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Use of artificial intelligence in algorithm-based product design tools in powder bed fusion of metals

A Literature Review

Bachelor’s thesis in Machine Technology

Department of Mechanical Engineering, Faculty of Technology

Author:
Luan Bujupi

Supervisor:
Heidi Piili

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Abstract:

This thesis reviews how algorithm-based design tools can support metal additive manufacturing, with a focus on powder bed fusion (PBF). It concentrates on three tool families: implicit modeling (with field-driven workflows such as nTopology), generative design based on topology optimization, and AI-enabled methods that accelerate or extend these approaches.

The thesis proposes a practical framework that links geometric design freedom to PBF constraints. It treats support requirements, minimum feature limits, residual stresses, thermal distortion, and the role of process parameters as design inputs rather than downstream issues. The review scope emphasizes recent academic work and summarizes how current tools address common PBF design problems and where they still fall short.

From the surveyed literature, algorithm-based workflows can reduce mass and improve structural performance by creating lattice or cellular architectures that follow load paths and stress fields. AI contributes mainly through surrogate models and generative methods (for example GANs, CNN-based predictors, diffusion approaches, and reinforcement learning) that reduce iteration time in topology optimization and expand early design exploration. Research also shows increasing integration of manufacturability rules into optimization loops, as well as data-driven approaches for predicting and compensating PBF distortion using hybrid simulation and machine-learning methods.

The thesis concludes that these methods are promising for PBF part design, but adoption still depends on computational cost, validation effort, and tighter coupling between data-driven models and physics-based simulation. It also includes a qualitative review of key equations and optimization methods used in the discussed workflows.

Key words: Additive manufacturing, Powder bed fusion, Implicit modeling, generative modeling, artificial intelligence

List of used abbreviations:

AM	Additive manufacturing
PBF	Powder bed fusion
CAD	Computer-aided design
FE	Finite element
SIMP	Solid isotropic material with penalization
GANs	Generative adversarial networks
TO	Topology optimization
SVM	Support vector machine
GE	Generative design
CNN	Convolutional neural network
LTSM	Long short-term memory
RL	Reinforcement learning
UCB	Upper confidence bound
DfAM	Design for additive manufacturing
GPR	Gaussian process regression
RVE	Representative volume element
NNS	Near net shape

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1 Introduction

1.1 Background and significance

Additive Manufacturing (AM), also known as industrial 3D printing, has revolutionized manufacturing processes by enabling the creation of complex structures that would be difficult or impossible to produce using traditional methods. AM of metals, particularly powder bed fusion (PBF), has gained significant attention due to its ability to produce lightweight yet strong components with high design flexibility.

Algorithm-based design tools have become essential to fully exploit the potential of AM. Tools, such as implicit modeling and generative design software, enable the optimization of structures to meet the specific requirements of AM. Using math-based equations instead of traditional geometry makes design changes faster and more adaptable. On top of that, AI-powered generative design can automatically produce optimized structures from your goals and constraints, often delivering better results in less time and with higher overall design quality.

PBF is one of the most widely adopted and researched processes in metal AM due to its capability to produce intricate geometries with high dimensional accuracy [1]. In PBF, a thin layer of metal powder is evenly spread across a build platform before an energy source. Commonly a laser or electron beam selectively melts regions of the powder according to cross-sectional data from a 3D model [2]. The platform then lowers incrementally, and subsequent layers of powder are deposited and fused in a similar manner, gradually building the part layer by layer [3].

1.2 Research problem and objective

Despite the advancements in AM, designing components for metal-based AM presents unique challenges. These challenges are support structure optimization, residual stress management, and AM constraints. Algorithm-based tools offer potential solutions, but their application and effectiveness in metal AM require further investigation.

This study aims to explore the following research questions:

- What methods and tools, algorithm-based design provide for metal additive manufacturing?
- How do these tools address the specific design challenges associated with AM?
- What are the current limitations and future development prospects for these design tools?

1.3 Scope and limitations

This literature review focuses on recent developments in algorithm-based design tools for metal AM, particularly within the last three years. The study considers academic research and publications while excluding commercial industry sources. Additionally, the review specifically examines:

- Implicit design methodologies rather than traditional CAD-based approaches.
- Powder Bed Fusion (PBF) technology, as it is widely used in metal AM.

By analyzing state-of-the-art algorithm-driven design tools, this study seeks to highlight their capabilities, limitations, and potential future directions in the field of metal additive manufacturing.

