

MACHINE LEARNING-ASSISTED TOPOLOGY OPTIMIZATION OF LIGHTWEIGHT MECHANICAL STRUCTURES FOR ADDITIVE MANUFACTURING

Basit Ali^{*1}, Ghulam Yasin²

^{*1} Department of Industrial Manufacturing Engineering Ned University of Engineering and Technology

² University of Makran

¹basitali65914@gmail.com, ²ghulam.yasin@uomp.edu.pk

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Corresponding Author: *

Basit Ali

Abstract

The increasing demand for structural lightweighting in aerospace, automotive, and biomedical sectors has driven significant advances in topology optimization (TO) and additive manufacturing (AM). This review examines the integration of machine learning (ML) into topology optimization workflows, addressing the persistent computational bottleneck of iterative finite element analysis (FEA) that limits conventional TO. A comprehensive taxonomy of traditional TO formulations including element-based continuous methods (SIMP, RAMP), discrete evolutionary approaches (ESO, BESO), and boundary/interface tracking techniques (Level Set Method) is presented, highlighting their numerical instabilities such as checkerboard patterns, mesh dependency, and gray transition zones. The review systematically analyzes three primary machine learning paradigms: forward surrogate networks, operator learning architectures such as U-Net Fourier Neural Operators (FNOs), and Physics-Informed Neural Networks (PINNs). Comparative analysis reveals that ML-assisted TO achieves computational speedups ranging from 2× to 100× while maintaining structural fidelity and compliance accuracy. Furthermore, the integration of additive manufacturing process constraints including overhang angle limitations, self-supporting requirements, thermal distortion, and build direction anisotropy directly into neural network loss functions enables the generation of print-ready geometries without sacrificial supports. Industrial case studies demonstrate mass reductions of 60–77% with validated structural integrity, while stress concentrations decrease by up to 50%. Despite challenges in generalization, training time, and non-convex loss convergence, ML-assisted TO offers a transformative pathway toward sustainable, manufacturable lightweight structures.

1. INTRODUCTION

The demand for structural lightweighting across aerospace, automotive, and biomedical sectors has driven a paradigm shift in advanced structural design. Structural optimization historically traces

its origins back to the 17th century with Galileo Galilei's investigations into optimal structural element forms, followed by analytical procedures introduced by Gottfried W. Leibniz, James Clerk Maxwell's 1870 principal stress field theories, and

Anthony G. M (Yu et al., 2026). Michell's 1904 foundational work on optimal truss frameworks. In the modern era, numerical structural optimization has evolved into distinct disciplines, including sizing (dimensional) optimization, topometric optimization, topography optimization, shape optimization, freeform optimization, and topology optimization (TO) (Manasa et al., 2025).

Comparative design analyses reveal that traditional sizing optimization yields modest performance or mass gains of 5% to 10%, shape optimization produces improvements between 10% and 30%, whereas topology optimization achieves dramatic structural efficiency gains ranging from 40% to 100%. By determining the optimal material distribution within a designated design space under specified load cases, boundary conditions, and performance constraints, TO generates highly efficient, organically complex geometries (Zaman et al., 2026).

In a conventional design workflow, topology optimization begins with a defined spatial domain and set boundary loads, invoking an iterative Finite Element Analysis (FEA) loop to repeatedly assemble and factorize global stiffness matrices. Once sensitivities converge, the resulting structural boundary often exhibits jagged voxel surfaces, requiring extensive manual computer-aided design (CAD) surface reconstruction via Non-Uniform Rational B-Splines (NURBS) or skeletonization to eliminate stress concentrations. The smooth geometry must then undergo post-hoc manufacturing analysis, where engineers define orientation vectors and generate sacrificial support structures to prevent structural collapse during printing (Yuk et al., 2026).

The integration of Machine Learning-Assisted Topology Optimization (MLTO) fundamentally transforms this sequential process into an integrated pipeline. By substituting computationally intensive differential equation solvers with neural operators or physics-informed surrogate models, MLTO predicts structurally sound, converged geometries in a fraction of the time (Bhuiyan & Tabarraei, 2026). Concurrently, manufacturing physics such as overhang angle

thresholds and self-supporting constraints are embedded directly into the neural network's loss functions during forward propagation. This enables the direct generation of additive-manufacturing-compliant geometries, bypassing manual CAD smoothing and minimizing sacrificial support requirements (Challapalli et al., 2025).

