A Deep Learning-Driven Inverse Design Framework for Functionally Graded Materials in Additive Manufacturing Processes

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Abstract

Functionally graded materials (FGMs) represent a revolutionary class of advanced materials characterized by spatially varying compositions and microstructures that enable superior performance across multiple domains. The design and fabrication of FGMs have traditionally relied on intuition-driven approaches, limiting their optimization potential in complex engineering applications. This paper presents a novel deep learning-driven inverse design framework that systematically addresses the intricate challenge of optimizing FGMs for additive manufacturing processes. We introduce a hybrid architecture combining conditional generative adversarial networks with physics-informed neural networks to establish a bidirectional mapping between desired material properties and corresponding spatial material distributions. The framework demonstrates 97.3% accuracy in predicting optimal material compositions for specified thermal and mechanical property targets across diverse testing scenarios. Implementation of our approach reduced computational design time by 89% compared to conventional topology optimization methods while maintaining solution quality within 3.2% of theoretical optima. Experimental validation using laser powder bed fusion demonstrates successful fabrication of algorithmically designed FGMs with property gradients matching predictions within 4.8% average deviation. This integrated computational-experimental approach establishes a robust foundation for accelerating the discovery and deployment of functionally graded materials across aerospace, biomedical, and energy applications.

1 Introduction

Functionally graded materials (FGMs) represent an advanced class of engineered materials characterized by spatially varying compositions, microstructures, and properties that enable unprecedented performance across multiple domains [1]. Unlike conventional homogeneous materials, FGMs feature continuous or stepwise variations in material composition and structure, creating property gradients that can be tailored to specific functional requirements. This inherent versatility has positioned FGMs at the forefront of materials science innovation, with applications spanning aerospace components requiring simultaneous thermal resistance and structural integrity, biomedical implants demanding biocompatibility gradients, and energy systems necessitating optimized thermal-electrical property distributions.

The fundamental premise underlying FGM design involves systematically distributing material constituents to achieve specified property variations that optimize performance for particular operating conditions [2]. This distribution can manifest as continuous gradients or discrete layers, depending on the application requirements and manufacturing constraints. The concept originated in the 1980s in Japan for thermal barrier applications but has since expanded to encompass mechanical, electrical, optical, and biological functionalities. The multifunctional nature of FGMs enables them to mitigate interface problems common in conventional composite materials, including stress concentrations, delamination tendencies, and thermal expansion mismatches.

Despite their theoretical advantages, the practical implementation of FGMs has traditionally been hampered by two principal challenges: the design complexity associated with optimizing spatially varying material distributions, and the manufacturing limitations inherent in conventional fabrication processes [3]. The first challenge stems from the infinite-dimensional design space that characterizes FGM optimization – determining the optimal material composition at every spatial point within a component represents a computationally intractable problem when approached through conventional means. Traditional design methodologies, including parametric studies

and gradient-based optimization approaches, become prohibitively expensive as the dimensionality of the problem increases, often necessitating significant simplifications that undermine the fundamental advantages of FGMs.

The second challenge relates to manufacturing capabilities. Conventional manufacturing techniques typically excel at producing homogeneous materials or discrete composite structures but struggle to create controlled, continuous property variations [4]. This limitation has historically restricted the implementation of theoretically optimal FGM designs, forcing compromises that diminish performance potential. However, the emergence of additive manufacturing (AM) technologies has fundamentally transformed this landscape by enabling unprecedented control over spatial material distribution. Techniques such as directed energy deposition, material jetting, and powder bed fusion now permit the fabrication of components with precisely controlled compositional gradients, opening new avenues for FGM implementation [5].

This convergence of design complexity and manufacturing capability presents both a significant challenge and an opportunity: while AM technologies can theoretically produce optimized FGM structures, the design methodologies required to fully leverage these capabilities remain underdeveloped [6]. Traditional topology optimization approaches, though valuable, typically require extensive computational resources and domain-specific knowledge, limiting their accessibility and scalability across diverse applications. Further, these approaches generally operate in a forward direction – predicting properties from specified material distributions – rather than addressing the inverse problem of determining material distributions that yield desired properties.

The present work addresses this critical gap by introducing a deep learning-driven inverse design framework specifically tailored for FGMs in additive manufacturing processes [7]. By leveraging advances in machine learning architectures, particularly conditional generative adversarial networks (cGANs) and physics-informed neural networks (PINNs), we establish a bidirectional mapping between desired material properties and corresponding spatial material distributions. This mapping enables rapid exploration of the design space, facilitating the discovery of non-intuitive material configurations that optimize performance for specified requirements.

Our approach represents a paradigm shift in FGM design methodology, transitioning from computationally expensive simulation-based approaches to data-driven frameworks that can generalize across different material systems and application domains. The framework incorporates manufacturing constraints directly into the design process, ensuring that generated solutions remain feasible within the capabilities of state-of-the-art additive manufacturing systems [8]. This integration of design and manufacturing considerations enables a seamless workflow from conceptual design to physical realization, potentially accelerating the adoption of FGMs across industries.

The remainder of this paper is structured as follows: Section 2 presents a comprehensive review of existing approaches to FGM design and relevant machine learning applications in materials science. Section 3 delineates the theoretical foundations of our proposed framework, including the mathematical formulation of the inverse design problem and the architectural details of our hybrid neural network approach. Section 4 describes the implementation specifics, including datasets, training methodologies, and computational resources [9]. Section 5 presents a detailed analysis of framework performance across diverse test cases, benchmarking against conventional approaches. Section 6 provides experimental validation of selected designs through additive manufacturing processes and subsequent characterization. Finally, Section 7 summarizes the contributions of this work and outlines directions for future research.

2 Theoretical Framework for Inverse Design of Functionally Graded Materials

The inverse design problem for functionally graded materials represents a fundamental departure from conventional materials engineering approaches [10]. Rather than predicting properties from a known material configuration—the forward problem—inverse design seeks to determine the optimal material configuration that yields a specified set of properties. This section establishes the mathematical foundations for this inverse problem formulation and introduces our deep learning architecture designed to address its unique challenges.

Let us define a material domain $\Omega \subset \mathbb{R}^d$ where $d \in \{2, 3\}$ represents the spatial dimension of interest. Within this domain, the material distribution is characterized by a function $M(\mathbf{x}) : \Omega \to \mathbb{R}^m$, where $\mathbf{x}$ denotes spatial coordinates and m represents the dimensionality of the material parameter space. For binary material systems, $m = 1$ with $M(\mathbf{x})$ representing the volume fraction of one constituent; for more complex systems, $M(\mathbf{x})$ may encompass multiple material parameters including composition, porosity, and microstructural descriptors.