2 Design significance in powder bed fusion

Metal AM is a transformative approach to producing components by adding material layer by layer, typically from metal powder or wire feedstock [4]. Among the various metal AM techniques, PBF has emerged as one of the most widely adopted methods. PBF enables the possibility to fabricate complex geometries with high precision and near net shape (NNS) accuracy [3]. This technique uses a high energy laser or electron beam to selectively melt and fuse metallic powder particles according to a computer aided design (CAD) model [2]. As a result it offers advantages which are: reduced material waste, design freedom for intricate structures, and the possibility of on-demand production [5].

Effective control of process parameters such as laser power, scanning speed, and layer thickness is critical to achieve consistent part quality [5]. These parameters influence the shape and stability of the melt pool, as well as the formation of defects like lack of fusion or keyhole porosity [4]. The high cooling rates and temperature gradients characteristic of PBF also contribute to the generation of residual stresses, which may require post-processing, such as stress relief and heat treatments [1]. Nevertheless, PBF offers remarkable design freedom and enables the production of NNS components from a variety of metallic powders, including titanium alloys, stainless steels, and nickel-based superalloys [4]. This versatility has led to the use of PBF in aerospace, medical, and automotive industries, where complex geometries and high-performance materials are required.

Design plays a pivotal role in ensuring the success and reliability of metal AM processes. While in the design part of PBF, key factors that must be taken account for are material properties, energy absorption, and melt pool dynamics to minimize manufacturing defects [5]. Design rules specifically tailored for AM have become central to mitigating issues such as porosity and residual stresses, both of which can compromise mechanical performance and lead to unexpected failures in service [4].

Another critical factor is the need for support structures. While these supports are often essential for stabilizing overhangs and dissipating heat during the build, their design and placement can significantly affect production efficiency [2]. Poorly planned support structures can be challenging to remove, creating unwanted surface damage or leaving inaccessible cavities that trap powder [5]. Thoroughly evaluating parts geometry, build orientation, and support layout is a necessity to create a balance between complexity, material usage, and post processing requirements. By incorporating these considerations early in the design phase, it is possible to optimize the overall manufacturing workflow and achieve higher performance in metal AM [3].

3 Algorithm-based design tools

3.1 Implicit modeling and nTopology

3.1.1 Definition of implicit modeling

In CAD, solids are commonly represented through a boundary representation (B-rep), in which geometry is stored explicitly via surfaces, edges, and vertices that collectively define the object's boundaries. Although this representation is efficient for many engineering applications, it becomes cumbersome for geometries that exhibit high internal complexity or frequent topological changes.

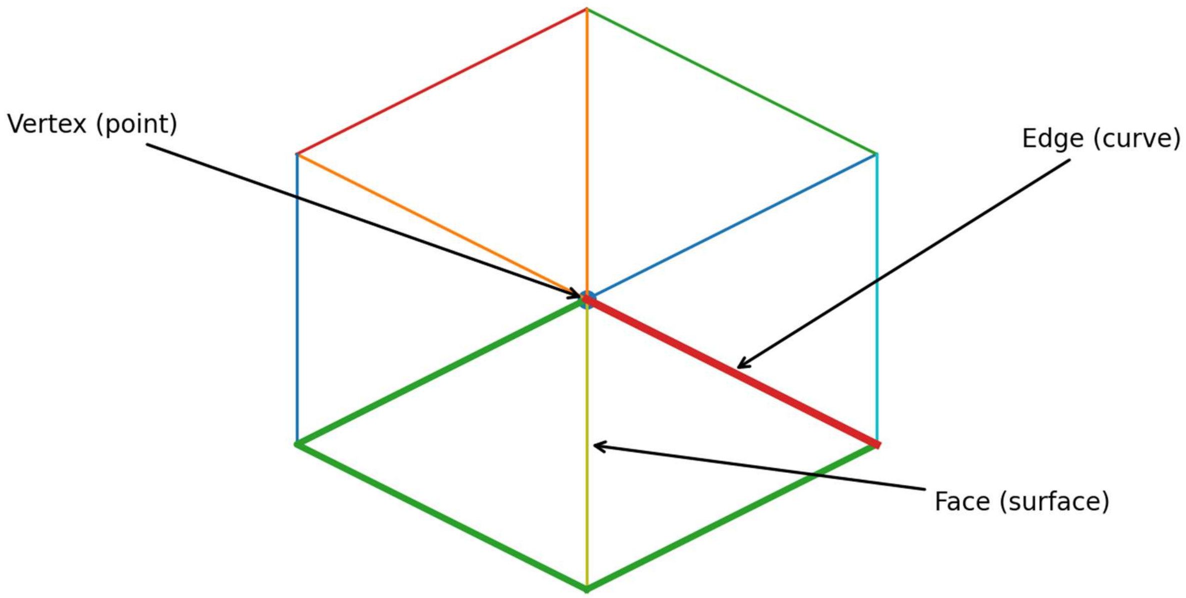

Figure 1 A simple B-rep diagram

Figure 1 shows a simple (B-rep solid. The model is described using faces (surfaces), edges (boundary curves between faces), and vertices (points where edges meet). One face, one edge, and one vertex are highlighted to illustrate the main B-rep entities.

