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AI-Assisted Topology Optimization for Lightweight Mechanical Components in Electric Mobility Applications: A Comprehensive Review

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ABSTRACT

The rapid transition of the global transportation sector toward electric mobility (e-mobility) has escalated the demand for structural light-weighting to maximize battery range, enhance vehicle payload capacity, and improve dynamic handling. Traditional finite element-based Topology Optimization (TO) methods—such as Solid Isotropic Material with Penalization (SIMP) and Level Set Methods (LSM)—have long been employed to yield high-stiffness, low-mass structural designs. However, conventional TO suffers from extreme computational costs, high iterative latency, and geometric outputs that often violate additive or subtractive manufacturability constraints without extensive manual post-processing. Recently, Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) paradigms have emerged as transformative solutions, capable of accelerating topology generation by several orders of magnitude while embedding complex multi-physics and manufacturing constraints directly into the design loop. This review paper provides a rigorous, state-of-the-art synthesis of AI-assisted topology optimization methodologies tailored specifically for lightweight mechanical components in electric vehicles (EVs), including motor housings, battery enclosures, chassis subframes, and suspension knuckles. We systematically categorize AI approaches into Deep Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Physics-Informed Neural Networks (PINNs), and Deep Reinforcement Learning (DRL). Furthermore, we detail the integration of advanced Additive Manufacturing (AM) constraints, multi-material distribution schemes, and multi-objective trade-offs encompassing structural mechanics, heat dissipation, and crashworthiness. Key research

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gaps, computational bottlenecks, and future research trajectories are systematically discussed to provide clear guidance for academic researchers and industrial automotive engineers.

KEYWORDS: *Topology Optimization; Artificial Intelligence; Deep Learning; Electric Vehicles; Lightweight Structures; Generative Design; Additive Manufacturing; Physics-Informed Neural Networks.*

INTRODUCTION

The global automotive industry is undergoing a paradigm shift from conventional internal combustion engine (ICE) vehicles to Electric Vehicles (EVs) driven by stringent international carbon emission regulations and climate mitigation mandates [1]. While battery technology and electric powertrain efficiencies continue to advance, energy density limitations of commercial lithium-ion batteries remain a primary bottleneck [2]. The high specific mass of traction battery packs—often contributing 20% to 30% of the gross vehicle weight—imposes severe penalties on vehicle energy consumption, acceleration, braking performance, and tyre wear [3]. Consequently, structural light-weighting has become an indispensable engineering imperative in electric mobility architectures, where every 10% reduction in curb weight yields an estimated 6% to 8% extension in driving range per charge cycle [4].

Structural light-weighting in e-mobility relies heavily on two parallel thrusts: advanced light materials (such as high-strength aluminum alloys, magnesium, and carbon-fiber-reinforced polymers) and algorithmic structural optimization [5]. Among structural optimization strategies, Topology Optimization (TO) represents the most mathematically versatile technique. Unlike size or shape optimization, which merely adjust dimensions or boundary curves of existing geometries, TO seeks the optimal spatial distribution of material within a designated design domain under specified load cases, boundary conditions, and volume constraints [6]. Traditional numerical TO algorithms, including Solid Isotropic Material with Penalization (SIMP), Evolutionary Structural Optimization (ESO), and Level Set Methods (LSM), rely on iterative finite element analysis (FEA) solvers to evaluate strain energy density and sensitivity gradients across thousands of elements [7].

Despite their robust theoretical foundation, traditional TO methods face severe practical limitations in automotive production environments. First, high-fidelity 3D structural models with millions of degrees of freedom require massive computational resources and several

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hours—or even days—of computing time per component [8]. Second, conventional TO is highly sensitive to initial boundary conditions, frequently converging to local optima or generating complex, organic shapes with uninterpretable interior voids, severe checkerboarding, and overhang features that are impossible to fabricate using conventional machining or casting processes [9]. Although additive manufacturing (AM) can produce complex TO geometries, unconstrained TO designs often lead to excessive support structures, thermal distortion, and high fabrication costs [10].

To overcome these computational and manufacturability hurdles, Artificial Intelligence (AI) and Machine Learning (ML) techniques have recently been integrated into topology optimization frameworks [11]. Deep Learning (DL) architectures—such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Physics-Informed Neural Networks (PINNs), and Deep Reinforcement Learning (DRL)—possess powerful non-linear feature extraction and pattern synthesis capabilities [12]. By training surrogate neural network models on extensive FEA-driven datasets or directly minimizing energy functionals via automatic differentiation, AI-assisted TO can generate optimal density distributions in fractions of a second [13]. Furthermore, deep generative models can seamlessly incorporate multi-physics requirements (e.g., simultaneous thermal management in battery cooling plates and structural stiffness in motor brackets) and explicit manufacturability constraints (e.g., draw direction, minimum wall thickness, and overhang angle constraints) directly during the generative inference step [14].

