Data-Driven Structural Performance Assessment of 3D-Printed Spatial Lattice Architectures

Ignazio Sbarbaro
Department of Computer Science, Colorado State University, Fort Collins, CO, USA.
sbarbaro12@colostate.edu

Ricciotti Belletini
Department of Computer Science, Binghamton University, Binghamton, NY, USA.
ricciottib@binghamton.edu

Cyprian Teodorowicz
Department of Computer Science, University of Alabama at Birmingham, Birmingham, AL, USA.
cyprianteodorowicz@uab.edu

Bilal Velderman
Department of Computer Science and Engineering, University at Buffalo, Buffalo, NY, USA.
bilal2003@buffalo.edu

Abstract

Three-dimensional printed spatial lattice architectures concentrate material along connected struts and nodes, producing stiffness, strength, and buckling behavior that cannot be inferred reliably from bulk material properties alone. Their performance is governed by coupled geometric, topological, and process-induced effects, including strut slenderness, nodal connectivity, manufacturing deviations, and anisotropic as-built properties. This article formulates a data-driven assessment framework for spatial lattice architectures that links design and process descriptors to homogenized and structural performance labels through physics-based simulation, surrogate modeling, and uncertainty quantification. The contribution is a coherent assessment logic rather than a single fitted model: lattice geometry is parameterized by graph-based and continuum descriptors; effective elastic properties, compliance, and buckling margins are defined through representative-volume homogenization and finite element analysis; and Gaussian-process surrogates with active learning are used to approximate performance across design space. Bayesian calibration separates process variability from model-form uncertainty, while explicit error modes address scale separation, nodal defects, print orientation, and extrapolation beyond the training domain. The framework clarifies how sparse, heterogeneous data from simulation and calibrated testing can be combined without treating surrogate predictions as validated design allowables. It also provides decision rules for when low-cost surrogate screening is defensible and when high-fidelity analysis or physical qualification remains necessary. These results are significant for the design and qualification of additively manufactured lattice components because they make performance assessment auditable, uncertainty-aware, and compatible with the geometric complexity of spatial wireframe architectures.

Keywords

3D-printed lattices; spatial lattice architectures; structural performance; data-driven surrogate modeling; uncertainty quantification; homogenization

1. Introduction

Architected cellular materials achieve combinations of low mass and high specific stiffness by distributing material in connected struts, plates, or shells rather than in a continuous solid [1]. The mechanical response of such architectures depends on whether deformation is dominated by stretching or bending of the constituent members, a distinction that controls stiffness scaling, strength, and failure mode [2]. Ultralight metallic microlattices [3], ceramic nanolattices [4], and ultrastiff mechanical metamaterials [5] have demonstrated that topology and relative density can expand the accessible property space far beyond that of conventional foams. For spatial lattice architectures produced by additive manufacturing, this design freedom is accompanied by a difficult assessment problem: the realized geometry differs from the nominal geometry, the process introduces anisotropy and defects, and the number of candidate architectures is too large for exhaustive high-fidelity analysis.

The theoretical basis for lattice assessment is well established. Micro-architected materials connect topology, relative density, and scaling laws [6], and property charts provide a compact language for comparing architectures [7]. Topology optimization offers a systematic route to material and component layout [8], while additive-manufacturing constraints have been incorporated into topology optimization workflows to avoid designs that cannot be printed or post-processed [9]. These methods define candidate designs, but they do not by themselves provide a defensible performance assessment under as-built uncertainty. The assessment problem therefore requires a separate methodological layer that maps a design and its manufacturing state to performance quantities and quantifies the confidence attached to those quantities.

Finite element analysis remains the workhorse for this mapping [10]. For powder-bed lattice structures, as-built geometry, strut defects, and process-induced anisotropy can alter stiffness and strength substantially [11], and computational models of strut defects have been developed to represent such deviations [12]. Metal additive manufacturing processes introduce additional complexity through melt-pool dynamics, residual stress, porosity, and orientation-dependent properties [13], [14], and the broader family of additive technologies imposes different resolution and surface-quality constraints [15]. A purely analytical scaling law cannot represent these effects with sufficient fidelity, while direct nonlinear finite element analysis of every candidate architecture is often too expensive for design exploration.

