

Review Article

Blending Data-Driven Surrogates with Physics - Based Topology Optimization: A Critical Review of Machine Learning - Accelerated Design in Fibre - Reinforced Polymer and Concrete Structures

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Abstract

Blending data driven surrogates with physics based topology optimization holds the promise of revolutionizing the design of fibre reinforced polymer (FRP) composites and concrete structures by dramatically reducing computational cost while preserving-or even enhancing-solution quality. This critical review synthesizes developments from last decade in which machine learning (ML) models such as deep neural networks, Gaussian processes, and ensemble learners have been trained to approximate finite element analyses within iterative optimization loops. The author investigates the applications of Fiber Reinforced Polymer (FRP) composites, wherein the exigencies of continuous fiber orientation and constraints imposed by additive manufacturing necessitate the employment of high-fidelity yet efficient computational solvers. Additionally, The author explore the domain of concrete structures, wherein the inherent heterogeneity, prevalence of cracking, and considerations of durability present distinctive challenges for modeling. By conducting a comprehensive literature review utilizing databases such as Scopus, Web of Science, IEEE Xplore, and MDPI, alongside stringent inclusion criteria, we extract and analyze algorithmic selections, training data configurations, performance metrics (including prediction error and speed-up factors), and outcomes pertaining to manufacturability. The findings indicate that workflows driven by neural surrogate models can achieve accelerations of up to 50 times while maintaining deviations of less than 5% from full-order models; however, limitations in generalizability across various loading scenarios persist. The author delineate critical deficiencies, including the scarcity of benchmark datasets, restricted transfer learning across diverse material systems, and integration challenges with Computer-Aided Design (CAD) and Finite Element Analysis (FEA) frameworks, and The author propose avenues for future research which encompass hybrid physics-based machine learning frameworks and real-time optimization. By elucidating best practices as well as existing challenges, this review offers a strategic roadmap for researchers and practitioners aiming to exploit machine learning-accelerated topology optimization in the advancement of next-generation composite and concrete design.

Keywords

Topology Optimization, Machine Learning, Fibre-Reinforced Polymer Composites, Surrogate Modeling, Manufacturing Constraints, and 3D Printing

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1. Introduction

Topology optimization (TO) have emerged as a powerful computational tool for distributing material within a prescribed design domain so as to maximize structural performance under given loads and constraints. In its classical form—often based on the Solid Isotropic Material with Penalization (SIMP) or level-set methods—TO relies on repetitive finite-element analyses (FEA) within an iterative optimization loop, resulting in substantial computational expense for high-fidelity models [1]. This bottleneck is especially acute for advanced materials such as fibre-reinforced polymer (FRP) composites, where anisotropic behavior and manufacturing constraints (e.g., continuous fibre orientation, automated fibre placement) demand both fine spatial resolution and complex constitutive models [2].

Machine-learning (ML) surrogates—ranging from deep neural networks (DNNs) to Gaussian-process regressors and ensemble learners—offer a promising remedy by learning to approximate the FEA response surface, thereby enabling orders-of-magnitude speed-ups in the optimization loop [3]. Early demonstrations report up to $50\times$ acceleration with minimal loss in accuracy, effectively transforming the TO workflow from overnight batch runs to near-real-time design exploration [4]. In parallel, the heterogeneous and quasi-brittle nature of concrete structures introduces unique challenges—such as crack initiation, aggregate-matrix interactions, and long-term durability—that complicate physics-based TO and stand to benefit from data-driven modeling [5].

Despite these advances, the literature remains fragmented: surveys exist either on ML for polymer composites broadly [6] or on TO for FRP without deep ML integration [7], but a unified critical assessment of ML-accelerated TO across both FRP composites and concrete is lacking. Key questions persist regarding surrogate generalizability across load cases, the trade-off between training data cost and optimization speed-up, and the integration of ML surrogates into established CAD/FEA pipelines. This review addresses these gaps through a systematic literature search (2015–2025), rigorous inclusion criteria, and a side-by-side comparison of algorithmic strategies, performance metrics, and manufacturability outcomes. By synthesizing best practices and highlighting open challenges, we aim to chart a roadmap for next-generation ML-accelerated TO in composite and concrete structural design.

2. Fundamentals

This part reviews (a) the core principles of topology optimization (TO), (b) the role of machine-learning (ML) surrogates in accelerating TO, and (c) the key performance metrics used to evaluate surrogate-accelerated workflows.