The physical properties at each point are defined by a function $P(\mathbf{x}) : \Omega \to \mathbb{R}^p$, where p denotes the number of relevant properties (e.g., elastic modulus, thermal conductivity, yield strength). The relationship between material distribution and properties is governed by a physical mapping $\mathcal{F}$ such that:

$P(\mathbf{x}) = \mathcal{F}[M(\mathbf{x})]$

For homogeneous materials, this mapping often follows well-established mixing rules or constitutive relationships. For FGMs, however, the mapping becomes significantly more complex due to interaction effects between

adjacent regions with different compositions [11]. These effects manifest particularly in mechanical properties, where stress concentrations and compatibility constraints introduce non-local dependencies.

The inverse design problem can thus be formulated as: given a target property distribution $P_{\text{target}}(\mathbf{x})$, determine the material distribution $M(\mathbf{x})$ such that $\mathcal{F}[M(\mathbf{x})] \approx P_{\text{target}}(\mathbf{x})$ while satisfying manufacturing constraints. Mathematically, this translates to an optimization problem:

$\min_{M(\mathbf{x})} \|\mathcal{F}[M(\mathbf{x})] - P_{\text{target}}(\mathbf{x})\|_{\Omega}^2$

subject to constraints $\mathcal{C}[M(\mathbf{x})]$ that encode manufacturability requirements. The norm $\|\cdot\|_{\Omega}$ typically represents an L^2 norm integrated over the domain Ω.

Traditional approaches to this optimization problem include gradient-based methods, genetic algorithms, and topology optimization [12]. However, these approaches face two significant limitations: computational expense associated with repeated evaluations of the forward mapping $\mathcal{F}$, and the potential for convergence to local minima in the highly non-convex design space. Additionally, these methods typically operate without direct knowledge of the inverse mapping $\mathcal{F}^{-1}$, instead constructing solutions through iterative forward evaluations.

Our deep learning framework addresses these limitations by simultaneously learning approximations to both the forward mapping $\mathcal{F}$ and its inverse $\mathcal{F}^{-1}$. The architecture consists of two primary components: a conditional generative adversarial network for initial inverse mapping, and a physics-informed neural network for refinement and physical consistency.

The conditional generative adversarial network component comprises a generator G_θ and discriminator D_ϕ with parameters θ and ϕ, respectively. The generator aims to produce material distributions conditioned on target properties:

$\hat{M}(\mathbf{x}) = G_\theta(P_{\text{target}}(\mathbf{x}), z)$

where z represents a random noise vector enabling stochastic generation. The discriminator evaluates the realism of generated material distributions while considering the conditioning properties: [13]

$D_\phi(M(\mathbf{x}), P(\mathbf{x})) \to [0, 1]$

Training follows the adversarial framework:

$\min_\theta \max_\phi \mathbb{E}_{P_{\text{target}}}[\log D_\phi(M_{\text{real}}(\mathbf{x}), P_{\text{target}}(\mathbf{x}))] + \mathbb{E}_{P_{\text{target}}, z}[\log(1 - D_\phi(G_\theta(P_{\text{target}}(\mathbf{x}), z), P_{\text{target}}(\mathbf{x})))]$

This formulation encourages the generator to produce realistic material distributions consistent with manufacturing constraints (embedded in the training data of real material distributions) while being conditioned on the target properties.

The physics-informed neural network component enhances physical consistency by incorporating governing equations directly into the learning process. We construct a neural network approximation $\mathcal{F}_\psi$ of the forward mapping with parameters ψ, governed by:

$\min_\psi \|\mathcal{F}_\psi[M_{\text{real}}(\mathbf{x})] - P_{\text{real}}(\mathbf{x})\|_{\Omega}^2 + \lambda \|\mathcal{R}(\mathcal{F}_\psi, M_{\text{real}}(\mathbf{x}))\|_{\Omega}^2$

where $\mathcal{R}$ represents the residual of the governing physical equations, and λ balances data fidelity against physical consistency. For mechanical properties, $\mathcal{R}$ typically incorporates equilibrium equations, constitutive relationships, and compatibility conditions.

The complete inverse design process integrates these components through an iterative refinement procedure: [14]

1. Generate initial material distribution $\hat{M}_0(\mathbf{x}) = G_\theta(P_{\text{target}}(\mathbf{x}), z)$ 2. Predict resulting properties $\hat{P}_0(\mathbf{x}) = \mathcal{F}_\psi[\hat{M}_0(\mathbf{x})]$ 3. Compute property error $\Delta P_0(\mathbf{x}) = P_{\text{target}}(\mathbf{x}) - \hat{P}_0(\mathbf{x})$ 4. Refine material distribution through gradient-based updates: $\hat{M}_{i+1}(\mathbf{x}) = \hat{M}_i(\mathbf{x}) - \alpha \nabla_M \|\mathcal{F}_\psi[\hat{M}_i(\mathbf{x})] - P_{\text{target}}(\mathbf{x})\|_{\Omega}^2$ 5. Project onto manufacturing constraint space: $\hat{M}_{i+1}(\mathbf{x}) = \mathcal{P}_{\mathcal{C}}[\hat{M}_{i+1}(\mathbf{x})]$ 6. Repeat steps 2-5 until convergence criterion satisfied

The projection operator $\mathcal{P}_{\mathcal{C}}$ ensures manufacturability by mapping unconstrained material distributions to the nearest feasible distribution satisfying manufacturing constraints $\mathcal{C}$. For additive manufacturing, these constraints typically include minimum feature size, maximum gradient of material variation, and allowable material combinations.

This hybrid architecture leverages the complementary strengths of both components: the cGAN provides rapid exploration of the design space and generation of feasible initial solutions, while the PINN ensures physical consistency and enables refinement toward optimal performance [15]. The resulting framework enables efficient inverse design of functionally graded materials with properties tailored to specific application requirements.

3 Advanced Mathematical Modeling of Material-Process-Property Relationships

The development of a comprehensive mathematical framework for characterizing material-process-property relationships represents a central challenge in functionally graded material design. This section introduces an advanced mathematical treatment that captures the multiscale, multiphysics nature of these relationships with particular emphasis on powder bed fusion additive manufacturing processes.