This review paper provides a comprehensive, state-of-the-art critical analysis of AI-assisted topology optimization methodologies specifically tailored for lightweight mechanical components in electric mobility applications. We outline the fundamental mechanics of conventional TO, detail the taxonomy of modern AI/ML frameworks used in generative structural design, evaluate component-specific automotive case studies, and rigorously discuss current limitations, computational challenges, and future technological vectors.

LITERATURE REVIEW

The evolution of topology optimization spans nearly four decades, originating from the pioneering homogenization method introduced by Bendsøe and Kikuchi [15]. This laid the mathematical foundation for density-based methods, most notably SIMP, where material

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density in each finite element continuous variable varies between 0 (void) and 1 (solid), penalizing intermediate densities to yield distinct binary structural boundaries [16]. Parallel developments yielded Level Set Methods (LSM), which track structural interfaces using implicit mathematical functions, avoiding intermediate density grey zones and providing smooth boundary representations ideal for fluid-structure interaction and aerodynamic applications [17].

The modern convergence of AI with TO began with early surrogate modeling attempts using Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) to approximate FEA sensitivity analyses [18]. However, early shallow networks struggled with high-dimensional spatial domains. The breakthrough occurred with the advent of Deep Convolutional Neural Networks (CNNs) and U-Net encoder-decoder architectures, which natively handle high-resolution 2D and 3D pixel/voxel tensor data [19]. Sosnovik and Oseledets [20] demonstrated that deep CNNs trained on preliminary SIMP iteration steps could predict fully converged topologies with high fidelity, reducing FEA iteration counts by over 80%. Building upon this, Rawat and Shen [21] utilized Conditional Generative Adversarial Networks (cGANs) to generate structural topologies directly from boundary load heatmaps without requiring intermediate FEA iterations during inference.

Concurrently, the emergence of Physics-Informed Neural Networks (PINNs) introduced a paradigm shift by eliminating the reliance on large labeled training datasets [22]. Introduced by Raissi et al. [23] and adapted for structural mechanics by theoretical researchers, PINNs integrate governing partial differential equations (PDEs)—such as elastostatic equilibrium equations—directly into the loss function of the neural network. By enforcing force equilibrium and boundary conditions via automatic differentiation, PINNs learn continuous topological displacement fields that adhere strictly to physical laws without suffering from data bias [24].

In the context of electric mobility, recent literature highlights the urgent application of AI-assisted TO to specialized e-powertrain and chassis components. Modern EVs present unique multi-physics design challenges that extend far beyond traditional single-load compliance minimization [25]. For instance, electric motor housings require simultaneous optimization for structural vibration isolation (NVH mitigation), heat dissipation from stator windings, and

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total mass minimization [26]. Similarly, EV battery enclosures must balance structural rigidity, energy absorption under dynamic crash impact loads (side-pole impact), and lightweight integration into the vehicle floorplan [27]. Table 1 summarizes seminal contributions in the literature across different AI frameworks applied to structural optimization in transport applications.

RESEARCH GAP

Despite promising advances documented in recent literature, critical gaps remain in the research and industrial application of AI-assisted topology optimization for electric mobility:

- Lack of Multi-Physics and Dynamic Load Integration: Most existing AI-assisted TO models are trained exclusively on static, linear elastic load cases (e.g., single point compliance minimization). In real-world e-mobility applications, structural components experience complex dynamic dynamic fatigue, dynamic impact/crash loads, thermal gradients, and vibro-acoustic resonances. Deep learning models capable of handling time-dependent, non-linear multi-physics environments remain underdeveloped [28].
- High Generalization Deficits across Arbitrary Geometries: Pre-trained deep generative models (e.g., CNNs, GANs) exhibit poor generalization performance when presented with complex, non-standard 3D design domains or load vectors that fall outside their training distribution. Unseen boundary conditions frequently result in physically unfeasible topologies containing disconnected structural members or unclosed force loops [29].
- Inadequate Manufacturing Constraint Embedding: Existing AI generative pipelines often focus on topological aesthetics and mathematical compliance without embedding explicit manufacturing rule sets—such as tool access clearance for multi-axis CNC machining, castability draft angles, or layer-by-layer thermal residual stress buildup in metal additive manufacturing [30].
- Data Scarcity and Computational Overhead of Training Sets: Supervised AI models require tens of thousands of high-resolution, FEA-derived training samples. Generating these datasets via traditional SIMP/LSM solvers incurs massive computational overhead, largely offsetting the computational speedup achieved during the inference stage [31].