2.1. Topology Optimization Principles

Topology optimization seeks the optimal distribution of material within a prescribed design domain to maximize structural performance (e.g. stiffness, strength) under given loads and constraints. Two dominant formulations are:

I. Density-based SIMP (Solid Isotropic Material with Penalization)

Introduced by Bendsøe and Sigmund (1999), the SIMP method assigns a density variable $0 \leq \rho_i \leq 1$ to each finite-element cell and penalizes intermediate densities via a power law to drive solutions toward void (0) or solid (1). The optimization problem reads:

$$\min F(\mathbf{p}) \text{ subject to } \mathbf{K}(\mathbf{p})\mathbf{u} = \mathbf{F}, \sum \rho_i v_i \leq V^*, 0 \leq \rho_i \leq 1$$

Where:

$\mathbf{K}(\mathbf{p})$ is the stiffness matrix, interpolated as:

$$E(\rho) = \rho^p E_0, \text{ with } p > 1,$$

V^* is the prescribed volume constraint [8].

II. Level-set Methods

Represent the material boundary implicitly via a level-set function $\phi(\mathbf{x})$, evolving ϕ according to shape-derivatives information. This naturally enforces crisp boundaries but requires careful re-initialization and regularization to maintain numerical stability [9].

2.2. ML Surrogate Modeling in TO

Standard TO require hundreds to thousands of FEA solves per design iteration, posing a computational bottleneck for high-fidelity models. ML surrogates (also called metamodels or response surface models) learn an approximation.

$$\mathbf{f}^{\text{ML}} : \rho \mapsto \{ \text{structural responses: displacements, stresses} \}$$

To replace expensive FEA calls within the optimization loop. Common surrogate types included in table 1.

Table 1. Common surrogate with Respective merits.

Surrogate Type	Representative Reference	Key Advantage
Deep Neural Networks	[10]	High expressivity for complex, nonlinear FEA
Gaussian Process Regression	[11]	Uncertainty quantification; closed-form variance
Random Forests (Ensemble)	[12]	Robust to overfitting; interpretable feature importance

Surrogates are trained on a dataset $\{(\rho(j), u(j))\}_{j=1}^N$ obtained from high-fidelity FEA samples. Once trained, $f_{\text{ML}}^{\text{hat}}$ predicts responses at new ρ in $O(1)$ time, enabling rapid fitness eval-

uation in the TO loop.

2.3. Key Performance Metrics

To assess ML-accelerated TO workflows, the following metrics are routinely reported in Table 2.

Table 2. Performance Metrics with respective definition.

Metric	Definition
Prediction error	L_2 or L_∞ norm between surrogate-predicted and FEA-computed responses over test set.
Speed-up factor	$\frac{\text{Total FEA time}}{\text{Surrogate inference time} + \text{retraining time}}$
Generalizability	Surrogate accuracy under unseen load cases or boundary conditions (extrapolation capability).
Manufacturability	Quality of resulting topology under real-world constraints (e.g. minimum feature size, printability).

A well-trained surrogate achieves low prediction error (e.g. $<5\%$) while delivering large speed-ups (e.g. $10\times$ to $50\times$) in the TO loop. However, high speed-up often trades off with reduced generalizability, necessitating careful design of training datasets and hybrid physics-ML strategies.

By grounding TO in established SIMP and level-set theory, and by leveraging proven ML surrogates (DNNs, Gaussian processes, random forests), modern workflows can dramatically accelerate design iteration. The next sections will examine how these fundamentals are specialized to FRP composites and concrete structures.

3. ML Algorithms in TO

Modern topology-optimization workflows leverage a variety of machine-learning (ML) techniques to approximate expensive finite-element analyses (FEA) and to explore design spaces via trial-and-error agents. We group these methods into four main categories: deep neural networks (DNNs), Gaussian-process (GP) surrogates, ensemble learners (e.g. random forests), and reinforcement-learning (RL) agents. Table 3 summarizes their key attributes; the subsections that follow provide critical discussion.

Table 3. Summarizes their key attributes; the subsections that follow provide critical discussion.

Algorithm	Reference (Author, Year, DOI)	Strengths	Limitations
Deep Neural Networks	[14]	I. Extremely high expressivity for nonlinear FEA response surfaces II. Amortized inference-once trained, near-real-time predictions	I. Training demands large datasets ($\geq 10^3$ samples) II. Risk of overfitting; limited extrapolation beyond training regime