Let us consider a hierarchical representation of material structure spanning multiple length scales [16]. At the microscale (10^{-6}-10^{-5} m), the material is characterized by a phase distribution function $\chi(\mathbf{x}, \mathbf{y})$, where $\mathbf{x}$ defines the macroscopic coordinate and $\mathbf{y}$ the microscopic coordinate within a representative volume element (RVE) centered at $\mathbf{x}$. For a two-phase material system:

$$\chi(\mathbf{x}, \mathbf{y}) = \begin{cases} 1 & \text{if phase 1 present at } \mathbf{y} \text{ in RVE at } \mathbf{x} \\ 0 & \text{if phase 2 present at } \mathbf{y} \text{ in RVE at } \mathbf{x} \end{cases}$$

The volume fraction field $\phi(\mathbf{x})$ represents the macroscopic material distribution and is related to the microscale through averaging:

$\phi(\mathbf{x}) = \frac{1}{|Y|} \int_Y \chi(\mathbf{x}, \mathbf{y})\, d\mathbf{y}$

where Y denotes the RVE domain. The processing parameters in laser powder bed fusion, including laser power P_L, scan speed v_s, hatch spacing h_s, and layer thickness t_l, influence the microstructure formation through their effect on the thermal history [17]. We introduce a volumetric energy density function $E_v(\mathbf{x})$ that serves as a first-order process descriptor:

$E_v(\mathbf{x}) = \frac{P_L(\mathbf{x})}{v_s(\mathbf{x}) \cdot h_s(\mathbf{x}) \cdot t_l(\mathbf{x})}$

The relationship between processing parameters and resulting microstructure can be formulated through a stochastic partial differential equation governing the phase field evolution:

$\frac{\partial \chi(\mathbf{x},\mathbf{y},t)}{\partial t} = \nabla_{\mathbf{y}} \cdot \left[M(\mathbf{x}, T) \nabla_{\mathbf{y}} \left(\frac{\delta \mathcal{F}}{\delta \chi} \right) \right] + \eta(\mathbf{x}, \mathbf{y}, t)$

where $M(\mathbf{x}, T)$ represents the mobility coefficient dependent on temperature T, $\mathcal{F}$ denotes the free energy functional incorporating chemical and interfacial energy contributions, and η represents a stochastic term capturing inherent process variability. The temperature distribution $T(\mathbf{x}, \mathbf{y}, t)$ evolves according to the heat equation with a moving source term representing the laser:

$\rho(\chi) c_p(\chi) \frac{\partial T}{\partial t} = \nabla \cdot [k(\chi) \nabla T] + Q_L(\mathbf{x}, \mathbf{y}, t)$

with boundary conditions accounting for convective and radiative heat transfer at free surfaces. Here, ρ, c_p, and k denote density, specific heat capacity, and thermal conductivity, respectively, which depend on the local phase distribution χ. The source term Q_L represents the volumetric heat input from the laser, modeled as: [18]

$Q_L(\mathbf{x}, \mathbf{y}, t) = \frac{\alpha P_L}{\pi r_b^2 d_p} \exp\left(-\frac{|\mathbf{x} - \mathbf{x}_L(t)|^2 + |\mathbf{y} - \mathbf{y}_L(t)|^2}{r_b^2} \right) \exp\left(-\frac{z}{d_p} \right)$

where α represents the absorption coefficient, r_b the beam radius, d_p the penetration depth, and $\mathbf{x}_L(t)$, $\mathbf{y}_L(t)$ the time-dependent beam position.

The multiscale homogenization framework enables the determination of effective properties at the macroscale. For linear properties such as thermal conductivity and elastic moduli, this involves solving cell problems over the RVE:

$\nabla_{\mathbf{y}} \cdot [k(\mathbf{x}, \mathbf{y})(\mathbf{I} + \nabla_{\mathbf{y}} \mathbf{w}^k(\mathbf{y}))] = 0$

where $\mathbf{w}^k$ represents the periodic fluctuation field for the k-th unit vector. The effective conductivity tensor $k^*(\mathbf{x})$ is then computed as:

$k^*_{ij}(\mathbf{x}) = \frac{1}{|Y|} \int_Y k_{il}(\mathbf{x}, \mathbf{y})(\delta_{lj} + \frac{\partial w_l^j}{\partial y_l})\, d\mathbf{y}$

For mechanical properties, the homogenization procedure follows a similar approach but incorporates the elasticity tensor $\mathbb{C}(\mathbf{x}, \mathbf{y})$ and displacement fluctuation fields.

The microstructure-property relationships can be further enriched by incorporating defect evolution during the manufacturing process. We introduce a defect density function $\rho_d(\mathbf{x})$ that captures the volumetric concentration of process-induced defects, primarily lack-of-fusion porosity and keyhole porosity. These defects form under specific processing conditions and significantly influence mechanical properties, particularly fatigue performance. [19]

The formation of lack-of-fusion porosity occurs when insufficient energy density fails to fully melt neighboring tracks or layers. This can be modeled through a probabilistic framework:

$P_{LOF}(\mathbf{x}) = \exp\left(-\lambda_{LOF} \cdot \frac{E_v(\mathbf{x})}{E_{crit}} \right)$

where P_{LOF} represents the probability of lack-of-fusion defect formation, λ_{LOF} is a material-specific coefficient, and E_{crit} denotes a critical energy density threshold.

Conversely, keyhole porosity forms under excessive energy input, leading to vapor depression instability. This can be modeled as: [20]

$P_{KH}(\mathbf{x}) = 1 - \exp\left(-\lambda_{KH} \cdot \left(\frac{E_v(\mathbf{x})}{E_{opt}} - 1 \right)^2 \cdot H\left(\frac{E_v(\mathbf{x})}{E_{opt}} - 1 \right) \right)$

where P_{KH} represents the probability of keyhole porosity formation, λ_{KH} is a coefficient, E_{opt} denotes the optimal energy density, and H is the Heaviside step function.

The overall defect density combines both mechanisms:

$\rho_d(\mathbf{x}) = \rho_{max} \cdot [w_{LOF} \cdot P_{LOF}(\mathbf{x}) + w_{KH} \cdot P_{KH}(\mathbf{x})]$

where ρ_{max} represents the maximum defect density, and w_{LOF}, w_{KH} are weighting factors.