While effective for many conventional components, B-rep workflows can become cumbersome when geometry includes high internal complexity (e.g., cellular infill) or frequent topological changes. In such cases, repeated Boolean operations and tolerance driven surface intersections may lead to non-manifold conditions or degeneracy issues that complicate robust modeling and downstream processing.

Implicit modeling provides an alternative representation in which a part is defined by a scalar field $\phi(\mathbf{x})$, where $\mathbf{x} \in \mathbb{R}^3$denotes spatial position and the boundary is given by the zero level set $\phi(x) = 0.$ [5]

In this formulation, the sign of ϕclassifies space into interior and exterior regions (with a chosen sign convention), enabling inside–outside evaluation without explicitly tracking boundary topology. This approach is particularly beneficial in additive manufacturing, where complex internal and external surfaces (such as lattice or cellular structures) can be generated directly from field definitions with reduced reliance on extensive Boolean construction steps.

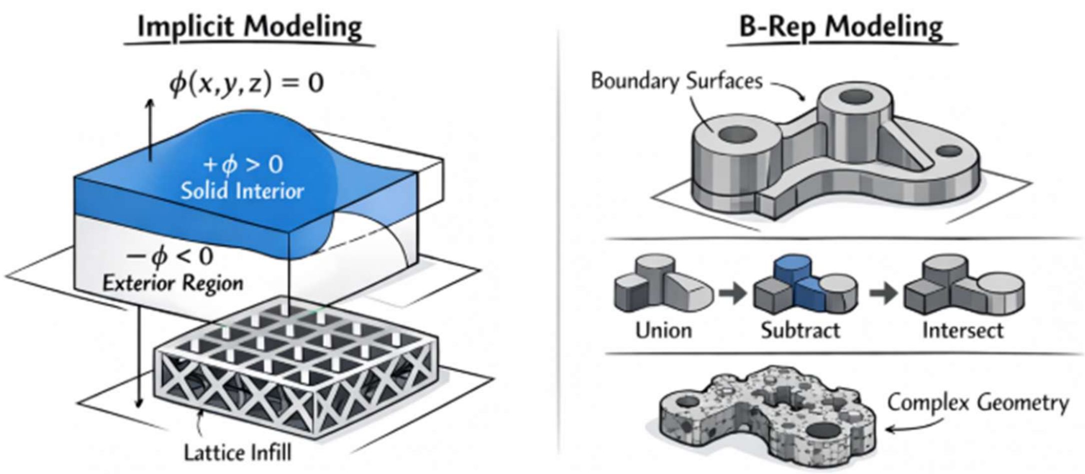

Figure 2 Implicit versus boundary representation modeling.

Figure 2 contrasts implicit modeling with traditional B-rep approaches. In implicit modeling, the part is encoded by a scalar level-set function ϕ(x,y,z), and the physical boundary is defined implicitly by the zero set ϕ=0. The sign of the function provides a straightforward inside–outside classification (e.g., ϕ>0 inside the solid and ϕ<0), which supports robust evaluation of membership and smooth generation of complex morphologies. This representation is particularly advantageous for additive manufacturing, where highly intricate internal architectures (e.g., lattice or cellular infill) can be produced directly from the field description without assembling the geometry through many intermediate operations.

By comparison, B-rep modeling stores geometry explicitly as faces, edges, and vertices that collectively define the boundary surfaces of a solid. Constructing complex parts often requires successive Boolean operations to combine or modify primitives and features. As geometric intricacy increases (especially with dense internal structures) B-rep workflows can become computationally heavy and more prone to topological inconsistencies such as non-manifold edges, sliver faces, or other degeneracies.

The figure 2 highlights why implicit modeling is frequently preferred when the design space includes complex internal/external surfaces typical of advanced additive manufacturing components.

3.1.2 Mathematical foundation

The core idea behind implicit modeling is that the boundary of the part is given as the zero of a signed distance function $\boldsymbol{\phi}(x, s)$, where *x* is a point in space and **s** is a set of control parameters.

The implicit model is defined across the entire volume rather than just the boundary. The function **ϕ** can be constructed using distance fields, periodic functions (e.g., to create repeated lattices), or other custom scalar functions. Because of this unified volume-based representation, geometry is no longer restricted to conventional, explicitly defined surfaces. [5] As can be seen from Figure 2.