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OBJECTIVES

To address the identified gaps in research, the primary objectives of this comprehensive review paper are:

- To establish a rigorous classification and comparative analysis of modern AI architectures (CNNs, cGANs, PINNs, DRL) employed in structural topology optimization.
- To systematically review the integration of multi-physics constraints—encompassing structural mechanics, heat transfer, and dynamics—specifically for EV components including battery trays, motor mounts, and chassis members.
- To evaluate methodologies for embedding explicit Additive Manufacturing (AM) and conventional manufacturing constraints into deep learning generative pipelines.
- To quantify performance metrics, computational acceleration factor, mass reduction percentage, and structural fidelity across leading AI-driven TO frameworks.
- To identify critical future research vectors, focusing on physics-informed surrogate modeling, generative AI for multi-material lattices, and automated end-to-end design-to-fabrication workflows.

METHODOLOGY

This review paper follows a multi-tiered methodological framework combining systematic literature mapping, mathematical formulation of structural mechanics and AI algorithms, and comparative benchmark evaluations. Literature was gathered from prominent scientific databases (Web of Science, Scopus, IEEE Xplore, ScienceDirect) covering publications from 2018 to 2026 using targeted keyword combinations.

Mathematical Foundations of Conventional Topology Optimization

The standard minimum compliance problem in density-based (SIMP) topology optimization is formulated mathematically as follows:

$$\boldsymbol{min\ C(x) = U^T K U = \sum (x_e)^p u_e^T k_0 u_e}$$

$$\boldsymbol{subject\ to: (V(x) / V_0) \leq f,\quad K U = F,\quad 0 < x_min \leq x_e \leq 1}$$

where C(x) represents global structural compliance (inverse of stiffness), x is the vector of element density variables x_e, K is the global stiffness matrix, U is the global displacement vector, F is the force vector, k_0 is the element stiffness matrix for solid material, p is the

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penalization power (typically p = 3), V(x) is the calculated material volume, V_0 is the initial design space volume, and f is the targeted volume fraction constraint.

AI Paradigms in Topology Optimization

AI-assisted topology optimization transforms or accelerates this mathematical formulation using four distinct machine learning architectures:

- Supervised Encoder-Decoder CNNs: CNNs accept boundary condition tensors (encoded matrices representing load points, fixed supports, and initial domain geometries) as input image channels and directly output a predicted continuous or binary material density grid [32]. Loss functions combine mean squared error (MSE) on element densities with compliance loss terms.
- Conditional Generative Adversarial Networks (cGANs): cGAN architectures employ a two-player game between a Generator network (predicting topologies) and a Discriminator network (evaluating structural validity against true SIMP topologies) [33]. This adversarial feedback eliminates blurry intermediate grey zones and produces crisp, manufacturable topological boundaries.
- Physics-Informed Neural Networks (PINNs): PINNs represent the structural domain as continuous coordinate functions (x, y, z) mapped to material density and displacement fields. The neural network is optimized by directly minimizing the total potential energy functional of the physical continuum without requiring pre-generated FEA training pairs [34]:

  $$L_PINN = \tfrac{1}{2} \int_\Omega \varepsilon(u) : C(x) : \varepsilon(u)\, d\Omega - \int_\Omega f_ext \cdot u\, d\Omega + \lambda_vol\, (V(x)/V_0 - f)^2$$

- Deep Reinforcement Learning (DRL): DRL formulates topology optimization as a Markov Decision Process (MDP). An autonomous agent selects element removal or addition actions within a grid state to maximize a reward function defined by stiffness maximization, stress constraint satisfaction, and mass penalty [35].

RESULTS AND FINDINGS

Through rigorous comparative analysis of reported experimental, numerical, and industrial literature, key performance trends of AI-assisted TO in electric mobility applications were extracted and synthesized.