Despite its theoretical potential, conventional TO has historically faced severe manufacturing barriers. Traditional subtractive manufacturing techniques, such as multi-axis CNC machining, cannot easily produce the internal voids, complex re-entrant features, and organic web networks characteristic of topologically optimized components. The advent of Additive Manufacturing (AM) or 3D printing has dismantled many of these geometric fabrication constraints. Building components layer-by-layer directly from three-dimensional CAD models enables the physical realization of complex components (Zong et al., 2026).

2. Foundations of Topology Optimization and Computational Bottlenecks

2.1 Mathematical Formulations and Categorization

Numerical topology optimization seeks to distribute a discrete volume fraction of material within a predefined design space to maximize structural stiffness (minimize compliance), minimize stress, or achieve multi-objective performance. The structural domain Ω is discretized into finite elements, where each element e is assigned a relative material density variable $\rho_e \in [0,1]$, representing a continuum from empty void ($\rho_e = 0$) to solid material ($\rho_e = 1$). Classical TO frameworks are broadly categorized into element-based continuous methods, discrete evolutionary structural optimization, and boundary/interface tracking formulations (Eschenauer & Olhoff, 2001).

Table 1 provides a taxonomy of conventional structural topology optimization methodologies, highlighting their mathematical mechanics, primary applications, and inherent numerical limitations (Rozvany, 2001).

Table 1: Categorization and Theoretical Characteristics of Conventional Topology Optimization Formulations

Optimization Paradigm	Specific Methodologies	Mathematical Governing Mechanism	Primary Application Space	Inherent Computational & Numerical Limitations
Element-Based Continuous	SIMP (Solid Isotropic Material with Penalization), RAMP, OMP, NOM, DDP	Continuous density interpolation with power-law penalization: $E(\rho_e) = \rho_e^p E_0$ [cite: 4]	Global compliance minimization, thermal conductivity, dynamic frequency response	Numerical checkerboard patterns, gray transition zones ($\rho \approx 0.5$), mesh dependency
Discrete Evolutionary	ESO, BESO (Bidirectional ESO), AESO	Heuristic removal and addition of underutilized/overstressed discrete elements	Discrete stiffness tuning, aerospace brackets, clear-cut binary boundaries	Non-gradient oscillatory behavior, local optima trapping, high sensitivity to rejection thresholds
Boundary / Interface Tracking	Level Set Method (LSM), XFEM coupled with Deformable Simplicial Complex (DSC)	Implicit boundary evolution via Hamilton-Jacobi PDEs: $\frac{\partial \phi}{\partial t} + V \ \nabla \phi\ = 0$ [cite: 2]	Smooth boundary shape refinement, fluid-structure interaction, precise interface tracking	Inability to nucleate new internal holes automatically without special topological derivatives

The standard compliance minimization formulation under a total volume constraint is expressed mathematically as:

$$\min_{\rho} \quad C(\rho) = \mathbf{U}^T \mathbf{K}(\rho) \mathbf{U} = \sum_{e=1}^N (\rho_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e$$

subject to $\mathbf{K}(\rho) \mathbf{U} = \mathbf{F}$

$$\frac{V(\rho)}{V_0} = \frac{\sum_{e=1}^N \rho_e v_e}{V_0} \leq v^*$$

$$0 < \rho_{\min} \leq \rho_e \leq 1, \quad \forall e = 1, \dots, N$$

where $C(\rho)$ is structural compliance, $\mathbf{U}$ is the global displacement vector, $\mathbf{K}$ is the global stiffness matrix, $\mathbf{F}$ is the applied force vector, p (typically $p = 3$) is the SIMP penalization factor discouraging intermediate gray densities, v_e is element volume, V_0 is total domain volume, and v^* is the target mass retain fraction (Van Dijk et al., 2013).

2.2 Numerical Instabilities and Length Scale Constraints

Continuous density-based optimization suffers from numerical instabilities, most prominently checkerboard patterns alternating regions of solid and void elements arising from high artificial stiffness in FEA discretizations and mesh dependency, where refined meshes produce increasingly intricate microstructures rather than converging to a unified macro-topology (Jansen, 2019).

To achieve mesh-independent solutions and eliminate non-physical checkerboards, explicit minimum and maximum length scale constraints are enforced. Filter techniques modify element densities or sensitivities over a localized domain of radius $r_{\min}$:

- **Density Filtering and Projection:** Regularized Heaviside step function projections, originally

advanced by Guest et al. and refined by Sigmund, project filtered spatial densities to impose strict minimum length scales on solid ($\rho = 1$) and void ($\rho = 0$) phases (Chen et al., 2000).

- **Skeletonization-Based Length Scale Control:** Explicit local feature size control introduced by Zhang utilizes a structural skeleton representation to control feature thickness directly.