Algorithm	Reference (Author, Year, DOI)	Strengths	Limitations
Gaussian Processes	[15, 16]	I. Built-in uncertainty quantification II. Closed-form variance aids active sampling (EGO)	I. Cubic scaling in sample size ($\mathcal{O}(N^3)$) II. Challenging in high-dimensional design spaces
Random Forests	[12]	I. Robust to overfitting; interpretable via feature importance II. Fast training and inference for moderate data sizes	I. Limited smoothness-stepwise predictions can hinder gradient-based TO II. Uncertainty estimates are heuristic
Reinforcement Learning	[17, 18]	I. Learns optimization policy end-to-end; can handle discrete/binary variables II. Capable of exploring very large, nonconvex spaces	I. Sample-inefficient-requires many environment queries II. Reward-shaping and stability remain open challenges

3.1. Deep Neural Networks (DNNs)

Deep architectures-especially convolutional encoder-decoder networks-have been widely adopted as fast surrogates for FEA within topology-optimization loops. [14] Introduced the Self-Directed Online Learning Optimization (SOLO) framework, in which a DNN surrogate is iteratively refined by querying only in the region of interest, achieving 2-5 orders of magnitude speed-up over heuristic methods with provable convergence guarantees. Demonstrated a DNN surrogate for electromagnetic TO, reporting comparable accuracy to full-order models while reducing compute by an order of magnitude. However, these gains rely on large initial training sets (often >1,000 samples) and may degrade when extrapolating beyond learned load cases.

3.2. Gaussian-Process Regression (GPR)

Gaussian processes (GPs) serve as Bayesian surrogates, offering not only mean predictions but also variance estimates that guide adaptive sampling. Cong et al. Developed a GP-based surrogate with a novel “expected prediction-error” acquisition, achieving robust constrained-TO performance on truss benchmarks (Three-Bar Truss) with minimal function evaluations [15]. The classical Efficient Global Optimization (EGO) framework Jones, D et al remains a staple for continuous TO, balancing exploration and exploitation via the Expected Improvement criterion [19]. The cubic training cost ($\mathcal{O}(N^3)$) and kernel-selection sensitivity, however, limit GPs to moderate dataset sizes ($N \approx 10^3$).

3.3. Ensemble Learners (Random Forests)

Random forests (RFs) combine many decision trees to yield stable regression surrogates. Breiman, L. Established RFs’ resilience to overfitting and their ease of parallelization,

making them attractive for moderate-scale surrogate TO task [20] RFs also provide feature-importance measures that help interpret which design variables most influence compliance [12]. Their piecewise-constant nature, though, can impede gradient-based update schemes and deliver non-smooth sensitivity predictions, necessitating hybrid strategies (e.g., smoothing post-processing).

3.4. Reinforcement Learning (RL)

RL formulates topology optimization as a sequential decision-making problem: an agent places or removes material “pixels” to maximize a reward (e.g. negative compliance). Hayashi & Ohsaki applied a policy-gradient method with graph embedding to binary truss TO, achieving viable designs under stress/displacement constraints [17]. Paulin used Proximal Policy Optimization (PPO) and DreamerV3 agents in a mesh-independent RL gym (SOgym), generating 2D structures within 54 % of compliance-optimal benchmarks and demonstrating RL’s ability to learn diverse load-path strategies [18, 21]. RL’s main drawback is sample inefficiency-millions of FEA calls may be needed to train a robust policy-though model-based or hybrid physics-RL schemes are emerging to mitigate this.

By critically comparing these ML algorithms, we observe a trade-off triangle among accuracy, compute cost, and generalizability. DNNs and RFs excel in raw inference speed, GPs in uncertainty-aware sampling, and RL in autonomous exploration. Hybrid frameworks-e.g. physics-informed neural networks (PINNs) or GP-accelerated RL-represent promising frontiers for future work.

4. Application to FRP Composites

Machine-learning (ML)-accelerated topology optimization (TO) have been adopted in fibre-reinforced polymer (FRP) composites to address the twin challenges of anisotropic behav-

hour and manufacturing constraints (e.g. continuous fibre orientation, automated fibre placement). This section critically re-

views key studies, grouped by surrogate-TO integration, fibre-orientation optimization, and manufacturing-aware design.

Table 4. Surrogate-Based TO of Variable-Stiffness FRP.

Study	ML Surrogate	Composite System	Key Outcome
[22]	Neural network + active learning	Variable-stiffness CFRP	Achieved 30× speed-up; <3% error in compliance prediction versus FEA
[13]	Implicit neural representation	Functionally graded continuous FRC	Enabled high-resolution fibre path extraction; end-to-end sensitivity via autodiff

Critical insight:

- I. Active-learning DNN surrogates reduce training samples by focusing on regions of interest; however, they require careful sampling strategies to avoid “blind spots”

in load-space coverage.

- II. Implicit NN representations decouple design resolution from FE mesh, yet integration with standard CAD/AFP toolchains remains an open challenge.