Data-driven surrogates offer a middle path. Gaussian-process models are attractive because they provide nonparametric regression with predictive variance [16], which is essential when surrogate outputs are intended to inform engineering decisions. The assessment framework developed here uses such surrogates inside a physics-based labeling pipeline rather than as a replacement for mechanics. The aim is not to claim that a surrogate is universally valid, but to define the conditions under which its predictions are informative, the uncertainty sources that must be propagated, and the validation evidence required before a prediction can support design or qualification.

2. Physical Mechanisms and Assessment Variables

A spatial lattice architecture is represented as a connected graph of nodes and struts embedded in three dimensions. Its structural performance is controlled by several interacting variables: relative density, coordination number, strut slenderness, nodal geometry, cell topology, and anisotropy of the unit cell. Relative density is the most basic scalar descriptor. For an ideal strut-based lattice with straight members and negligible nodal volume, it can be written as

$$\bar{\rho} = (\rho_s / V_\Omega) \sum_{e=1}^{N_s} A_e \, l_e$$

where $\bar{\rho}$ is the relative density, ρ_s is the solid material density, V_Ω is the volume of the representative domain, N_s is the number of struts, and A_e and l_e are the cross-sectional area and length of strut e. The expression assumes that strut overlap and nodal mass are small; for as-built lattices, these contributions must be corrected using measured or simulated geometry. Relative density alone does not determine performance. Two architectures with the same $\bar{\rho}$ can exhibit different stiffness scaling if one is stretching-dominated and the other bending-dominated [2]. Coordination number, nodal rigidity, and strut alignment therefore belong in the descriptor set alongside density.

The performance variables of interest are also multi-dimensional. For small deformations, the effective elastic stiffness tensor describes directional stiffness and coupling. For strength assessment, the relevant quantities are yield or fracture initiation, post-yield collapse, and localized strut failure. For stability, the critical buckling load and the associated mode shape are required. In architectural applications, thermal or acoustic properties may matter, but the structural assessment considered here prioritizes stiffness, compliance, buckling margin, and failure mode. These quantities are not interchangeable; a design that is stiff under one load case may be buckling-sensitive under another.

3. Methodological Framework

3.1 Geometric and process parameterization

The input to the assessment framework is a descriptor vector x that combines geometry, topology, and process state. Geometric descriptors include relative density, strut diameter distribution, strut length distribution, nodal overlap, minimum feature size, and orientation tensor. Topological descriptors include coordination number, cycle structure, and connectivity of the strut graph. Process descriptors include build orientation, layer thickness, energy density, hatch spacing, and material state. The descriptor set must be sufficiently rich to distinguish architectures that have similar density but different load paths, yet compact enough to support surrogate learning from limited data.

Print-path-aware representation is a specific concern for spatial wireframe architectures. Mesh optimisation for spatial wireframe robotic 3D printing is relevant because the chosen mesh determines how nodal connectivity and strut segmentation are represented, which in turn affects geometric fidelity and manufacturability [17]. In the present framework, the lattice graph is therefore converted into a printable mesh only after the assessment descriptors have been defined, so that mesh refinement does not silently change the topology or density used for performance labeling. Printability constraints are treated as feasibility conditions rather than as post hoc filters: a candidate design is admissible only if strut diameter, overhang angle, and accessible clearance satisfy the process window.

3.2 Homogenized performance labels

For architectures whose unit cell is small relative to the component and whose boundary layers are limited, effective properties can be computed by representative-volume homogenization. The effective stiffness tensor is obtained from the strain-energy expression

$$C^H_ijkl = (1/|\Omega|) \int_\Omega C_pqrs\, e_ij\^pq\, e_kl\^rs\, d\Omega$$

where C^H_ijkl is the homogenized stiffness tensor, Ω is the representative domain with volume |Ω|, C_pqrs is the local elastic tensor, and e_ij^pq = ε⁰_pq^(ij) − ε_pq^(ij) is the difference between the applied unit strain and the fluctuating strain field for load case (ij). Periodic boundary conditions are imposed on the representative volume, and the separation-of-scales assumption must be checked against the component size and the expected deformation wavelength. If the unit cell is comparable to the component dimension, homogenization is not appropriate and the full structure must be analyzed directly.