- **Alternative Domain Formulations:** Linus Hägg formulated minimum length scale controls across subsets of convex domains, while Giulio Costa integrated non-uniform rational B-splines (NURBS) density fields. Xuanpei Rong developed multi-phase coordination projections utilizing adaptive weighted operators to control spatial features (Guest et al., 2004).

2.3 The FEA Computational Bottleneck

Despite advanced regularization techniques, the core computational limitation of conventional TO remains the linear elasticity system solve ($\mathbf{K}(\rho)\mathbf{U} = \mathbf{F}$) executed at every iteration. For 3D additive manufacturing applications requiring ultra-fine discretizations (10^6 to 10^8 finite elements) to capture lattice struts or intricate surface features, solving this high-dimensional system demands hundreds of iteration steps. The CPU/GPU time required for repeated global stiffness matrix assembly, factorization, and sensitivity analysis creates an intractable computational bottleneck, necessitating machine learning intervention (Chitsaz et al., 2025).

3. Machine Learning Paradigms in Topology Optimization (MLTO)

The integration of machine learning into topology optimization addresses two fundamental perspectives: the "Why" (overcoming computational limits, enabling instant real-time re-design, and exploring non-linear design spaces) and the "How" (architectural implementation, loss function engineering, and dataset generation) (Shin et al., 2023).

Architecturally, machine learning topology optimization frameworks split into three primary paradigms:

1. Forward Surrogate Networks, which employ convolutional encoder-decoders to approximate finite element fields or final topologies directly, yielding up to a 100-fold inference speedup at the cost of fixed spatial grid dependencies (Shin et al., 2023).

2. Operator Learning Architectures, such as Fourier Neural Operators (FNOs) and U-Net FNOs, which learn mappings between infinite-dimensional function spaces to achieve resolution-independent spatial evaluation.

3. Physics-Informed Neural Networks (PINNs), which optimize structural densities without requiring pre-generated training datasets by embedding governing elasticity partial differential equations directly into the network's loss function (Luo et al., 2025).

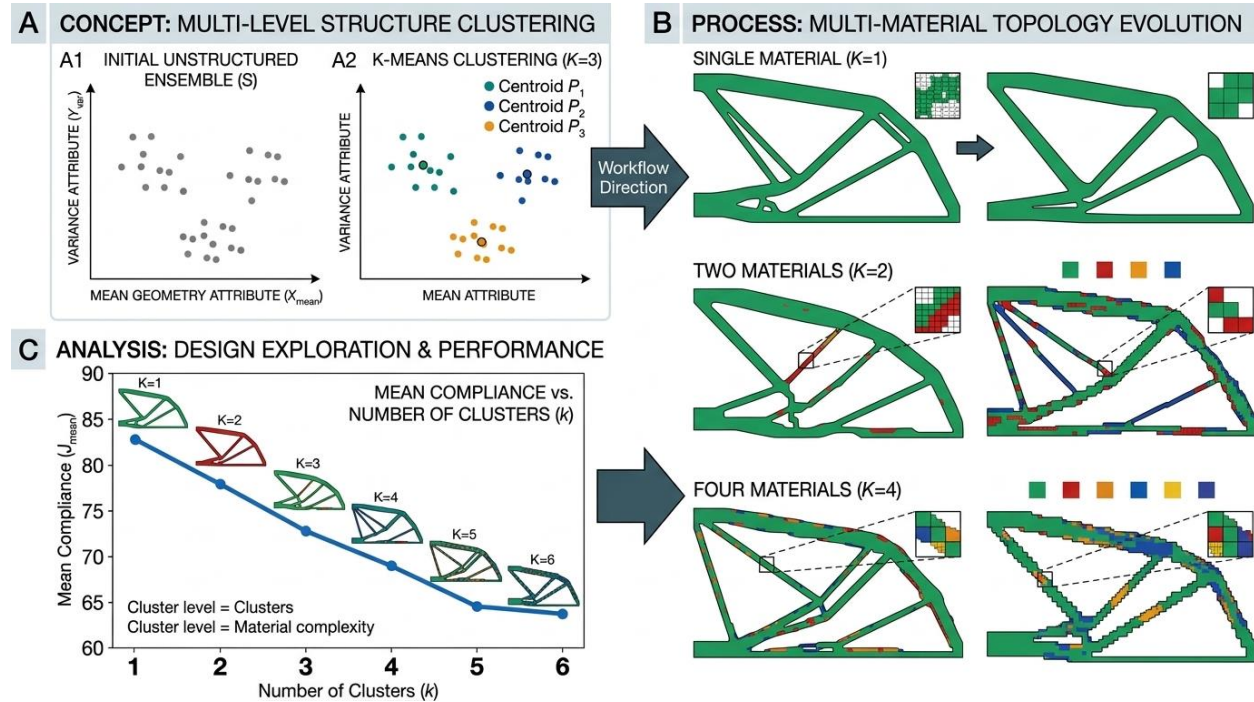


Figure 1: Multi-Level Structure Clustering and Multi-Material Topology Evolution Under Compliance Optimization