Table 5. Fibre-Orientation Optimization under Manufacturing Constraints.

Study	Method	Manufacturing Context	Result
[24]	End-to-end RL (SOgym)	3D-printed composites	Generated fibre paths achieving 95% of optimal stiffness; mesh-independent
[25]	ML + Taguchi-Grey analysis	Automated fibre placement	Optimized ply angles and AFP process parameters; 12% improvement in strength

Critical insight from Table 5:

- I. RL agents can autonomously learn deposition policies, but sample inefficiency (millions of FEA calls) hinders large-scale 3D applications.
- II. Hybrid ML-Taguchi methods bridge data-driven and statistical design of experiments, yet they often focus on single-stage optimisation (ply angle) rather than full topology.

Manufacturing-Aware Topology Workflows

Researchers have begun embedding AFP constraints directly into surrogate-TO loops. For instance, x Zhao, Y et al propose a two-stage pipeline: (1) DNN surrogate for compliance prediction, (2) geometric post-processing enforcing minimum fibre curvature and placement head kinematics [26]. They report a manufacturable topology with only 5% loss in stiffness relative to unconstrained TO.

Key challenges:

- I. Constraint encoding: Representing AFP kinematics as differentiable constraints in ML surrogates is nontrivial.
- II. Data scarcity: Few open-source datasets exist coupling topology designs with AFP process parameters, hampering surrogate generalization.

Summary of Gaps and Opportunities

- I. Benchmark datasets: Standardized FRP-TO benchmarks (geometry + AFP parameters) are lacking.
- II. Physics-ML hybrids: Embedding constitutive anisotropy directly into surrogates (PINNs) remains under-explored.
- III. Toolchain integration: Seamless CAD/AFP export from ML-TO outputs is critical for industrial uptake.

By synthesizing these studies, we see that ML-accelerated TO in FRP composites can deliver substantial speed-ups and manufacturable designs, but faces data, integration, and generalization hurdles that warrant targeted research.

5. Application to Concrete Structures

Machine-learning (ML)-accelerated topology optimization (TO) for concrete structures remains nascent compared to composites, yet recent studies demonstrate its potential to greatly reduce computational cost, incorporate durability effects, and embed additive-manufacturing constraints. We group the literature into three areas: (a) surrogate-based TO of reinforced-concrete components, (b) ML models for durability/crack prediction, and (c) manufacturing-aware TO for 3D-printed concrete (3DCP).

Table 6. Surrogate-Based TO of Reinforced Concrete Components.

Study	ML Surrogate	Component	Key Outcome
[27]	Physics-informed neural network	RC corrosion modeling	Replaced FE model of rebar corrosion; 10 × faster with <5% error in stress fields
[28]	CNN-enhanced surrogate FEA	Prestressed beams with openings	~50% reduction in solve-time; displacement error <5%, stress error <10%

Table 6 shows that Surrogate FE models trained via neural networks enable rapid compliance evaluations of reinforced-concrete elements under complex loads, achieving order-of-magnitude speed-ups with engineering-acceptable accuracy. However, these studies typically focus on sin-

gle-member performance (e.g. beams), leaving system-level TO of frames and slabs underexplored. Moreover, integration of surrogate uncertainty quantification into constraint handling remains limited.

Table 7. ML Surrogates for Durability and Crack Prediction.

Study	ML Model	Application	Key Outcome
[29]	Random forest, ensemble methods	Compressive strength prediction	Achieved $R \geq 0.90$ in strength estimation; informs TO material models
[31]	PINN-based surrogate	Crack - initiation forecasting	Matched high-fidelity FE crack patterns with <3% error; guides damage-aware TO

Durability and cracking critically affect concrete TO, since quasi-brittle failure modes must be anticipated in the design stage. Ensemble surrogates predict compressive strength from mix proportions with high fidelity, enabling TO objectives that couple stiffness and durability. Physics-informed neural

networks (PINNs) further allow direct emulation of crack initiation in a surrogate TO loop, supporting reliability-based constraints with minimal extra cost. Yet, multi-physics coupling (e.g. shrinkage, thermal effects) within TO remains an open challenge.

Table 8. Manufacturing-Aware TO for 3D-Printed Concrete.

Study	TO Method + ML	3DCP Context	Key Outcome
[32]	Density - based TO + CNN post-processing	Internal topology of 3DCP	Up to 40% material saving while preserving external envelope
[33]	BESO with manufacturing constraints	Layer-resolution, printability	Enforced nozzle-path constraints; produced feasible toolpaths with <5% stiffness loss

Embedding layer-by-layer deposition constraints into TO be essential for 3DCP. Yin et al. demonstrated an ML-accelerated workflow that optimizes internal infill topology, then refines via a CNN to respect print-layer continuity, yielding substantial material savings without sacrificing strength [23]. Bi-directional evolutionary structural optimization (BESO) augmented with ML-informed constraint

surrogates enforces nozzle-kinematics and layer-resolution limits, producing directly printable designs [30]. Scalability to large - scale structural elements and multi-material printing are promising future avenues.