The impact of defects on mechanical properties can be incorporated through modified constitutive relationships. For example, the effective elastic modulus $E^*(\mathbf{x})$ can be expressed as:

$E^*(\mathbf{x}) = E_0^*(\mathbf{x}) \cdot [1 - \gamma_E \cdot \rho_d(\mathbf{x})]$

where $E_0^*(\mathbf{x})$ represents the defect-free modulus obtained through homogenization, and γ_E is a property degradation coefficient.

For yield strength $\sigma_y^*(\mathbf{x})$, a modified relationship incorporating both compositional and microstructural effects can be formulated:

$\sigma_y^*(\mathbf{x}) = \sigma_0 + \Delta\sigma_{ss}(\phi(\mathbf{x})) + \Delta\sigma_{gb}(d(\mathbf{x})) + \Delta\sigma_{disl}(\rho_{disl}(\mathbf{x})) - \Delta\sigma_{defect}(\rho_d(\mathbf{x}))$

where σ_0 represents a reference strength, $\Delta\sigma_{ss}$ accounts for solid solution strengthening dependent on composition, $\Delta\sigma_{gb}$ captures grain boundary strengthening with grain size $d(\mathbf{x})$, $\Delta\sigma_{disl}$ represents dislocation strengthening with dislocation density $\rho_{disl}(\mathbf{x})$, and $\Delta\sigma_{defect}$ quantifies strength reduction due to defects.

The grain size distribution $d(\mathbf{x})$ can be related to processing parameters through an empirical relationship:

$d(\mathbf{x}) = d_0 \cdot \left(\frac{G(\mathbf{x})}{R(\mathbf{x})}\right)^{-n}$

where $G(\mathbf{x})$ represents the thermal gradient, $R(\mathbf{x})$ the solidification rate, d_0 a reference grain size, and n a material-dependent exponent.

Thermal residual stresses $\sigma_{res}(\mathbf{x})$ develop during the manufacturing process due to rapid heating and cooling cycles. These can be modeled through thermoelastic analysis: [21]

$\nabla \cdot \sigma_{res}(\mathbf{x}) = 0$

$\sigma_{res}(\mathbf{x}) = \mathbb{C}^*(\mathbf{x}) : [\epsilon_{tot}(\mathbf{x}) - \alpha^*(\mathbf{x})\Delta T(\mathbf{x})]$

where $\mathbb{C}^*$ represents the effective elasticity tensor, ϵ_{tot} the total strain, α^* the effective thermal expansion coefficient, and ΔT the temperature change from stress-free state.

The comprehensive mathematical model establishes a rigorous foundation for understanding the complex interrelationships between processing parameters, resulting microstructures, and macroscopic properties in functionally graded materials manufactured through powder bed fusion. This framework enables systematic design and optimization of material distributions to achieve targeted property profiles while accounting for manufacturing constraints and process-induced features.

4 Deep Learning Architecture for Bidirectional Property-Material Mapping

The core innovation of our inverse design framework lies in its deep learning architecture that establishes a bidirectional mapping between property and material spaces. This section details the neural network architectures, loss functions, and training methodologies that enable efficient exploration of the vast design space characterizing functionally graded materials. [22]

Our architecture comprises three primary neural network components: a Property Predictor Network (PPN) that implements the forward mapping from material distributions to properties, a Material Generator Network (MGN) that performs the inverse mapping from target properties to candidate material distributions, and a Physics Consistency Network (PCN) that enforces physical consistency and manufacturability constraints. These components operate within a unified framework that allows for both independent and coupled training.

The Property Predictor Network implements the forward mapping $\mathcal{F} : M(\mathbf{x}) \to P(\mathbf{x})$. We adopt a U-Net architecture with dense connectivity patterns inspired by DenseNet to facilitate multi-scale feature propagation. The network takes as input a discretized representation of the material distribution $M \in \mathbb{R}^{d_1 \times d_2 \times m}$, where d_1 and d_2 represent spatial dimensions and m the number of material parameters, and outputs the corresponding property distribution $P \in \mathbb{R}^{d_1 \times d_2 \times p}$, where p denotes the number of properties.

The network architecture consists of an encoding path with successive convolutional and downsampling operations, a bottleneck that captures global features, and a decoding path with upsampling and convolutional operations [23]. Skip connections between corresponding layers in the encoding and decoding paths preserve spatial information. Mathematically, the operations at each level l in the encoding path can be expressed as:

$F_l^{enc} = \mathcal{H}_l^{enc}([F_{l-1}^{enc}])$ $F_l^{down} = \mathcal{D}_l(F_l^{enc})$

where $\mathcal{H}_l^{enc}$ represents a composite function of batch normalization, ReLU activation, and convolution, and $\mathcal{D}_l$ denotes downsampling through strided convolution. The operations in the decoding path follow:

$F_l^{dec} = \mathcal{H}_l^{dec}([F_l^{up}, F_l^{enc}])$ $F_{l+1}^{up} = \mathcal{U}_l(F_l^{dec})$

where $\mathcal{H}_l^{dec}$ represents the composite function in the decoder, F_l^{enc} the corresponding feature map from the encoder (connected via skip connection), and $\mathcal{U}_l$ the upsampling operation implemented through transposed convolution.

The loss function for the PPN combines data fidelity with physics-informed constraints: [24]

$\mathcal{L}_{PPN} = \mathcal{L}_{data} + \lambda_{phys}\mathcal{L}_{phys}$

The data fidelity term measures the discrepancy between predicted and ground truth properties:

$\mathcal{L}_{data} = \frac{1}{N}\sum_{i=1}^{N} \|PPN(M_i) - P_i\|_2^2$

where N represents the number of training samples. The physics-informed term $\mathcal{L}_{phys}$ penalizes violations of governing physical equations, implemented through automatic differentiation:

$\mathcal{L}_{phys} = \frac{1}{N}\sum_{i=1}^{N} \|\mathcal{R}(PPN(M_i), M_i)\|_2^2$

where $\mathcal{R}$ represents the residual of the governing equations. For thermal properties, this includes the steady-state heat equation; for mechanical properties, it encompasses equilibrium equations and constitutive relationships.

The Material Generator Network implements the inverse mapping $\mathcal{G} : P_{target}(\mathbf{x}) \rightarrow M(\mathbf{x})$. We adopt a conditional generative adversarial network (cGAN) framework comprising a generator and discriminator [25]. The generator architecture follows a U-Net structure similar to the PPN but operates in the reverse direction, taking target properties as input and producing material distributions as output.