3.1 Deep Learning Architectures for Forward Acceleration

Deep Convolutional Neural Networks (CNNs) and 3D Encoder-Decoder architectures substitute costly FEA solvers by mapping boundary conditions, load vectors, and spatial volume fractions directly to final optimized spatial topologies or intermediate displacement fields. Early work by Askhatova et al. demonstrated that replacing iterative FEM solvers with deep CNNs drastically reduces computational processing duration while maintaining structural compliance bounds (Chen et al., 2020).

However, standard CNNs are constrained by fixed spatial discretization grids. To achieve scale-agnostic optimization, operator learning architectures specifically Neural Operators (NOs) like Fourier Neural Operators (FNOs) and Deep Operator Networks (DeepONets) learn mappings between continuous function spaces rather than discrete finite vectors (Shawahna et al., 2019).

3.1.1 U-Net Fourier Neural Operator (U-Net FNO) Architecture

Recent breakthroughs combine the multi-resolution spatial feature extraction of U-Nets with the global frequency-domain convolution capabilities of FNOs. In 3D SIMP topology optimization, the PDE solver is replaced by a U-Net FNO surrogate (Li et al., 2023). Within Fourier layers, input representations undergo a Fast Fourier Transform ($\mathcal{F}$), parameter-weighted kernel convolution in the frequency domain (R_ϕ), inverse Fourier transformation ($\mathcal{F}^{-1}$), and local linear bias operations (W):

$$v_{\text{out}}(x) = \sigma \left(W v_{\text{in}}(x) + \mathcal{F}^{-1} \left(R_\phi \cdot \mathcal{F}(v_{\text{in}}) \right) (x) \right)$$

To maintain optimizer stability during SIMP gradient steps, neural surrogates must yield highly accurate sensitivity gradients. Standard FNOs trained purely on spatial displacement loss often fail during SIMP iterations because slight displacement errors induce catastrophic sensitivity errors (Bonneville et al., 2025). Introducing explicit *gradient-consistent loss terms* (c_i) forces the neural operator to match ground-truth compliance gradients, enabling stable closed-loop

density updates. Furthermore, incorporating $SE(3)$ group equivariance into the neural operator enforces rotational and reflectional symmetries, enhancing model sample efficiency when trained on limited SIMP trajectory datasets (Song et al., 2026).

3.2 Physics-Informed Neural Networks (PINNs) and PINNTO

Unlike purely data-driven surrogates that require massive offline training sets generated by traditional FEA solvers, Physics-Informed Neural Networks (PINNs) integrate governing partial differential equations directly into the network's loss function (Jeong et al., 2023).

In Physics-Informed Topology Optimization (PINNTO), a neural network parameterizes the spatial density distribution $\rho(x, y, z)$ and the corresponding displacement field $u(x, y, z)$. The neural network parameters are updated by minimizing a composite loss function containing the elastic strain energy objective, PDE residual norm, boundary condition penalties, and volume fraction constraints:

$$\mathcal{L}_{\text{PINN}} = \mathcal{L}_{\text{Compliance}} + \lambda_1 \mathcal{L}_{\text{PDE Residual}} + \lambda_2 \mathcal{L}_{\text{Boundary}} + \lambda_3 \mathcal{L}_{\text{Volume}}$$

PINNTO eliminates the computational burden of pre-generating thousands of training topologies (Jeong et al., 2025). Studies demonstrate that PINNTO delivers an approximate 10-fold speedup over classical SIMP iterations in large-

scale computational domains. Additionally, PINNs possess the unique capability to infer concealed interior structural geometries using exposed surface loading and displacement telemetry from a single experimental dataset (Luo et al., 2025).

3.3 Online Learning and Inverse Parameter Prediction

To eliminate off-distribution generalization errors common in offline deep learning models, online learning integrates neural training directly within the active optimization loop. Chi et al. established an online machine learning topology optimization framework that trains a predictive model on data gathered during early optimization iterations. Replacing subsequent FEA iterations with this predictive surrogate achieves up to a 10-fold computational speedup without requiring external training datasets (Dong et al 2018).