Structural performance is assessed through load-case functionals. For a linear elastic structure with displacement field u, traction $\bar{t}$ on the loaded boundary Γ_t, and body force b, the compliance is

$$J(u) = \int_\{\Gamma_t\} \bar{t} \cdot u\, d\Gamma + \int_\Omega b \cdot u\, d\Omega$$

where J is the scalar compliance functional and the displacement field satisfies equilibrium and the prescribed boundary conditions. Lower compliance corresponds to higher stiffness for the same load. For stability, a linearized buckling analysis solves

$$\left(K + \lambda K_g\right)\varphi = 0$$

where K is the elastic stiffness matrix, K_g is the geometric stiffness matrix, λ is the critical load factor, and φ is the buckling mode. The smallest positive λ defines the first buckling margin. Nonlinear post-buckling and mode interaction require a separate analysis, because the linearized eigenvalue problem can overestimate stability when localized strut buckling precedes global buckling.

3.3 Surrogate assessment model

The mapping from descriptor x to performance y is approximated by a surrogate model. A Gaussian-process formulation is

$$y(x) = f(x)\^T \beta + Z(x) + \varepsilon,\ Z(x) \sim GP(0, k(x, x'))$$

where y(x) is a scalar performance output, f(x) is a basis of trend functions, β is a coefficient vector, Z(x) is a zero-mean Gaussian process with covariance function k(x,x′), and ε is observation noise. The covariance function encodes smoothness assumptions about the performance landscape. For multiple outputs, independent Gaussian processes can be used, or outputs can be linked through coregionalization when stiffness, strength, and buckling margin are known to be correlated. The model is trained by maximizing the marginal likelihood, and predictive mean and variance are retained for decision-making.

The surrogate is not intended to replace mechanics-based labels. It is trained on labels produced by homogenization, nonlinear finite element analysis, or calibrated tests, and its role is to interpolate within a bounded descriptor domain. Data-driven materials frameworks that propagate uncertainty through surrogate models provide a useful precedent for this separation between simulation, calibration, and prediction [18], while materials-informatics workflows illustrate how descriptor selection and model complexity affect extrapolation [19]. In the present setting, model complexity must be controlled explicitly because lattice performance surfaces can contain sharp transitions associated with failure-mode changes.

3.4 Active learning and calibration

Because high-fidelity labels are expensive, the framework uses active learning to select new design points. Expected improvement is a standard acquisition criterion:

$$EI(x) = \big(y_b est - \mu(x)\big)\Phi(z) + \sigma(x)\varphi(z), z = \frac{\big(y_b est - \mu(x)\big)}{\sigma}(x)$$

where y_best is the best observed performance, μ(x) and σ(x) are the posterior mean and standard deviation, Φ is the standard normal cumulative distribution function, and φ is its density. For minimization of compliance or maximization of buckling margin, the sign of the improvement is adjusted accordingly. The acquisition function balances exploitation of promising regions with exploration of high-uncertainty regions. In practice, candidate points are also filtered by printability and by the requirement that they lie inside the convex hull of the training descriptors, which reduces the risk of unphysical extrapolation.

4. Performance Assessment Under Manufacturing and Model Uncertainty

The central difficulty in assessing 3D-printed spatial lattices is that the quantity of interest is not a deterministic property of a nominal geometry. Strut diameter varies along the build direction, nodes may be over- or under-melted, and surface roughness changes the effective slenderness. These effects are partly aleatoric, in the sense that they vary from build to build, and partly epistemic, in the sense that the model form is incomplete. Bayesian calibration provides a disciplined way to separate them:

$$p(\theta|D) \propto p(D|\theta)p(\theta)$$

where θ is the calibration parameter vector, D is the available data, p(θ) is the prior, p(D | θ) is the likelihood, and p(θ | D) is the posterior. The parameter vector may include process-dependent stiffness knockdown factors, effective strut diameters, or model-discrepancy terms. The distinction between measured variability and model discrepancy is important: increasing the noise term to absorb model error produces overconfident predictions and weakens the assessment.