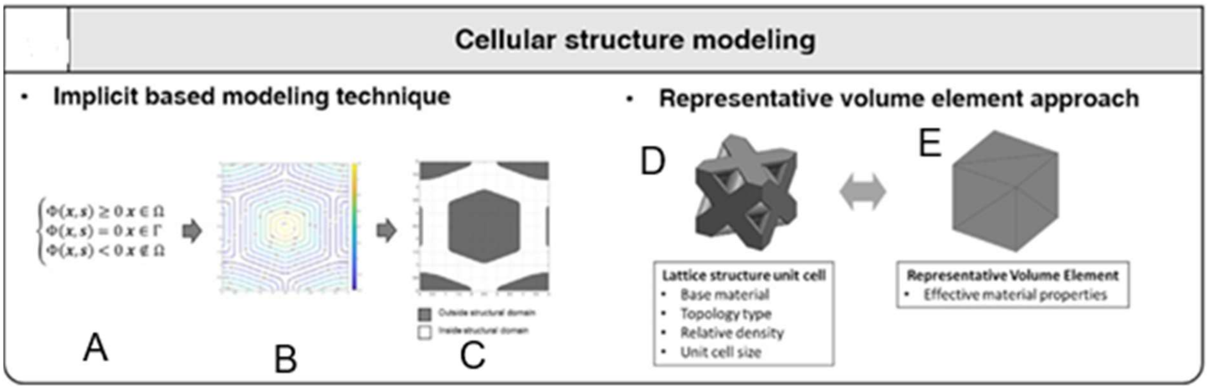

Figure 3 Overall design framework.

Image A of Figure 3 shows that the function $\phi(x,s)$ represents a level-set approach to defining geometry. Here, $\phi(x,s) \geq 0$ indicates points inside the structural domain, $\phi(x,s) = 0$ denotes the boundary (or interface) Γ, and $\phi(x,s) < 0$ corresponds to points outside the domain.

In practical terms, the color map in image B shows contours of ϕ gradually transitioning from inside to outside the structure. Image C in this sequence shows the resulting solid geometry based on those contours. This approach enables complex, freeform lattice or cellular structures to be generated by continuously modifying the level-set function rather than discretely manipulating meshes.

Image D of figure 3 shows a lattice structure unit cell, which encapsulates properties such as base material, topology type (e.g., gyroid, strut-based, etc.), relative density, and unit cell size.

Image E shows representative volume element is a homogenized model that captures these effective material properties in a simpler geometric form. Using an representative volume element (RVE) allows computationally efficient analyses: instead of simulating an entire, highly detailed lattice, engineers can treat it as a periodic repeat of the representative cell, greatly reducing the computational cost.

3.1.3 Flexibility and parametric nature

In an implicit representation, altering a small set of parameters of the defining function can systematically change the geometry of the part. For instance, adjusting wall thickness, lattice spacing, or orientation. This makes it straightforward to incorporate functional grading (functionally graded structures), where properties such as stiffness or density vary across the part. When used together with design optimization and automation, implicit models enable swift, multiscale adjustments without repeated re-meshing, or the extensive updates typically required by explicit (B-rep) models.[5]