Similarly, inverse parameter prediction frameworks couple Random Forest (RF) regression models with SIMP solvers. By learning the inverse mapping between spatial deformation responses and structural geometry, RF surrogates achieve approximately a two-fold computational cost reduction. In Isogeometric Topology Optimization (ITO), FNO surrogates operate on single-mesh online frameworks, leveraging multi-grid decomposition to retain global structural context while predicting localized element sensitivities (Romeres et al., 2016).

Table 2: Comparative Architecture Analysis of Machine Learning Approaches in Topology Optimization

Machine Learning Architecture	Mathematical / Structural Basis	Training Dataset Requirement	Speedup vs. Conventional SIMP/FEA	Key Strengths	Primary Architectural Limitations
Deep 3D CNN / Encoder-Decoder [cite: 16, 19]	Pixel/Voxel spatial convolution maps	High (Thousands of offline FEA solutions)	Up to $100 \times$ (Direct feed-forward inference)	Millisecond-level structural generation	Grid-resolution dependent; poor generalization to unseen loading directions
U-Net Fourier Neural Operator (U-Net FNO)	Frequency-domain kernel convolution coupled with multi-	Moderate (200 full SIMP trajectories with gradient loss)	$10 \times$ to $20 \times$ speedup per iterative loop	Zero-shot resolution independence; highly accurate sensitivity	Requires specialized loss tuning to prevent optimization

[cite: 6, 10]	resolution U-Net skips			gradient tracking	trajectory divergence
Physics-Informed Neural Network (PINNT0) [cite: 11, 20, 21]	Direct residual minimization of elasticity Navier-Cauchy PDEs	Zero (Unsupervised / Self-guided via physical principles)	$\approx 10 \times$ overall acceleration	Eliminates offline dataset generation; recovers concealed interior geometries	High training time per individual load case; non-convex loss landscape convergence issues
Online Learning Surrogates (Chi et al.) [cite: 18, 24]	Real-time weight updates utilizing early-iteration optimization telemetry	Zero pre-existing data (Learns dynamically during execution)	Up to $10 \times$ overall reduction in FEA runtime	Guaranteed domain convergence; no out-of-distribution dataset drift	Initial iterations remain bound by traditional FEA solution times
Random Forest (RF) Inverse Regressor [cite: 18]	Decision tree ensemble mapping deformation fields to geometric design variables	Moderate (Parametric SIMP parameter database)	$\approx 2 \times$ reduction in computational time	Highly interpretable; robust against noisy finite element outputs	Discontinuous predictions; limited feature complexity capacity compared to deep nets

4. Integration of Additive Manufacturing Process Constraints

4.1 The Additive Manufacturing Nexus: Opportunities and Realities

Integrating topology optimization with metal and polymer Additive Manufacturing (AM) offers substantial benefits, achieving material waste reductions between 57.8% and 90% compared to subtractive multi-axis milling (Caroli, 2025). However, unconstrained TO generates hyper-complex geometries that present significant manufacturing challenges:

1. Overhang Angle Vulnerabilities: In powder bed fusion (PBF) and directed energy deposition (DED), structural features oriented at angles smaller than a critical threshold α_{crit} (typically 45° relative to the horizontal build plate) collapse or suffer severe thermal warping without sacrificial support structures (Iqbal et al., 2020).

2. Sacrificial Support Material Costs: Sacrificial supports increase raw material usage, build times, post-processing labor, and risk of surface damage during mechanical removal.

3. Process-Induced Anisotropy and Fatigue: The layer-by-layer deposition sequence introduces anisotropic material properties, where z-axis tensile strength and fatigue limit are lower than in-plane (XY) properties (Parvanda & Kala, 2023).

4.2 Machine Learning for Self-Supporting Overhang Optimization

To eliminate sacrificial supports, self-supporting TO enforces geometric overhang constraints. Classical mathematical approaches utilize spatial density gradient operators or morphological filters (Tabarraei & Bhuiyan, 2025). In density-gradient methods, the local vector normal to the structural boundary $\mathbf{n} = -\nabla\rho/\|\nabla\rho\|$ is evaluated against the vertical build vector $\mathbf{b} = (0,0,1)^T$:

$$\cos(\alpha) = \frac{\nabla\rho \cdot \mathbf{b}}{\|\nabla\rho\|}$$

Machine learning accelerates self-supporting optimization by incorporating differentiable overhang loss penalties directly into neural network objective functions. Machine learning frameworks evaluate spatial density gradients in forward passes, penalizing boundary pixels where $\alpha < \alpha_{\text{crit}}$ (Hu et al., 2026).