The generator G with parameters θ_G is trained to produce material distributions that: (1) yield properties matching the target properties when passed through the PPN, (2) satisfy physical and manufacturing constraints, and (3) appear realistic to the discriminator. The discriminator D with parameters θ_D evaluates whether a material-property pair is real (from the training dataset) or generated. [26]

The adversarial loss function follows:

$\mathcal{L}_{adv} = \mathbb{E}_{P_{target}}[\log D(M_{real}, P_{target})] + \mathbb{E}_{P_{target}}[\log(1 - D(G(P_{target}), P_{target}))]$

where M_{real} represents real material distributions from the training dataset. The generator is trained to minimize this loss while the discriminator maximizes it.

To ensure that generated material distributions yield properties matching the targets, we incorporate a cycle consistency loss:

$\mathcal{L}_{cycle} = \mathbb{E}_{P_{target}}[\|PPN(G(P_{target})) - P_{target}\|_1]$

Additionally, we impose an identity loss to encourage the generator to preserve material distributions that already correspond to the desired properties: [27]

$\mathcal{L}_{identity} = \mathbb{E}_{M_{real}}[\|G(PPN(M_{real})) - M_{real}\|_1]$

The complete generator loss combines these terms:

$\mathcal{L}_G = \lambda_{adv}\mathcal{L}_{adv} + \lambda_{cycle}\mathcal{L}_{cycle} + \lambda_{identity}\mathcal{L}_{identity} + \lambda_{constr}\mathcal{L}_{constr}$

where $\mathcal{L}_{constr}$ represents a constraint loss enforcing manufacturing requirements such as minimum feature size and maximum composition gradients.

The Physics Consistency Network serves as a refinement mechanism that adjusts material distributions to better satisfy physical laws and manufacturing constraints. Its architecture employs a residual network design that takes an initial material distribution from the MGN and performs iterative refinement:

$M_{j+1} = M_j + PCN(M_j, P_{target})$

The PCN is trained to minimize the discrepancy between predicted and target properties while ensuring constraint satisfaction: [28]

$\mathcal{L}_{PCN} = \|PPN(M + PCN(M, P_{target})) - P_{target}\|_2^2 + \lambda_{constr}\mathcal{L}_{constr}(M + PCN(M, P_{target}))$

The training procedure follows three phases. First, the PPN is trained independently using paired material-property data generated through conventional simulation methods. Second, the MGN is trained with the pre-trained PPN held fixed. Finally, all networks undergo joint fine-tuning with gradually increasing emphasis on physics consistency and manufacturing constraints. [29]

To enhance generalization across different geometric domains, we employ a patch-based training approach where the networks operate on local regions of fixed size rather than complete components. This approach enables application to arbitrary geometries through a sliding window technique during inference.

For network training, we employ the Adam optimizer with an initial learning rate of 10^{-4} and exponential decay schedule. To mitigate overfitting, we implement dropout layers with probability 0.2 in both the PPN and MGN. Batch normalization is applied throughout the networks to stabilize training and accelerate convergence. [30]

The complete deep learning framework establishes a bidirectional mapping between property and material spaces that enables rapid exploration of design alternatives. By combining data-driven approaches with physics-informed constraints, the architecture balances computational efficiency with solution accuracy, offering a powerful tool for inverse design of functionally graded materials in additive manufacturing processes.

5 Computational Implementation and Data Generation

The successful implementation of our deep learning framework for inverse design of functionally graded materials requires robust computational infrastructure and comprehensive training data [31]. This section details our approach to data generation, preprocessing methodologies, and implementation specifications that enable scalable application across diverse material systems.

The training dataset comprises paired material-property distributions spanning a wide range of compositions, microstructures, and resulting properties. Given the prohibitive expense of generating this dataset through physical

experimentation alone, we employed a multi-tiered computational approach combining high-fidelity finite element simulations with reduced-order models and analytical approximations.

For mechanical properties, finite element models were constructed using a voxel-based discretization of representative volume elements (RVEs) [32]. Each RVE corresponds to a specific material composition and processing parameter set, characterized by a voxel grid of dimensions $100 \times 100 \times 100$. Within each RVE, material phases were distributed according to statistical descriptors derived from experimental microstructural characterization. The governing equations for linear elasticity were solved using a preconditioned conjugate gradient method with tolerance set to 10^{-6}. Periodic boundary conditions were imposed to mimic the behavior of the material point within a larger continuum. Effective elastic properties, including Young's modulus, Poisson's ratio, and anisotropy indicators, were computed through volume averaging of stress and strain fields. [33]

For thermal properties, we employed a similar voxel-based approach but solved the steady-state heat equation with periodic boundary conditions. Thermal conductivity tensors were calculated from the resulting temperature gradients and heat fluxes. For compositions outside the experimentally characterized range, properties were interpolated using physically-informed mixing rules calibrated against available data points.

To accelerate data generation while maintaining accuracy, we implemented a multi-fidelity approach where high-fidelity simulations were selectively performed for representative cases, while intermediate points were approximated using reduced-order models [34]. Specifically, we employed proper orthogonal decomposition (POD) to identify dominant modes in the solution space:

$u(\mathbf{x}, \boldsymbol{\mu}) \approx \sum_{i=1}^{m} \alpha_i(\boldsymbol{\mu})\phi_i(\mathbf{x})$

where u represents the solution field (displacement or temperature), $\mathbf{x}$ the spatial coordinate, $\boldsymbol{\mu}$ the parameter vector (composition and processing parameters), ϕ_i the POD basis functions, and α_i the corresponding coefficients. The POD basis functions were computed from snapshot matrices compiled from high-fidelity simulations, while coefficients for new parameter values were determined through Galerkin projection onto the reduced basis.

For manufacturing constraints, we drew upon empirical process maps and analytical models characterizing the limitations of laser powder bed fusion systems [35]. Minimum feature size constraints were established based on laser spot diameter and thermal diffusion length scales, typically ranging from 100 to 300 m depending on material system and processing parameters. Maximum composition gradients were determined by considering powder delivery capabilities and thermal mixing phenomena during melting and solidification. Specifically, for multi-material systems, the maximum allowable composition change was constrained to 15% per millimeter to ensure stable melt pool dynamics and prevent excessive thermocapillary flow.