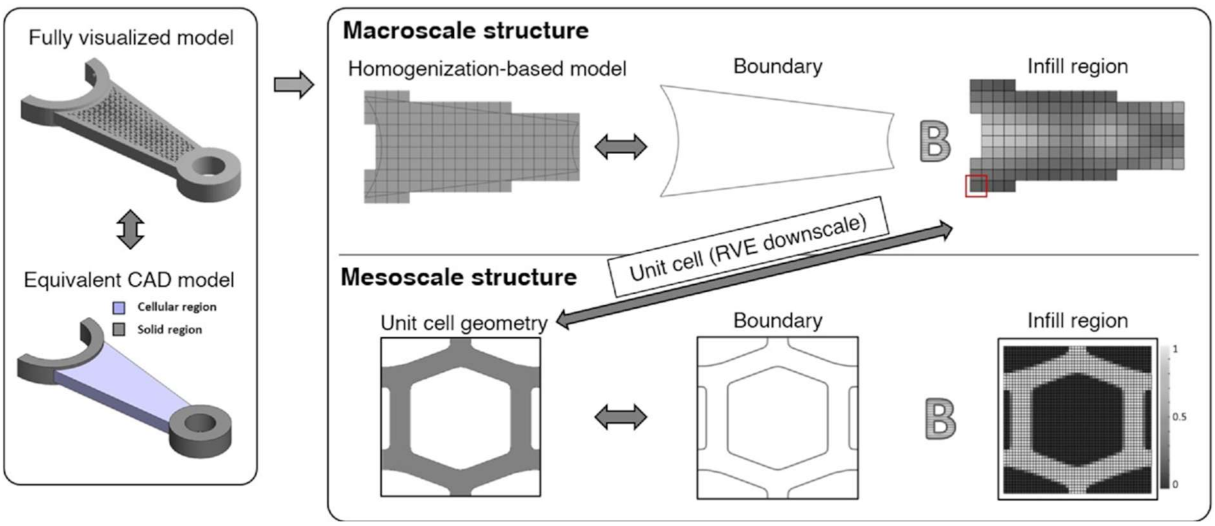

Figure 4 Multiscale modeling using RVE and implicit representation.

Figure 4 illustrates a multi-scale modeling approach for parts that combine solid and cellular (lattice) regions.

In the left panel of figure 4, two contrasting digital representations clarify how the geometry is treated. The fully visualized model depicts the component exactly as it will be printed, combining its intricate lattice (cellular) infill with the surrounding solid regions. Beside it, the equivalent CAD model strips away that geometric detail and simply labels which zones are solid and which are filled with lattice. By abstracting the geometry in this way, the CAD version becomes much easier to prepare for computational analysis or optimization.

The top-right panel of figure 4 moves up a level of abstraction to the macroscale. Here the entire part is translated into a homogenization-based model: the lattice infill is not represented strut-by-strut but is instead treated as a single "effective" material, while the outer boundary of the part remains a distinct region. Within this homogenized domain the infill is divided into finite elements, and a highlighted red square singles out one of those elements for potential "downscaling," should a more detailed investigation be required.

That extra detail appears in the bottom-right panel of figure 4, which zooms to the mesoscale. At this resolution the geometry of an individual unit cell (the representative volume element of the lattice) is shown explicitly. The boundary of the part is kept separate from the infill, but the emphasis now lies in depicting the exact cell layout, shape, and relative density. Shifting to this mesoscale view converts the simplified macroscale model into a detailed representation capable of capturing local stresses, deformations, and material behavior.

3.1.4 Reinforcements and complex structures

A key use case in additive manufacturing is creating lightweight yet strong internal structures, such as lattice or cellular infill. Implicit modeling excels at defining periodic or aperiodic cellular patterns (e.g., honeycomb, gyroid, or Voronoi based cells), while automatically clipping them to a component's boundary. By simply combining mathematical functions that define each cell's shape, one can smoothly transition between different cell sizes or densities. This is vital for lightweight design, as local mechanical properties (stiffness or strength) can be tuned while keeping mass to a minimum. Implicit modeling thus offers a more robust and automated pathway to generate complex, hierarchical designs that are well suited for modern additive manufacturing processes. [5]

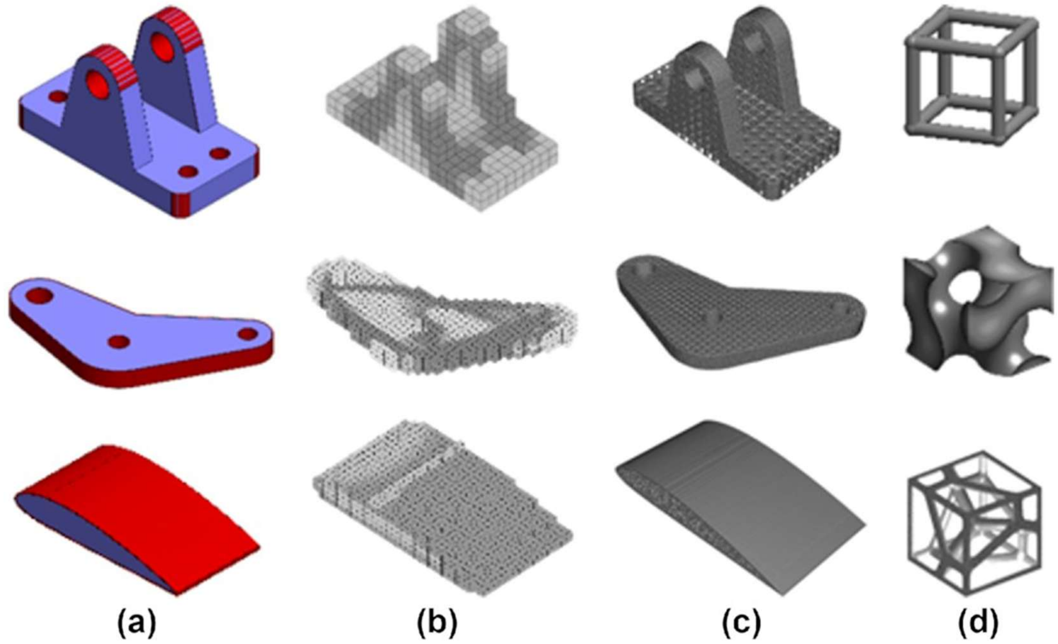

Figure 5 Examples of the proposed framework for 3D application (from top to bottom): pillow bracket, control arm, and UAV wing. (a) Design infill and boundary domain. (b) Optimally designed density map. (c) Ray-casting visualization. (d) Applied unit cells