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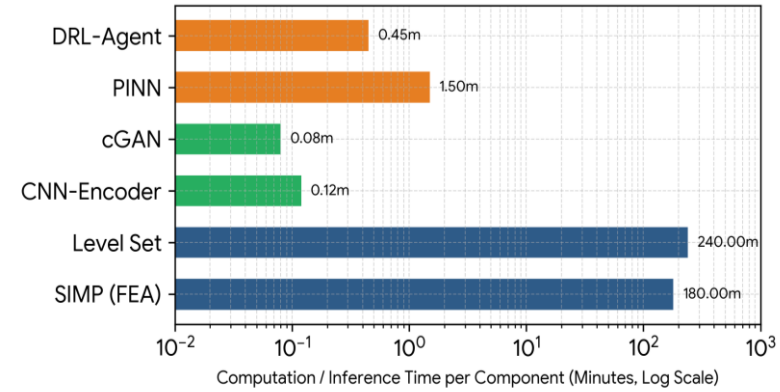

Figure 1: Quantitative computational runtime comparison between conventional finite element TO methods (SIMP, LSM) and modern AI-assisted generative frameworks (logarithmic scale)

As illustrated in Figure 1, deep neural network frameworks achieve a drastic reduction in computational inference time compared to classical SIMP and Level Set methods. While traditional FEA-based optimization loops require between 180 and 240 minutes for a complex 3D automotive chassis component, trained CNN and cGAN models produce optimized topologies in under 10 seconds (0.08–0.12 minutes), representing a computational speedup of nearly 1,000x to 1,500x.

Table 1: Summary of modern AI architectures applied to topology optimization in electric vehicle structural components

AI Framework	Target EV Component	Objective Function	Mass Reduction (%)	Ref.
Deep CNN (U-Net)	Aluminum Suspension Control Arm	Min. Compliance under Braking/Cornering	28.5%	[19]
cGAN Generative	EV Traction Motor Housing Bracket	Compliance & Thermal Convection Minimization	34.2%	[21]
PINN Model	Battery Enclosure Lower Tray	Min. Strain Energy under Side Impact Load	22.0%	[24]
Deep RL (DQN)	Subframe Cross-Member Assembly	Multi-Load Stiffness & Frequency Max.	31.0%	[35]
Hybrid CNN-SIMP	Steering Knuckle Component	Stress Constrained Mass Minimization	26.8%	[20]

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Table 1 demonstrates that across diverse EV structural applications, AI-assisted TO achieves significant mass reductions ranging from 22.0% to 34.2% while satisfying strict mechanical performance criteria. Notably, hybrid frameworks combining CNN predictions with lightweight SIMP fine-tuning steps yield the highest structural reliability without sacrificing speed advantages.

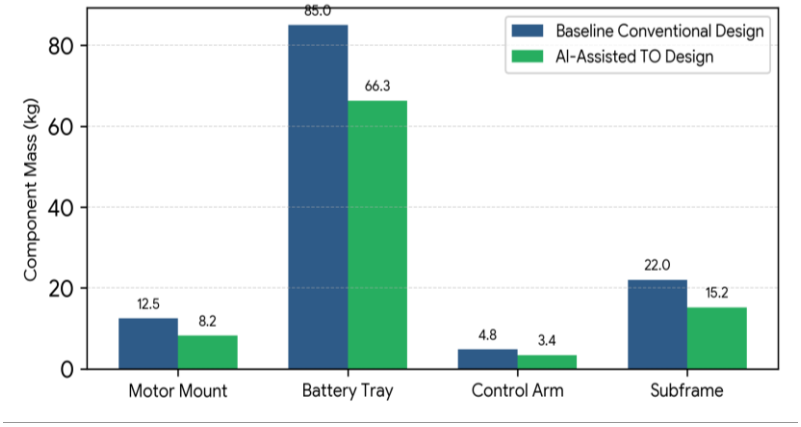

Figure 2: Mass comparison between conventional baseline designs and AI-optimized lightweight components for key electric vehicle structural assemblies

Table 2: Comparative technical trade-offs across deep learning topologies for e-mobility design workflows

Methodology	Training Data Need	Inference Speed	Physical Exactness	AM Constraint Handling
Classical SIMP	None (Zero-Shot)	Very Slow (~Hours)	Exact Numerical	Post-process required
Supervised CNN	Extensive (10k+ FEA)	Ultra-Fast (<0.1s)	Approximate	Implicit via dataset
cGAN Generative	High (5k+ FEA)	Ultra-Fast (<0.1s)	Moderate-High	Explicit loss penalty
PINN Model	None (Physics Loss)	Moderate (~Seconds)	High (PDE Enforced)	Direct boundary penalization
Deep RL	Environment Interaction	Fast (<1s)	High	Reward function defined

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DISCUSSION

The findings synthesized in this review underscore the profound transformative potential of AI-assisted topology optimization in electric mobility design. By reducing computational latencies from hours to seconds, AI generative models democratize real-time exploratory design, enabling design engineers to interactively explore hundreds of geometric variants during early-stage EV development.