Key Challenges & Opportunities

- I. System-level TO: Extending surrogate-based methods from single members to multi-story frames and slabs

under combined loadings.

- II. Multi-physics coupling: Integrating shrinkage, thermal, and moisture effects into ML surrogates for durability-aware TO.
- III. Benchmark datasets: Public repositories of FE-simulated concrete TO cases (mix, reinforcement, boundary conditions) to standardize comparisons.
- IV. Toolchain integration: Seamless export of topology-optimized layouts into concrete-3D-printing slicers and reinforcement detailing software.

By synthesizing these emerging studies, we see ML-accelerated TO for concrete offers significant speed-ups and new capabilities (durability, printability), yet demands further work on multi-physics, system integration, and open benchmarks.

6. Comparative Analysis of ML-Accelerated Topology Optimization in FRP Composites vs Concrete Structures

This section provides a critical comparative evaluation of the machine learning (ML)-assisted topology optimization (TO) methodologies applied to fibre-reinforced polymer (FRP) composites and concrete structures. The analysis considers five key dimensions: material behaviour, data availability, ML-model integration, manufacturability, and current research maturity.

Table 9. Material Behaviour and Structural Complexity.

Aspect	FRP Composites	Concrete Structures
Material Type	Anisotropic, linear elastic	Quasi-brittle, nonlinear, heterogeneous
Failure Mechanism	Fibre/matrix debonding, delamination	Cracking, crushing, corrosion
Topology-Sensitivity	Highly dependent on fibre orientation	Strongly influenced by reinforcement placement and cracking path
Challenge	Embedding anisotropic mechanics in ML surrogate	Capturing nonlinear cracking in surrogate models

Insight: FRP TO must prioritize fibre path optimization and manufacturing constraints, while concrete TO require embedding nonlinear fracture and serviceability considerations in ML models.

Table 10. Data and Simulation Requirements.

Aspect	FRP Composites	Concrete Structures
Simulation Intensity	High due to anisotropic analysis	Extremely high for nonlinear cracking & durability simulations
Training Data Availability	Moderate (especially for aerospace composites)	Limited, especially for durability and cracking simulations
Benchmark Datasets	Few public sets; mostly proprietary	Rare or unavailable for structural TO

As shown in [table 10](#) both FRP composites and concrete structures domains lack comprehensive benchmark datasets. For concrete, the multi-physics nature (e.g., moisture, corrosion) amplifies the challenge. The ML community would benefit from domain-specific open-source datasets.

Table 11. Machine Learning Integration.

ML Use Case	FRP Composites	Concrete Structures
Surrogates Used	Deep neural networks (DNN), active learning, RL	DNN, PINNs, ensemble models
Objective Functions	Compliance, stiffness, fibre orientation	Compliance, crack probability, durability index

ML Use Case	FRP Composites	Concrete Structures
Constraint Handling	AFP constraints, fibre curvature	Printability, layer adhesion, durability
Innovation	Reinforcement learning for fibre path generation	Physics-informed crack prediction in TO

Insight: FRP research is leading in integrating advanced ML techniques (e.g., RL), whereas concrete TO is beginning to incorporate PINNs for durability and crack modeling.

Table 12. *Manufacturability and Toolchain Integration.*

Criterion	FRP Composites	Concrete Structures
Manufacturing Method	Automated fibre placement (AFP), filament winding	3D-printed concrete, formwork-less casting
ML-Manufacturing Link	ML-generated paths feed AFP toolpaths	CNNs ensure 3DCP layer-wise constructability
Export Compatibility	Limited CAD integration; custom AFP translators needed	Poor toolchain link to 3DCP slicers or rebar detailing

Insight: Both fields struggle with integration of optimized topologies into practical manufacturing pipelines, although FRP workflows show slightly better progress.

Table 13. *Research Maturity and Scalability.*

Criterion	FRP Composites	Concrete Structures
TRL (Tech Readiness Level)	5-7 (lab to pilot-scale)	3-5 (conceptual to lab validation)
Industrial Adoption	Growing interest in aerospace and automotive	Mostly academic/prototype scale
Scalability	Moderate (complex fibre placement still a barrier)	Limited by large-scale 3DCP reliability and reinforcement handling

Insight: ML-accelerated TO in FRPs is closer to real-world adoption, especially in aerospace sectors. Concrete systems, while promising, require significant advances in hardware and process reliability to scale.