Figure 5 shows Examples of the proposed framework for 3D application (from top to bottom): pillow bracket, control arm, and UAV wing. (a) Design infill and boundary domain. (b) Optimally designed density map. (c) Ray-casting visualization. (d) Applied unit cells: (from top to bottom) 3D Cubic, Gyroid, and Voronoi-based structures.

3.2 nTopology

nTopology, (founded in 2015) emerged to address the challenges in designing high-performance parts for advanced manufacturing, especially metal additive manufacturing [6]. Conventional CAD systems struggle with complex geometries such as lattices, organic forms, and lightweight structures. In response, nTopology introduced an implicit, field-driven modeling approach that is inherently well-suited for algorithmic or “generative” design [7].

The concept of “fields” allows geometry to be tied directly to engineering inputs such as thermal, stress, or topology-optimization data [8]. Instead of manually defining every dimension, designers establish rules or equations that algorithmically shape the model. This approach is invaluable when optimizing the internal lattice of a metal part for specific mechanical requirements.

By integrating with finite element (FE) data, nTopology can optimize material usage based on objectives like minimizing mass or maximizing stiffness. These outputs can then be converted into AM-ready shapes, either as solid forms or as lattices for weight reduction and performance gains [9].

3.3 Generative design and Gene3D

Generative design has emerged as a methodology for discovering high-performance product geometries optimized for additive manufacturing. By systematically exploring large sets of shapes under specified objectives and constraints, generative design strategies often yield innovative outcomes that traditional, manual design techniques cannot easily uncover. In parallel, Gene3D can be seen as a software or platform concept that integrates these generative methods. Especially those based on topology optimization (TO), support vector machine (SVM) postprocessing, and lattice-structure integration into a seamless toolchain for metal AM.[9], [10], [11]

Generative design is rooted in computational algorithms that blend design exploration with engineering simulation (e.g., finite element analysis). A common starting point is topology optimization, wherein a design domain is discretized, and every element’s “density” is tuned to meet criteria such as:

- Minimize compliance (i.e., maximize stiffness)

- Limit mass or volume fraction
- Maintain certain mechanical or thermal performance thresholds

One widely used method is SIMP (Solid isotropic material with penalization), which penalizes intermediate densities and steers the final distribution toward near-binary material layouts [12]. Once the TO converges, the result is typically a "patchy" density plot. Postprocessing steps are then applied to transform these partially discrete outputs into geometries smooth enough for manufacturing. Gene3D seeks to bundle each of these design stages: topology optimization, postprocessing, and advanced refinements into a single, user-friendly environment. Thereby reducing the complexity of running multiple software packages.

3.4 Generative AI in design

Generative AI is increasingly integrated into algorithm-based design tools for powder bed fusion of metals, enabling faster and more innovative product development. By employing machine learning models such as Generative adversarial networks (GAN) or diffusion-based methods, designers can automate early-stage concept exploration, quickly generate part geometries, and optimize them for mechanical performance, weight reduction, and manufacturability [13]. This extends traditional topology optimization by providing multiple near-optimal solutions that are sensitive to build constraints, support requirements, and target properties.[14]

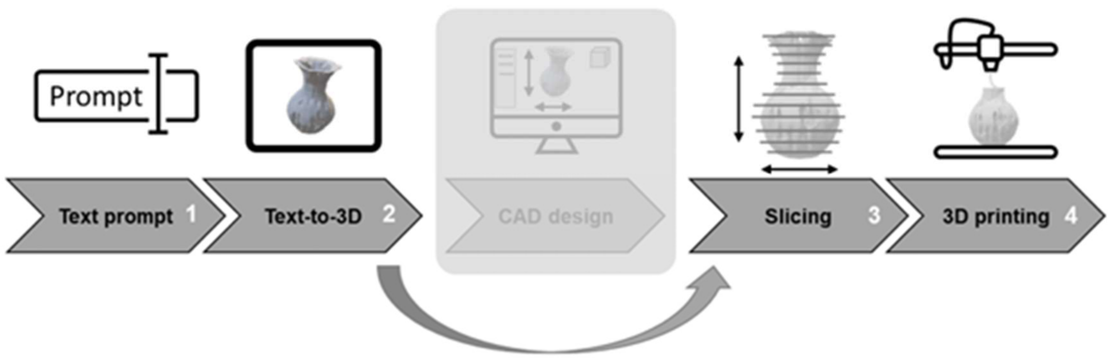

Figure 6 Text prompt to 3D-printed component, without CAD design

In Figure 6 left to right, the process of 3D printing starts with writing a text prompt, giving the text to AI to generate it into a 3D image and file. That process has made the use of self-designing away and saving time by using AI. Next step is slicing the AI created object and start printing. [15]