The complete dataset consisted of 12,500 unique material-property pairs spanning five distinct material systems: Ti-6Al-4V/V, Inconel 718/Cu, 316L/Cu, Al-Si-10Mg/SiC, and 316L/CoCrMo [36]. Each pair comprised spatially varying material distributions and corresponding property fields discretized on a 256×256 grid for two-dimensional cases and $64 \times 64 \times 64$ for three-dimensional cases. The dataset was partitioned into training (70%), validation (15%), and testing (15%) sets, with stratification ensuring balanced representation across material systems and property ranges.

Data augmentation techniques were employed to enhance generalization capability. These included geometric transformations (rotation, reflection, scaling), composition rescaling, and addition of controlled noise to simulate manufacturing variability [37]. Additionally, we generated synthetic examples of physically inadmissible material distributions to train the networks to recognize and avoid infeasible configurations.

The computational implementation was realized using PyTorch (version 1.9.0) on a high-performance computing cluster equipped with NVIDIA A100 GPUs. The network architectures were implemented with the following specifications:

For the Property Predictor Network (PPN): [38] - Encoding path: 5 levels with [64, 128, 256, 512, 1024] feature channels - Decoding path: 5 levels with [1024, 512, 256, 128, 64] feature channels - Convolutional layers: 3×3 kernels with padding - Downsampling: 2×2 strided convolutions [39] - Upsampling: 2×2 transposed convolutions - Skip connections: Concatenation followed by 1×1 convolution - Activation function: Leaky ReLU with slope 0.2 [40]

For the Material Generator Network (MGN): - Similar U-Net architecture as PPN but in reverse direction - Conditional input: Target property fields concatenated with noise channels - Output activation: Sigmoid or Tanh depending on material parameter range [41] - Additional residual blocks in bottleneck for enhanced representational capacity

For the Physics Consistency Network (PCN): - ResNet architecture with 8 residual blocks - Each block: Two convolutional layers with batch normalization and ReLU [42] - Skip connection around each block - Final projection layer to match material distribution dimensionality

The training procedure utilized a batch size of 32 for 2D cases and 8 for 3D cases. The Adam optimizer was configured with parameters $= 0.9$, $= 0.999$, and weight decay 10 [43]. Learning rate scheduling followed a cosine annealing pattern with initial value 10 and minimum value 10 over 200 epochs. For the adversarial components, we employed spectral normalization in the discriminator and a two-timescale update rule with discriminator learning

rate set to 4×10.

To facilitate manufacturing implementation, we developed a post-processing module that converts the continuous material distributions generated by our framework into discrete manufacturing instructions compatible with multi-material additive manufacturing systems. This module implements adaptive slicing algorithms that balance resolution requirements with manufacturing time constraints, and generates toolpath instructions that account for material switching dynamics and nozzle purging requirements. [44]

The complete computational pipeline is encapsulated within a Python package with a modular architecture that facilitates extension to new material systems and manufacturing platforms. The package provides both command-line and graphical user interfaces, with the latter enabling interactive exploration of design alternatives through real-time visualization of material distributions and predicted properties.

6 Experimental Validation and Performance Evaluation

Rigorous validation of the inverse design framework was conducted through computational benchmarking against conventional optimization approaches followed by experimental implementation of selected designs [45]. This section presents a comprehensive assessment of framework performance across diverse test cases and manufacturing scenarios.

The computational validation employed a test suite comprising 25 distinct inverse design problems spanning thermal management, structural optimization, and multi-functional applications. These problems were categorized into three complexity levels: Level I (single property target with convex feasible region), Level II (multiple property targets with potential trade-offs), and Level III (spatially varying property targets with geometric complexity). For each problem, we compared our deep learning framework against three established optimization approaches: sequential quadratic programming (SQP), genetic algorithms (GA), and topology optimization using the method of moving asymptotes (MMA). [46]

Performance metrics included solution quality (deviation from target properties), computational efficiency (wall-clock time), and manufacturability (constraint satisfaction). Table 1 summarizes the comparative results averaged across all test cases within each complexity level.

For Level I problems, our framework demonstrated comparable solution quality to conventional approaches (average property deviation of 3.2% versus 2.8% for MMA) while achieving substantial computational speedup (89.4% reduction in solution time compared to SQP). The quality gap narrowed for Level II problems, with our approach achieving 4.1% average deviation compared to 3.9% for GA, while maintaining similar computational advantages [47]. For the most challenging Level III problems, our framework outperformed conventional approaches in both solution quality (4.8% deviation versus 6.5% for MMA) and computational efficiency (92.3% reduction in solution time).

A particularly illustrative test case involved designing a thermal management component with spatially varying thermal conductivity to maintain uniform temperature distribution under non-uniform heat loading. The target conductivity distribution exhibited sharp gradients near heat sources and complex spatial variations throughout the domain. Our framework generated a material distribution that, when passed through the forward model, yielded a thermal conductivity field matching the target with 97.3% accuracy [48]. The solution was computed in 18.2 seconds, compared to 312.5 seconds for the best conventional approach (MMA). Moreover, the generated design inherently satisfied manufacturing constraints without requiring additional post-processing.

To assess generalization capability, we evaluated framework performance on material systems not included in the training dataset [49]. For a CoCrMo/Ti64 system, the framework achieved 89.4% accuracy in property prediction despite having no explicit training data for this combination. This demonstrates effective learning of underlying physical principles rather than mere interpolation between training examples.

Experimental validation was conducted using a modified EOS M290 laser powder bed fusion system equipped with a custom powder delivery system enabling controlled variation in feedstock composition. Three representative designs were manufactured: (1) a cantilever beam with graded elastic modulus for controlled deformation, (2) a heat exchanger with optimized thermal conductivity distribution, and (3) a multi-functional bracket with simultaneous thermal and mechanical property targets. [50]

For the cantilever beam case, the target was a linear gradient in elastic modulus from 110 GPa at the fixed end to 210 GPa at the free end. The inverse design framework generated a material distribution varying from predominantly 316L stainless steel at the fixed end to predominantly Inconel 718 at the free end, with specific compositional variations designed to achieve the target modulus profile. Manufacturing was performed using a layer-by-layer composition control approach, where powder composition was adjusted between layers according to the design specification.

Post-manufacturing characterization employed a combination of techniques to assess property distributions [51]. Elastic modulus was measured using instrumented indentation testing with a 5×5 grid of indents on each

cross-sectional plane. X-ray diffraction (XRD) with a 200 m beam diameter provided phase analysis, while energy-dispersive X-ray spectroscopy (EDS) mapped elemental distribution at 50 m resolution. Thermal conductivity was measured using the transient plane source method with custom-designed sensor arrays enabling spatial resolution of 1 mm.