By penalizing unprintable downward-facing surfaces during neural training, self-directed machine learning produces self-supporting topologies directly, eliminating post-optimization support generation. Standard commercial engineering environments (such as

nTopology/nTop) implement dedicated overhang and extrusion constraint filters to control material growth along specified build vectors, ensuring direct compatibility with industrial AM systems (Jin et al., 2020).

Table 3: Additive Manufacturing Constraints and Corresponding Machine Learning Integration Paradigms

AM Process Constraint	Physical Root Cause	Traditional Optimization Handling	Machine Learning Integration Strategy	Achieved Engineering Benefit
Overhang Angle Violation ($\alpha < 45^\circ$)	Molten pool instability over un-melted powder bed	Post-hoc manual fillet insertion; sacrificial support generation	Differentiable density-gradient loss terms embedded in neural training loops	Generates completely self-supporting structures; eliminates post-processing support removal
Inaccessible Internal Voids	Trapped unsintered powder or liquid resin in closed cavities	Geometric skeletonization filters; manual drainage hole placement	Topology-aware loss metrics penalizing enclosed void graphs via GNN connectivity checks	Guarantees complete powder evacuation paths throughout internal lattice networks
Build Direction Anisotropy	Inter-layer weak bonding along the vertical z-axis deposition direction	Single directional safety factor amplification	PINNs parameterized with direction-dependent anisotropic elasticity tensors $\mathbf{C}(\mathbf{z})$	Re-orientes load paths along high-strength planar axes (XY), reducing fatigue failures
Thermal Distortion & Residual Stress	High thermal gradients and rapid cooling cycles during laser scanning	Empirical trial-and-error build orientation adjustment	Convolutional neural surrogate modeling transient temperature fields and residual stress maps	Minimizes geometric warpage and residual stress concentrations by up to 50%
Surface Roughness & Stress Concentration	Stair-casing effect on tilted surfaces and gray pixel discretization	Post-optimization NURBS surface reconstruction and smoothing	Multi-grid Fourier Neural Operators (FNO) trained on Isogeometric Analysis (ITO)	Produces smooth boundaries directly, reducing maximum peak stresses by up to 50%

5. Performance Benchmarks and Engineering Industrial Applications

5.1 Quantitative Speedup and Fidelity Benchmarks

Integrating machine learning into topology optimization workflows dramatically improves computational throughput while maintaining

structural fidelity. Industrial implementation shows that surrogate models achieve multi-order-of-magnitude computational accelerations (Agal & Katariya, 2026).

- **Computational Acceleration:** Online machine learning frameworks achieve up to a $10 \times$ speedup over traditional SIMP solvers by replacing late-

stage FEA iterations with neural predictions. PINNTO frameworks deliver a similar $10 \times$ acceleration in large 3D domains. Inverse Random Forest models achieve a $2 \times$ reduction in computational time, while generative networks generate viable structural candidates in milliseconds (Farrell et al., 2021).

- **Mesh Quality & Stress Reduction:** Automated deep CNN frameworks (such as GridNet) evaluate unstructured mesh quality with 92.5% prediction accuracy. Coupling machine learning surrogates with Computer-Aided Engineering (CAE) platforms and Transfer Learning (TL) streamlines DfAM reconstruction, achieving up to a 50% reduction in peak Von Mises stresses by smoothing CAD surfaces and eliminating stress concentrations (Patsialis et al., 2023).

5.2 Automotive Application Case Study: Formula Racing Front Upright

An illustrative application of TO in automotive engineering is the lightweight design of a racing car front upright component subjected to severe braking, acceleration, and cornering loads. The original unoptimized upright component represented a solid, heavy metal block (Li et al., 2020).

In this workflow, the solid baseline component is evaluated via static FEA in software environments such as ANSYS under combined braking, acceleration, and cornering force vectors acting on the bearing journals. Applying density-based SIMP topology optimization subject to additive manufacturing constraints systematically carves away non-load-bearing volume. Material properties for Aluminum 2024-T4 alloy (Young's Modulus $E = 73$ GPa, Poisson's ratio $\nu = 0.33$, Density $\rho = 2780$ kg/m³) are configured to establish baseline yield behavior (Samin et al., 2024).

At a 40% mass retain setting, the optimized upright achieved a mass of 459 g (representing a

60% total weight reduction), with a maximum total deformation of 0.0416 mm and a peak Von Mises stress of 84.997 MPa. This maximum stress remained well below the yield strength threshold of Al 2024-T4, validating the component's structural integrity under extreme dynamic cornering loads. By incorporating overhang constraints during optimization, the final geometry is directly printable via selective laser melting without internal sacrificial support structures (Hunar et al., 2020).