Several error modes must be addressed explicitly. The first is scale separation. Homogenization assumes that the unit cell is much smaller than the component and that boundary layers are negligible. When this assumption fails, the effective stiffness tensor can be non-representative even if the local unit-cell analysis is correct. The second is failure-mode switching. A surrogate trained on stiffness-dominated designs may extrapolate poorly to designs that fail by buckling or nodal fracture. The third is geometric descriptor loss. A descriptor set that records only relative density and strut diameter may not distinguish two topologies with different load paths. The fourth is process anisotropy. Build orientation can change both the elastic modulus and the defect population, so process descriptors must be included in the input space rather than treated as fixed nuisance parameters. The fifth is data leakage. If multiple finite element meshes of the same architecture are split randomly into training and test sets, the surrogate can appear more accurate than it is. Grouped validation by architecture family and by build orientation is therefore required.

Reliability assessment follows from the posterior predictive distribution. For a performance limit y_lim, the probability of violation is the posterior probability that y(x) exceeds y_lim. This quantity is more informative than a point prediction because it exposes the trade-off between performance and confidence. A design with a slightly lower mean buckling margin but a much narrower predictive distribution may be preferable to a design

with a higher mean and a long tail of low-margin outcomes. The assessment framework therefore reports both the predicted performance and the uncertainty decomposition, including parameter uncertainty, process variability, and model discrepancy.

5. Technical Discussion and Design Implications

The proposed framework occupies a deliberate position between analytical scaling laws and direct high-fidelity analysis. Analytical models are fast and interpretable, but they cannot represent nodal defects, as-built anisotropy, or complex load paths with sufficient generality. Direct finite element analysis can represent these effects, but the cost of nonlinear analysis across a large design space is prohibitive. Surrogate-assisted assessment reduces the cost while preserving the physics-based labeling step, provided that the surrogate is used within its validated domain.

The practical value of the framework lies in its decision logic. During early design exploration, when the candidate set is broad and the consequences of a wrong decision are moderate, surrogate screening can rank architectures and identify promising regions. As a design approaches qualification, the acceptable uncertainty shrinks. At that stage, high-fidelity analysis of the selected architecture, calibrated by build-specific measurements, becomes necessary. The framework therefore does not collapse assessment into a single prediction; it defines a sequence of evidence requirements that become stricter as the decision becomes more consequential.

The same logic applies to process qualification. If a printer or material changes, the descriptor distribution shifts. A surrogate trained on previous process conditions may remain useful for ranking, but its absolute predictions require recalibration. Bayesian updating with a small number of build-specific tests can restore calibration without discarding the prior model. This is particularly relevant for spatial lattice architectures, where the number of struts and nodes is large and destructive testing of every architecture is impractical. The assessment framework makes the required extrapolation visible and allows engineers to decide whether additional simulation, testing, or conservative knockdown factors are warranted.

6. Conclusion

This article has formulated a data-driven structural performance assessment framework for 3D-printed spatial lattice architectures. The framework connects graph-based and continuum geometric descriptors, process descriptors, homogenized stiffness, compliance, and buckling margins to Gaussian-process surrogates with active learning and Bayesian calibration. Its central claim is methodological: reliable assessment requires a clear separation between physics-based labeling, surrogate interpolation, and uncertainty propagation. The framework identifies the conditions under which homogenization is appropriate, the failure modes that can invalidate a surrogate, and the validation logic needed to prevent extrapolation from being mistaken for evidence. It also clarifies how process variability and model discrepancy can be represented without overstating confidence. For engineering practice, the framework supports staged decision-making, from low-cost screening to build-specific qualification, and provides an auditable basis for assessing additively manufactured lattice components whose geometry and failure behavior are too complex for purely analytical treatment.

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