Table 14. *Opportunities and Challenges.*

Dimension	FRP Composites	Concrete Structures
Biggest Opportunity	RL-based fibre steering for lightweighting	Crack-aware ML surrogates for durability-aware TO
Biggest Challenge	Embedding anisotropy constraints into ML models	Data scarcity and multi-physics modeling
Key Research Need	Seamless AFP + TO toolchain	ML-integrated multi-physics TO for real-scale elements

In conclusion, Both FRP composites and concrete structures benefit significantly from ML-accelerated topology optimization, but the path forward diverges:

- I. FRP composites: The focus should be on enhancing RL-based design generation, embedding fibre con-

straints directly in differentiable frameworks, and ensuring CAD/AFP compatibility.

- II. Concrete structures: Future work should prioritize the development of multi-physics ML surrogates that capture long-term behaviour (e.g., cracking, shrinkage),

and integrate them into automated 3DCP-compatible optimization workflows.

7. Challenges and Limitations in ML-Accelerated Topology Optimization of FRP Composites and Concrete Structures

Despite the promise of machine learning (ML) in accelerating topology optimization (TO) for fibre-reinforced polymer (FRP) composites and concrete structures, significant challenges and limitations persist across computational, methodological, and practical domains. These obstacles must be critically assessed to guide future research and foster realistic deployment in engineering practice.

7.1. Data Scarcity and Generalization

- I. **Sparse and Task-Specific Datasets:** The effectiveness of supervised learning models in TO rely heavily on large-scale, high-quality datasets. However, datasets specific to FRP anisotropic behavior or concrete cracking evolution are scarce or proprietary.
- II. **Lack of Generalization:** ML models often overfit to limit training geometries or loading cases, resulting in poor generalization to new structural scenarios, materials, or boundary conditions.

Example: In concrete structures, models trained on small-scale specimens often fail when applied to large-scale or irregular geometries due to unmodeled heterogeneity.

7.2. Complexity of Multi-Physics and Multi-Scale Modeling

- I. **Coupled Behavior:** Both FRPs and concrete exhibit complex, often coupled behavior involving damage, cracking, fatigue, moisture ingress, and thermal effects.
- II. **Multi-Scale Challenges:** Accurate TO of FRPs requires capturing fiber-matrix interactions at the microscale, while concrete demands meso- and macro-scale fracture modelling.

Limitation: Current ML surrogates rarely integrate multi-physics constraints or multi-scale inputs, leading to reduced physical fidelity.

7.3. Black-Box Nature of ML Models

- I. **Lack of Interpretability:** Deep learning models used in TO (e.g., CNNs, GANs, DNNs) are often black boxes, which makes it difficult for engineers to interpret decisions, verify safety, or ensure regulatory compliance.

- II. **Uncertainty Quantification:** Many ML-driven TO frameworks lack robust mechanisms for quantifying prediction uncertainty, increasing the risk in safety-critical applications such as bridges or aircraft.

Challenge: Without explainability and uncertainty analysis, ML-based TO may remain confined to academic demonstrations.

7.4. Manufacturing Constraints and Real-World Integration

- I. **Unrealizable Topologies:** ML-optimized topologies may not adhere to manufacturing constraints such as minimum feature size, fibre turning radius (for AFP in FRP), or layer bonding strength (in 3D-printed concrete).
- II. **Limited Toolchain Compatibility:** A major bottleneck is the lack of seamless integration from ML models to CAD/CAM environments, finite element tools, or robotic fabrication interfaces.

Example: TO of FRP panels may suggest fibre paths that violate curvature or deposition limits of AFP robots.

7.5. Computational Cost and Training Instability

- I. **Expensive Simulations for Training:** Generating simulation data for anisotropic FRPs or cracking concrete is computationally expensive, especially when using high-fidelity FEM or X-FEM models for training.
- II. **Training Instabilities:** Adversarial models like GANs or reinforcement learning frameworks may suffer from non-convergence, mode collapse, or instability under dynamic reward systems.

Illustration: In reinforcement learning for TO, poorly shaped reward functions can trap the agent in suboptimal design regions.

7.6. Standardization and Benchmarking

- I. **No Standard Evaluation Protocols:** The absence of standardized datasets, benchmarks, or evaluation metrics makes it difficult to compare ML-based TO methods across research groups or materials.
- II. **Reproducibility Crisis:** Many published works do not provide code or models, making it hard to validate results or build upon existing studies.

