0000/5777/94/L-G-0000577794-0015285230.pdf

[2] Ferrer, A. (2019). SIMP-ALL: A generalized SIMP method based on the topological derivative concept. International Journal for Numerical Methods in Engineering, 120(3), 361–381. https://doi.org/10.1002/nme.6140

[3] Haupt, R. L., & Haupt, S. E. (2004). Practical genetic algorithms (2nd ed.). John Wiley & Sons.

[4] Holland, J. H. (1975). Adaptation in natural and artificial systems. University of Michigan Press. https://archive.org/details/adaptationinnatu0000holl

[5] Ibhadode, O., Zhang, Z., Sixt, J., Nsiempba, K. M., Orakwe, J., Martinez-Marchese, A., Ero, O., Shahabad, S. I., Bonakdar, A., & Toyserkani, E. (2023). Topology optimization for metal additive manufacturing: Current trends, challenges, and future outlook. Virtual and Physical Prototyping, 18(1), 1–23. https://doi.org/10.1080/17452759.2023.2181192

[6] Kahraman, F., & Küçük, M. (2020). Otomotiv endüstrisinde topoloji optimizasyonu ile ağırlık azaltma uygulaması üzerine bir araştırma. E-Journal of Science and Technology, 20, 623–631. https://doi.org/10.31590/ejosat.789424

[7] Kladovasilakis, N., Tsongas, K., & Tzetzis, D. (2020). Finite element analysis of orthopedic hip implant with functionally graded bioinspired lattice structures. Biomimetics, 5(3), 44. https://doi.org/10.3390/biomimetics5030044

[8] Sadrehaghighi, I. (2021). Non-gradient based optimization (Technical Report). CFD Open Series. https://dx.doi.org/10.13140/RG.2.2.28762.77764/4

[9] Shin, S., Shin, D., & Kang, N. (2023). Topology optimization via machine learning and deep learning: a review. Journal of Computational Design and Engineering, 10(4), 1736–1766. https://doi.org/10.1093/jcde/qwad072

[10] Tuninetti, V., Narayan, S., Ríos, I., Menacer, B., Valle, R., Al-lehaibi, M., Kaisan, M. U., Samuel, J., Oñate, A., Pincheira, G., Mertens, A., Duchêne, L., & Garrido, C. (2025). Biomimetic Lattice Structures Design and Manufacturing for High Stress, Deformation, and Energy Absorption Performance. Biomimetics, 10(7), 458. https://doi.org/10.3390/biomimetics10070458

[11] Xie, Y. M., & Steven, G. P. (1997). Basic evolutionary structural optimization. In Evolutionary structural optimization (pp. 1–27). Springer. https://doi.org/10.1007/978-1-4471-0985-3_2

[12] Xue, H., Yu, H., Zhang, X., & Quan, Q. (2021). A Novel Method for Structural Lightweight Design with Topology Optimization. Energies, 14(14), 4367. https://doi.org/10.3390/en14144367

[13] Yamada, T., Izui, K., Nishiwaki, S., & Takezawa, A. (2010). A topology optimization method based on the level set method incorporating a fictitious interface energy. Computer Methods in Applied Mechanics and Engineering, 199(45–48), 2876–2891. https://doi.org/10.1016/j.cma.2010.05.013

[14] Zhang, J., Xie, Y., Li, Z., Ye, G., Zhang, C., Wang, T., & Wang, L. (2025). Comparison of out-of-plane compression performance of cellular structures

with different configuration: Hexagon, re-entrant, chirality. Structures, 73, 108396. https://doi.org/10.1016/j.istruc.2025.108396

[15] Zhang, X., Sun, G.-Y., Wang, C., Li, H., & Zhou, S. (2025). A review of structural topology optimization for fiber reinforced composites. Composites Part B: Engineering, 299, Article 112393. https://doi.org/10.1016/j.compositesb.2025.112393