A key application is lattice and metamaterial design, where AI-driven techniques rapidly generate novel cellular architecture with enhanced strength-to-weight ratios. For example, training a GAN or diffusion model on existing lattice structures allows the network to propose new patterns that meet desired mechanical or thermal constraints in fewer iterations than rule-based approaches [16]. Commercial software such as nTopology and Autodesk Fusion 360 increasingly incorporate machine learning modules for generative design, allowing engineers to integrate physics simulations like thermal or stress analyses directly into AI-driven workflows. As a result, generative AI has become a valuable co-creator in PBF part design, streamlining complex optimization tasks and unleashing new design freedoms unique to metal additive manufacturing.

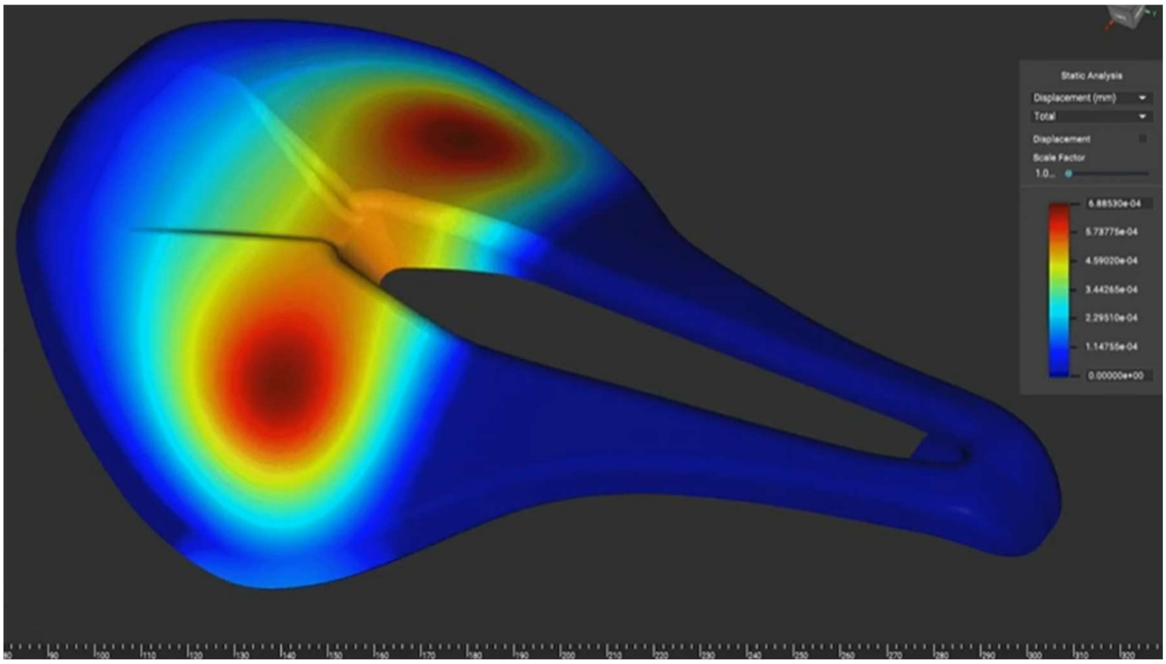

Figure 7 Heat map of a bike seat

Figure 7 shows a screenshot of a bike seat put to a stress test to analyze using nTopology, where most of the mass is absorbed. The analysis gives a good idea if the reddest parts need to be reinforced more, or to be made of more durable material.[8]

4 Use of artificial intelligence in design tools

4.1 AI-Driven topology optimization and generative design

Topology optimization is a computational design method that determines the best material distribution in a given design space for a set of loads and constraints. It has become a valuable tool for lightweighting and performance optimization in PBF. Traditional TO methods (e.g. SIMP and level-set methods) require numerous iterative FEA simulations and often do not directly consider manufacturing constraints. Recent studies encourage AI to overcome some of these limitations. For example, machine learning-enhanced TO can significantly reduce computational effort by learning from simulation data. Researcher Sacco noted that generative design (GD) and TO benefit from AI algorithms, which can produce near-optimal designs without exhaustive iteration. In particular, generative adversarial networks and deep neural networks have been used to bypass or accelerate the TO process. Studies report that GAN-based solutions can generate optimized structures in one shot, eliminating many iterative steps. Similarly, convolutional neural networks (CNNs) have achieved one-step topology optimization by learning the relationship between design inputs and optimal material layouts, serving as surrogates for the FEA solver. These approaches can dramatically speed up the design phase, although ensuring physical realism and generality remains an ongoing challenge.[17], [18]