Observation: There is a growing call for community benchmarks akin to MNIST or ImageNet, tailored to structural TO.

Table 15. Summary of Key Challenges.

Challenge Category	Description	Affected Domain
Data Availability	Limited datasets for FRP anisotropy and concrete fracture	Both
Multi-Physics Modeling	Difficult to capture coupled effects (e.g., cracking, fibre interaction)	Both
Interpretability	Models behave as black boxes with limited transparency	Both
Manufacturability	Output geometries may violate production constraints	Both
Computational Burden	High-fidelity FEM training simulations are time-consuming	Concrete (mainly)
Toolchain Integration	Poor linkage between ML outputs and CAD/FEM tools	FRP (mainly)
Standardization Gap	Absence of shared benchmarks or reproducibility protocols	Both

7.7. Summary and Outlook

To bridge the gap between research and practical application of ML-accelerated TO, future research should:

- I. Develop open-source datasets and benchmarks specific to TO of FRPs and concrete.
- II. Focus on physics-informed ML to embed constitutive knowledge into learning models.
- III. Incorporate uncertainty quantification to enable safer and more interpretable decisions.
- IV. Work toward toolchain interoperability, ensuring that TO outputs are manufacturable and verifiable.

These strategies will help transform ML-accelerated TO from promising prototypes into robust, industry-ready systems.

8. Future Directions for Machine Learning-Accelerated Topology Optimization of FRP Composites and Concrete Structures

Building upon the current limitations and progress, this part outlines strategic future research directions aimed at advancing the practical adoption, reliability, and performance of ML-accelerated topology optimization (TO) for fibre-reinforced polymer (FRP) composites and concrete structures. These directions consider technological, methodological, and systemic developments.

8.1. Development of Physics-Informed Machine Learning (PIML) Models

- I. Rationale: Purely data-driven models often neglect physical laws, leading to unrealistic or unfeasible designs. Embedding governing equations into ML frameworks (e.g., via Physics-Informed Neural Net-

works, or PINNs) can bridge this gap [1].

II. Application:

- a) For FRPs: Embed anisotropic elasticity and fibre-matrix interaction laws into learning frameworks.
- b) For concrete: Integrate fracture mechanics, shrinkage, and corrosion models.

III. Expected Impact: Improved generalizability, reliability, and physical fidelity of surrogate models.

8.2. Surrogate Models with Uncertainty Quantification (UQ)

- I. Challenge: Existing ML surrogates lack confidence estimation, which is critical in safety-sensitive domains.
- II. Future Path: Develop Bayesian neural networks, Gaussian Process (GP) regressors, and ensemble methods to quantify uncertainty.
- III. Application: Enable risk-informed decision-making in critical structures such as bridges or aerospace panels.
- IV. Outcome: Higher trust in ML-predicted topologies for structural certification and design codes.

8.3. Reinforcement Learning (RL) for Sequential Design Optimization

- I. Potential: Reinforcement learning offers a way to generate optimal topologies by learning sequential design policies rather than direct mappings.
- II. Direction:
 - a) Apply multi-agent RL to co-optimize structural form and fibre orientation in FRPs.
 - b) Use reward-shaping to incorporate constructability and performance metrics for 3D-printed concrete.
- III. Impact: Real-time adaptive topology design that evolves with constraints and environmental changes.

8.4. Integration with Generative Design and CAD Environments

- I. Need: Topologies generated through ML often require post-processing or manual remodelling to be transferred to CAD/CAE tools.
- II. Future Focus:
 - a) Direct coupling of ML models with generative design platforms like Autodesk Fusion 360 or Rhino/Grasshopper.
 - b) Use of implicit representations (e.g., signed distance functions) to generate manufacturable geometries.
- III. Outcome: Smooth digital workflow from optimization to fabrication.

8.5. Development of Open-Access Multi-Material Benchmark Datasets

- I. Gap: Lack of standardized, multi-physics datasets for TO of FRPs and concrete.
- II. Initiative:
 - a) Launch collaborative datasets containing FEM simulations, material properties, and experimental validations.
 - b) Include variations in load cases, geometries, and degradation conditions.
- III. Impact: Enhanced reproducibility, benchmarking, and

transfer learning across materials and scales.

8.6. ML-Driven Real-Time Structural Adaptation

- I. Vision: Move from offline TO to online, real-time adaptation of structures based on changing conditions.
- II. Strategy:
 - a) Incorporate sensor data (e.g., SHM) into ML models for in-situ learning.
 - b) Adapt fibre paths or 3D-printed geometry during fabrication based on real-time feedback.
- III. Use Case: Smart bridges or shelters that adapt geometry to loading, wind, or seismic conditions.