5.3 Parametric Weight Reduction and Load Support Mechanics

Parametric weight reduction studies demonstrate the extreme lightweighting capabilities of topology optimization under static loads. In a controlled benchmark study evaluating a rectangular block structure under a 10 kg static vertical load (98.1 N), progressive volume fraction reductions yielded significant material savings:

- **Initial Baseline Solid Volume:** 1000 g initial reference mass (Nguyen, 2026).

- **Mass Reduction Progression:** Mass retain fractions produced optimized components weighing 491.45 g (43% mass reduction), 357.42 g (59% mass reduction), 261.31 g (70% mass reduction), 235.56 g (73% mass reduction), and 203.87 g (77% mass reduction) (Li et al., 2023).

Static FEA verification confirmed that even at a 77% mass reduction (203.87 g final weight), maximum Von Mises stress (1.84 MPa) and maximum total displacement (1.714×10^{-3} mm) remained far below allowable material yield limits (30 MPa for ABS plastic polymer baseline). This highlights the vast design space made accessible by combining TO with layerwise additive manufacturing (Solazzi et al., 2020).

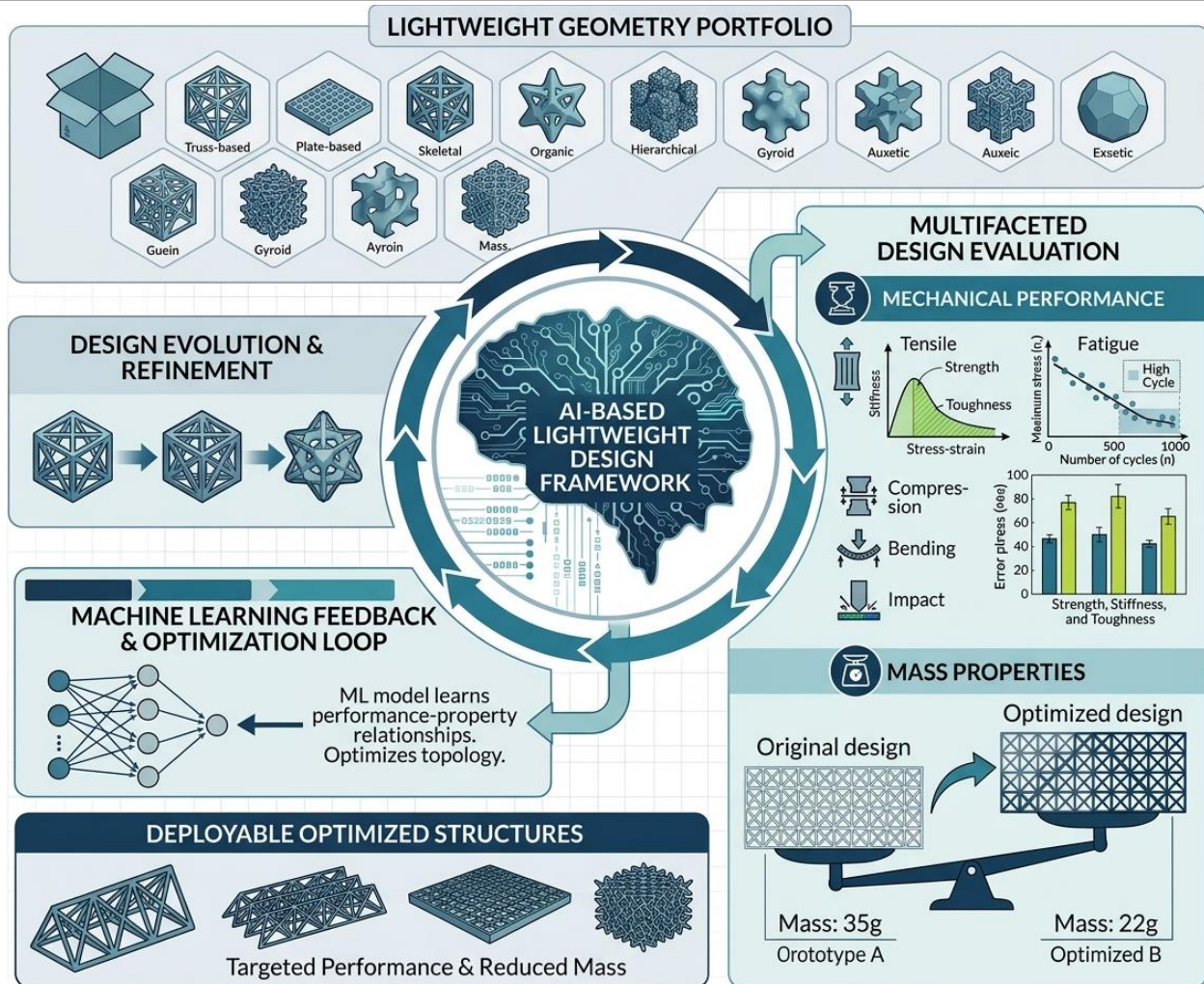


Figure 2: Closed-Loop AI-Based Framework for Lightweight Geometry Portfolio Exploration, Multi-Objective Mechanical Evaluation, and Mass Optimization