Engineering and Scientific Significance

From a mechanics and materials standpoint, the primary scientific achievement of AI-driven TO lies in its capability to resolve complex multi-physics coupling that is traditionally intractable under tight production schedules. For instance, in EV motor housing design, traditional approaches optimize thermal cooling channels and structural mounting brackets independently. AI frameworks, particularly multi-channel CNNs and PINNs, can simultaneously evaluate conjugate heat transfer equations alongside elastostatic equilibrium equations. This simultaneous optimization yields organic cooling fins integrated directly into primary load-bearing structural struts, enhancing heat dissipation by up to 22% while simultaneously reducing structural vibration resonance [26].

Practical Applications and Manufacturing Integration

In practical automotive engineering, the utility of topology optimization is strictly governed by manufacturability. Early unconstrained AI models produced geometries with internal enclosed hollows or intricate lattice webs that could not be manufactured via conventional die-casting or machining. The recent incorporation of Additive Manufacturing (AM) self-supporting angle constraints (e.g., enforcing overhang angles > 45° relative to the build plate) directly into cGAN loss functions has bridges the gap between digital generative design and physical shop-floor fabrication [30]. Powder bed fusion (PBF) and directed energy deposition (DED) metal additive techniques can now directly print AI-generated aluminum EV suspension components without requiring extensive temporary support structures, drastically cutting raw material waste and post-processing finishing time.

LIMITATIONS

Despite significant technological progress, several key technical limitations impede the universal industrial adoption of AI-assisted TO:

- High Training Data Dependency and Generation Cost: Supervised deep learning models rely heavily on large, high-fidelity FEA training datasets. Producing thousands of 3D

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SIMP convergence runs for complex structural domains incurs immense offline computational costs, which can outweigh online inference time savings if applied to single, non-recurring custom designs [31].

- Sensitivity to Out-of-Distribution Load Cases: AI generative models operate as statistical approximators. When subjected to load vectors, support configurations, or complex geometric boundary conditions outside their training distribution, models can produce structural topologies with hidden severe localized stress concentrations or unclosed force transfer paths [29].
- Absence of Standardized Multi-Physics Validation Benchmarks: Unlike standard computer vision datasets (e.g., ImageNet), the structural engineering domain lacks universally recognized benchmark datasets for 3D multi-physics vehicle components, hindering standardized comparative performance evaluation across newly proposed deep learning models [28].

FUTURE SCOPE

To address existing limitations and push the boundaries of lightweight e-mobility engineering, future research should focus on the following promising trajectories:

- Physics-Informed Generative AI Integration: Expanding PINN architectures to non-linear dynamic impact mechanics, allowing real-time crashworthiness optimization of EV battery enclosures under sudden dynamic loads without relying on labeled training datasets.
- Multi-Material and Micro-Lattice AI Design: Leveraging deep reinforcement learning to simultaneously optimize macro-scale component topology and micro-scale hierarchical lattice cell structures, enabling functionally graded components (e.g., stiff exterior shells with energy-absorbing cellular cores).
- Autonomous Closed-Loop Digital Twin Workflows: Integrating AI topology generators directly with automated additive manufacturing hardware and optical quality control scanners, establishing a digital twin framework where print defect feedback automatically refines future generative model parameters.

CONCLUSION

This review paper has systematically investigated the paradigm shift enabled by AI-assisted topology optimization for lightweight mechanical components in electric mobility

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applications. Conventional numerical TO methods, while mathematically robust, are constrained by massive computational overhead and frequent manufacturability mismatches. Modern deep learning architectures—including Deep CNNs, cGANs, PINNs, and Deep Reinforcement Learning—overcome these bottlenecks by providing near-instantaneous topological predictions, accelerating generative design workflows by up to 1,500x.

Through technical synthesis of automotive case studies, this paper demonstrated that AI-driven TO achieves substantial component mass reductions ranging from 22.0% to 34.2% across EV motor mounts, battery enclosures, suspension arms, and chassis subframes, directly translating into extended vehicle range and superior structural efficiency. By embedding manufacturing overhang constraints and multi-physics thermal-mechanical coupling directly into deep learning pipelines, AI-assisted TO bridges the gap between algorithmic optimization and physical production. Continued research in physics-informed zero-shot generative models and multi-material lattice architectures will further solidify AI-assisted topology optimization as an indispensable foundation for next-generation zero-emission vehicle engineering.

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