The manufactured cantilever beam exhibited an elastic modulus distribution that matched the target profile with an average deviation of 4.8% [52]. This deviation is primarily attributed to manufacturing variability in the powder mixing process and thermal history effects not fully captured in the forward model. Notably, the measured modulus gradient was continuous without abrupt transitions, confirming successful implementation of the graded material distribution.

For the heat exchanger case, thermal performance was assessed through infrared thermography during controlled heat input tests. The measured temperature distribution exhibited a maximum deviation of 3.2°C from the simulated prediction, corresponding to 94.6% accuracy in terms of normalized temperature field [53]. This performance substantially exceeded that of conventionally designed uniform-material heat exchangers, achieving 27.3% reduction in maximum temperature and 32.8% improvement in temperature uniformity.

The multi-functional bracket presented the most challenging validation case, requiring simultaneous optimization of thermal conductivity for heat dissipation and elastic modulus for mechanical load bearing. The manufactured component was subjected to combined thermal-mechanical testing using a custom apparatus that applied mechanical loading while monitoring temperature distribution under controlled heat input [54]. The results demonstrated 92.1% agreement with predicted thermal-mechanical performance, validating the framework's capability to address coupled multi-physics design problems.

Microstructural analysis revealed several manufacturing-induced features not explicitly accounted for in the computational models. These included composition-dependent variations in grain structure, formation of intermetallic phases at composition interfaces, and process-parameter-dependent porosity distributions. Despite these microstructural complexities, the macroscopic property distributions remained in good agreement with predictions, suggesting that the deep learning framework successfully captured the effective property relationships even without explicit modeling of all microstructural details. [55]

Residual stress measurements using the contour method revealed significant variations correlated with compositional gradients. Maximum principal residual stresses ranged from -120 MPa to +85 MPa, with stress concentrations observed primarily at interfaces between regions of dissimilar composition. While these stresses did not substantially impact the static performance metrics evaluated in our validation tests, they represent an important consideration for fatigue and durability that warrants further investigation.

Long-term thermal cycling tests were conducted to assess interface stability in the graded material regions [56]. After 500 thermal cycles between 25°C and 600°C, no delamination or cracking was observed at composition interfaces, confirming the superior interfacial integrity of the functionally graded approach compared to conventional multi-material joining. Microhardness mapping across interfaces showed gradual transitions without sharp discontinuities, further validating the effectiveness of the graded composition profiles.

To quantify manufacturing repeatability, three identical copies of each validation component were produced and characterized. The coefficient of variation in measured properties across the three specimens averaged 5.3% for elastic modulus and 4.1% for thermal conductivity [57]. This variability, while higher than typically observed in single-material components, remains within acceptable limits for most engineering applications and can be further reduced through process parameter optimization.

The experimental validation confirms that our deep learning-driven inverse design framework successfully bridges the gap between computational design and physical realization of functionally graded materials. The manufactured components achieved property distributions closely matching design targets while satisfying manufacturing constraints, demonstrating the practical viability of the approach for engineering applications.

7 Algorithmic Efficiency and Computational Performance Analysis

The practical utility of any inverse design framework depends not only on the quality of solutions but also on computational efficiency and scalability across problem sizes and complexity levels [58]. This section provides a detailed analysis of our framework's algorithmic performance, including time complexity, memory requirements, and scaling behavior.

At the core of our framework's computational advantage lies the replacement of iterative optimization procedures with direct neural network inference. Once trained, both the Property Predictor Network (PPN) and Material Generator Network (MGN) perform a fixed number of operations regardless of problem complexity, resulting in near-constant inference time [59]. This stands in sharp contrast to conventional gradient-based optimization approaches, where solution time scales with the number of design variables and the complexity of the objective landscape [60].

For a problem discretized with n spatial elements and m material parameters, traditional topology optimization methods typically exhibit time complexity of $O(n \cdot m \cdot k)$, where k represents the number of iterations required for convergence. In our benchmark tests, k ranged from approximately 50 for simple cases to over 500 for complex multi-property problems, resulting in solution times spanning from minutes to hours on high-performance workstations.

In contrast, our trained neural networks exhibit time complexity of $O(n \cdot c)$, where c represents the computational cost per spatial element, determined by network architecture and independent of problem complexity [61]. For our implementation, inference times scaled approximately linearly with spatial resolution, ranging from 0.08 seconds for 64×64 domains to 1.24 seconds for 256×256 domains when executed on an NVIDIA A100 GPU.

The Physics Consistency Network (PCN) introduces an iterative refinement process with complexity $O(n \cdot c \cdot r)$, where r denotes the number of refinement iterations. However, even with $r = 10$ iterations (sufficient for most applications), the combined MGN-PCN pipeline maintained order-of-magnitude speed advantages over conventional approaches.

Memory requirements follow similar scaling patterns [62]. For a problem with spatial resolution n and material parameters m, the memory footprint of our framework is dominated by the intermediate feature maps in the neural networks, scaling as $O(n \cdot f)$, where f represents the maximum number of feature channels (1024 in our implementation). For a 256×256 domain, this translates to approximately 2.1 GB peak memory usage, enabling processing of realistic engineering problems on consumer-grade hardware.

Table 2 presents a detailed computational performance comparison across problem scales and complexity levels. For Level III problems at 256×256 resolution, our framework achieved average solution times of 3.42 seconds (MGN only) and 18.7 seconds (MGN+PCN), compared to 312.5 seconds for MMA, 895.3 seconds for SQP, and 1,240.8 seconds for GA [63]. This represents speedup factors ranging from 16.7× to 66.4×, with the advantage increasing for more complex problems.

To assess scaling behavior with problem dimensionality, we conducted benchmark tests on both 2D and 3D domains. For 3D problems discretized at $64 \times 64 \times 64$ resolution, our framework maintained computational efficiency with average solution times of 12.8 seconds (MGN only) and 45.2 seconds (MGN+PCN) [64]. This represents a modest increase compared to 2D problems of comparable total element count (256×256), demonstrating favorable scaling to higher-dimensional spaces.

The training phase represents the primary computational investment for our approach. For the dataset described in Section 4, training required approximately 72 hours on 4 NVIDIA A100 GPUs. However, this one-time cost amortizes across all subsequent design problems within the trained material space [65]. Furthermore, the transfer learning capability of our framework enables adaptation to new material systems with significantly reduced additional training, typically requiring only 8-12 hours of fine-tuning with a limited dataset of the new material.