8.7. Holistic Sustainability-Integrated TO

- I. Trend: Move toward integrating environmental and lifecycle metrics into topology generation.
- II. Method:
 - a) Add sustainability objectives (e.g., embodied carbon, recyclability) into the optimization loss function.
 - b) Use ML to predict sustainability impact alongside performance metrics.
- III. Goal: Balance strength, weight, cost, and environmental performance in TO.

Table 16. Summary of Future Directions.

Research Direction	Key Contribution	Expected Benefit
Physics-Informed ML (PIML)	Embed governing laws into ML surrogates	Enhanced physical consistency
Uncertainty Quantification	Confidence-aware predictions	Risk-informed design
Reinforcement Learning (RL)	Sequential decision-making in TO	Dynamic adaptability
Generative Design Integration	ML-to-CAD workflow integration	Fabrication-readiness
Benchmark Dataset Development	Public multi-material TO datasets	Standardization and reproducibility
Real-Time Structural Adaptation	SHM-based adaptive manufacturing	Smart, resilient infrastructure
Sustainability-Integrated Optimization	Green-aware optimization objectives	Sustainable structural design

8.8. Final Perspective

The intersection of machine learning and topology optimization represents a transformative shift in structural engineering, offering unprecedented speed, customization, and integration across disciplines. However, realizing this vision requires a collaborative push toward:

- I. Interdisciplinary collaboration between data scientists, material scientists, and structural engineers.
- II. Ethical AI and transparency to ensure safety, fairness,

and auditability in engineering applications.

- III. Policy and standardization frameworks that adapt to new AI-driven design tools.

With these directions, ML-accelerated TO can move from theoretical promise to widespread structural innovation.

9. Conclusions

This critical review has explored the transformative potential of machine learning (ML)-accelerated topology optimi-

zation (TO) in the design and performance enhancement of fibre-reinforced polymer (FRP) composites and concrete structures. As the built environment faces rising demands for material efficiency, resilience, and sustainability, ML-enabled TO emerges as a vital innovation frontier in structural engineering.

Key Takeaways

- I. Integration of ML with TO significantly reduces computational costs and enables rapid design iterations compared to traditional gradient-based or heuristic optimization methods.
- II. The application of ML-accelerated TO to FRP composites addresses the complexity of anisotropic behavior and fibre orientation, optimizing performance-to-weight ratios while enabling advanced manufacturing methods like automated fibre placement (AFP).
- III. In concrete structures, ML-driven TO aids in optimizing complex geometries, enhancing crack resistance, and facilitating digital fabrication methods such as 3D concrete printing, contributing to structural efficiency and material conservation.
- IV. Despite these benefits, critical challenges remain-ranging from data scarcity and generalizability issues to black-box modeling concerns, fabrication constraints, and lack of standardized benchmarks.
- V. A comparative analysis of approaches across FRP and concrete structures reveals divergence in optimization goals, modelling complexity, and ML strategies, highlighting the need for material-specific TO workflows.

Research and Practical Outlook

Looking forward, the next generation of ML-accelerated TO frameworks must:

- I. Embrace physics-informed models and uncertainty quantification to enhance trust and robustness.
- II. Incorporate real-time data from sensors for adaptive and responsive topology updates during construction or operation.
- III. Establish open-access benchmarks and interoperable toolchains to improve reproducibility, adoption, and cross-disciplinary collaboration.
- IV. Embed sustainability and life-cycle metrics as integral optimization objectives, supporting circular economy principles in structural design.

Generally speaking, ML-accelerated topology optimization has the potential to completely transform the way we think about, design, and construct both large civil-scale concrete structures and lightweight aerospace-grade fibre reinforced polymers (FRPs) as structural materials and digital technologies come together. However, in order to go from prototype to practice, the discipline has to use engineering-informed deployment techniques, open research collaboration, and methodological rigour to remove existing barriers. This hybrid domain has the potential to significantly influence the development of intelligent and sustainable infrastructure in

the future through such initiatives.

Abbreviations

AI	Artificial Intelligence
FRP	Fibre-reinforced Polymer
ML	Machine Learning
FEA	Finite Element Analysis
3DCP	Three-dimensional Concrete Printing
DTs	Digital Twins
ML	Machine Learning
ANNs	Artificial Neural Networks
GAs	Genetic Algorithms
RL	Reinforcement Learning
TO	Topology Optimization
DNNs	Deep Neural Networks
GPR	Gaussian-Process Regression

Data Access Statement and Material Availability

The adequate resources of this article are publicly accessible.

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Conflicts of Interest

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Biography



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