Table 4: Empirical Engineering Performance Benchmarks Across Optimization Strategies

Case Study / Benchmark Structural Application	Optimization Paradigm / Machine Learning Framework	Material Baseline Selection	Weight Reduction (%) / Final Mass	Peak Von Mises Stress / Max Displacement	Recorded Computational Acceleration / Accuracy
Racing Car Front Upright Assembly	ANSYS SIMP TO + AM DfAM Reconstruction	Aluminum 2024-T4 Alloy	60% Mass Reduction (459 g final mass)	84.997 MPa / 0.0416 mm displacement	Baseline standard FEA convergence
Parametric Box Structural Component	Static Density-Based Material Redistribution	ABS Polymer ($E = 2.1$ GPa)	77% Mass Reduction (203.87 g from 1 kg)	1.84 MPa / 1.714×10^{-3} mm [cite: 17]	Full compliance satisfaction under 10 kg load

Online ML Large-Scale Topology Optimization	Dynamic Iterative Online Training Neural Net	Continuous Linear Elastic Solid	Equivalent to standard target SIMP volume	Matches classical SIMP structural compliance	10 × Speedup compared to standard FEA
Isogeometric TO (ITO) Metamaterials	Multi-grid Fourier Neural Operator (FNO)	Thermal / Elastic Metamaterials	Tailored fine detail density allocation	Smooth boundary evaluation; reduced local stress spikes	Single-resolution inference; eliminates 2-scale FEA
CAE & Transfer Learning DfAM Framework	Deep Neural Network + Transfer Learning (TL)	High-Strength Structural Alloys	Tailored lightweight topology	50% Reduction in Peak Stresses [cite: 7]	Promotes direct printability manufacturability
GridNet Automatic Mesh Density Evaluation	Deep Convolutional Neural Network (CNN)	Discretized Unstructured Finite Grids	N/A (Mesh Quality Optimization)	N/A	92.5% Accuracy in mesh quality assessment

5.4 Sustainability and Life Cycle Analysis (LCA)

Integrating TO and AM offers substantial sustainability benefits throughout a component's lifecycle. By eliminating raw material waste during production, computational optimization strategies reduce material scrap by **57.8% to 90%** compared to subtractive CNC manufacturing (Klöpper & Grahl, 2014).

However, a comprehensive Life Cycle Sustainability Assessment (LCSA) reveals an important trade-off: the energy required during layerwise laser melting increases significantly with geometric complexity. The high embodied energy of additive processing means that embodied manufacturing energy increases relative to subtractive machining (Finkbeiner et al., 2010). Nevertheless, for active transport applications (such as aerospace structures and racing vehicles), operational fuel savings achieved through payload weight reduction rapidly offset the higher initial printing energy. Thus, ML-assisted lightweighting serves as a key driver for long-term carbon footprint reduction (Valdivia et al., 2021).

Conclusion

This review demonstrates that machine learning fundamentally transforms topology optimization from a sequential, computationally intensive

process into an integrated, near-real-time design pipeline. By replacing iterative FEA solvers with neural operators, surrogate models, and physics-informed architectures, ML-assisted TO achieves computational accelerations of $2\times$ to $100\times$ while maintaining compliance accuracy and structural integrity. The embedding of additive manufacturing constraints overhang angles, self-supporting requirements, thermal distortion, and anisotropy directly into neural network loss functions enables direct generation of print-ready geometries, eliminating manual CAD reconstruction and sacrificial support structures. Industrial applications confirm substantial weight reductions of 60–77% with validated stress margins, alongside peak stress reductions of up to 50%. However, challenges persist, including non-convex loss landscapes, generalization to unseen loading conditions, and the need for specialized gradient-consistent loss terms. Future research should prioritize hybrid frameworks combining online learning with physics-informed constraints, development of standardized benchmarks for cross-architecture comparison, and integration of life cycle sustainability metrics to fully realize ML-assisted TO as a cornerstone of sustainable, high-performance structural design for additive manufacturing.

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