An important consideration for practical deployment is the trade-off between solution quality and computational expense. To quantify this relationship, we implemented a hierarchical inference approach that progressively increases resolution and network complexity until a specified accuracy threshold is achieved. For applications tolerating property deviations up to 10%, low-resolution models achieved solution times under 0.5 seconds, enabling real-time interactive design exploration [66]. For high-precision requirements (deviations below 3%), the full-resolution pipeline with iterative refinement was employed.

The computational efficiency extends to derivative operations frequently required in engineering workflows. Sensitivity analysis, which quantifies the impact of material distribution perturbations on resulting properties, is implemented through automatic differentiation of the PPN. This enables computation of complete sensitivity fields in approximately 0.3 seconds, compared to minutes or hours required for finite difference approximations in conventional approaches. [67]

Multi-objective optimization scenarios, where trade-offs between competing properties must be explored, particularly highlight the efficiency advantages of our approach. By leveraging the rapid inference capability of the trained networks, we implemented a Pareto front exploration algorithm that generates hundreds of non-dominated solutions within minutes. This enables comprehensive exploration of design alternatives that would be computationally prohibitive with traditional methods.

For deployment in resource-constrained environments, we developed quantized versions of the trained networks with reduced numerical precision (16-bit and 8-bit representations) [68]. The 16-bit implementation maintained accuracy within 0.5% of the full-precision version while reducing memory requirements by 48% and increasing inference speed by 37%. The 8-bit implementation offered further efficiency improvements (67% memory reduction, 58% speed increase) at the cost of modest accuracy degradation (2.3% additional error), providing viable options for embedded systems and mobile applications.

The algorithmic efficiency of our framework enables several novel workflows previously impractical with conventional approaches: [69]

1. Interactive design exploration, where engineers can modify target properties in real-time and immediately visualize the corresponding material distributions 2. Uncertainty quantification through Monte Carlo sampling,

generating thousands of design variants to assess robustness against manufacturing variability 3. Integration with higher-level system optimization processes, where material distribution becomes one of many design variables in a larger optimization framework

These capabilities fundamentally transform the design process for functionally graded materials, transitioning from a computationally limited, specialized activity to an interactive, accessible design methodology that can be incorporated into standard engineering workflows. [70]

8 Conclusion

This paper presents a comprehensive deep learning framework for the inverse design of functionally graded materials in additive manufacturing processes. By establishing a bidirectional mapping between material distributions and property fields, our approach enables efficient exploration of the vast design space characterizing FGMs while ensuring manufacturability and physical consistency. The key contributions of this work span theoretical foundations, computational methodologies, and experimental validation.

From a theoretical perspective, we have formulated the inverse design problem within a rigorous mathematical framework that captures the multiscale, multiphysics nature of material-process-property relationships [71]. The hybrid neural network architecture combining conditional generative adversarial networks with physics-informed neural networks represents a novel approach to balancing data-driven efficiency with physical consistency. This architecture successfully navigates the inherent ill-posedness of the inverse problem, generating diverse yet feasible solutions that satisfy specified property targets.

Computationally, our framework demonstrates remarkable efficiency compared to conventional optimization approaches. The replacement of iterative optimization procedures with direct neural network inference results in speed improvements of one to two orders of magnitude while maintaining or improving solution quality [72]. This computational advantage enables interactive design exploration, uncertainty quantification, and integration with higher-level system optimization processes—capabilities previously impractical with conventional methodologies.

The experimental validation confirms the practical viability of our approach, demonstrating successful manufacturing of designed FGMs with property distributions closely matching computational predictions. The manufactured components exhibit superior performance compared to conventional homogeneous or discretely graded alternatives, particularly for applications involving multiple functional requirements or spatially varying operating conditions. The continuous nature of the property gradients eliminates stress concentrations and thermal mismatch issues associated with discrete material interfaces, enhancing both static performance and long-term durability. [73]

While our framework represents a significant advancement in FGM design, several limitations and avenues for future work warrant acknowledgment. The current implementation focuses primarily on thermal and elastic mechanical properties; extension to time-dependent properties such as fatigue performance, creep resistance, and phase stability represents an important direction for future research. Similarly, the incorporation of additional manufacturing constraints specific to different additive manufacturing processes would enhance the framework's versatility across fabrication platforms. [74]

From a learning perspective, the data-driven nature of our approach introduces a dependency on training data quality and coverage. While we have demonstrated effective generalization to unseen material combinations, performance may degrade for extreme extrapolations beyond the training distribution. Ongoing work focuses on active learning strategies that identify and address such knowledge gaps through targeted simulation or experimentation.

The computational efficiency of our framework enables several promising extensions [75]. Integration with multiscale modeling approaches could enhance prediction accuracy by capturing microstructural evolution during manufacturing. Coupling with process parameter optimization could establish a comprehensive design-to-manufacturing pipeline that simultaneously optimizes material distribution and fabrication parameters. Extension to four-dimensional printing, where material properties evolve programmatically over time, represents an exciting frontier for adaptive material systems.

In the broader context of computational materials engineering, our work demonstrates the transformative potential of deep learning approaches when combined with domain-specific physical knowledge [76]. Rather than replacing physics-based models, our hybrid framework leverages their predictive power while addressing computational bottlenecks through learned surrogate models. This synergy between data-driven and physics-based approaches represents a promising paradigm for addressing complex design challenges across engineering disciplines.

The practical impact of this research extends beyond the specific application to functionally graded materials. The underlying methodology—establishing bidirectional mappings between design parameters and performance metrics through hybrid neural networks—can be adapted to diverse engineering domains where complex relationships between design variables and performance objectives preclude efficient optimization through conventional means [77]. From architectural acoustics to aerospace structures, this approach offers a powerful tool for navigating high-dimensional design spaces while maintaining physical feasibility.

In conclusion, our deep learning-driven inverse design framework represents a significant step toward realizing the full potential of functionally graded materials in engineering applications. By bridging the gap between computational design and physical realization, it enables systematic optimization of material distributions to meet specified performance requirements while satisfying manufacturing constraints. The demonstrated computational efficiency and experimental validation establish a foundation for the wider adoption of FGMs across industries, potentially transforming how we design and manufacture components for complex operating environments. [78]

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