Researchers have also begun integrating AI directly into the design workflow. Kallioras introduced “MLGen,” a generative design framework that combines classical TO with a long short-term memory (LSTM) neural network. In their approach, LSTM learns from prior TO results to inform new designs, accelerating convergence and incorporating knowledge of past designs. This machine learning-guided generative design was shown to produce innovative geometries more efficiently than brute-force optimization [10]. Another emerging strategy is the use of reinforcement learning (RL) for design exploration. Instead of training on fixed datasets, RL algorithms learn optimal design decisions through trial-and-error interactions with a simulation environment. Venugopal and Anand developed an RL-based generative design approach that treats topology optimization as a sequential decision process. Using an Upper confidence bound (UCB) algorithm for exploration, their method iteratively adds or removes material in a design domain to maximize structural performance while considering thermal constraints. This approach allowed simultaneous structural and thermal optimization, demonstrating how AI agents can navigate multi-objective design spaces that are difficult for gradient-based solvers. These RL-driven tools are still in early stages, but they point to a future where algorithms can "learn" how to design optimal PBF parts under multiple criteria.[19]

Notably, researchers are ensuring that AI-generated designs remain feasible for PBF manufacturing. One key aspect is incorporating PBF process constraints (like support requirements and minimum feature sizes) into the generative algorithms. For instance, Trovato integrated an additive manufacturing knowledge base into the topology optimization loop, so that the optimized automotive component respected support angle limitations and orientation constraints.[17] In a similar vein, there has been presented a lattice optimization tool that automatically trims unsupported overhangs during the design process, yielding a self-supporting structure. By embedding such manufacturability filters, the resulting geometries can be printed without extensive support material, directly addressing PBF process needs.[20], [21]

4.2 Integrating AI with simulation and manufacturability

For AI-driven design tools to be practical in metal PBF, they must integrate with physics-based simulations and account for manufacturing realities. One major integration point is using simulation data to train AI models, thereby creating hybrid approaches that combine data-driven learning with engineering knowledge. For example, many of the deep learning applications in topology and lattice design rely on datasets generated by FEA or analytical models. Jadhav's diffusion model was conditioned on stiffness information obtained via homogenization simulations of candidate structures[22].

Lee et al.'s lattice optimization used FEA to evaluate each design iteration, feeding results back into the learning algorithm. In such cases, AI does not replace simulation but rather augments it: once trained, the AI model can rapidly predict outcomes (like stress distribution or effective modulus) without needing to run a full simulation for every design tested. This significantly speeds up design-space exploration. Physics-informed AI models are an active research area, aiming to embed physical laws into machine learning so that predictions respect principles like equilibrium and conservation. By training on simulation data and sometimes enforcing physics-based loss functions, these models strive to ensure that AI-generated designs are not only optimal in a numerical sense but also physically valid.[22], [23]

Beyond performance predictions, AI is increasingly used to predict and compensate for PBF-specific distortions and defects at the design stage. Metal PBF processes (such as laser powder bed fusion) induce complex thermal cycles, often leading to residual stresses and part deformation (warping) as the part cools. Traditionally, designers would address this by trial-and-error or overbuilding and machining. Recent research instead uses AI to preemptively adjust the design to counteract such distortions. A data-driven distortion compensation framework for laser PBF using Gaussian process regression (GPR) combined with an inherent strain simulation method has been introduced [24]. In the approach, an experimentally calibrated inherent strain model provides initial predictions of how a given geometry will deform during printing. Those predictions are used to train a GPR model that can quickly estimate distortions for new geometries. Designer (or an automated routine) then geometrically offsets the original CAD model in the opposite direction of the predicted distortion. The result is a pre-deformed design that, after printing and cooling, comes out much closer to the intended dimensions. Dong reported that this GPR-driven compensation significantly reduced shape errors in test builds [24].

Another critical manufacturability concern is the need for support structures in PBF. Overhanging features beyond a certain angle require supports to print correctly, which can be wasteful and affect surface quality. AI-based design tools are starting to incorporate these constraints automatically. One method is to include support penalties or overhang angle limits in topology optimization algorithms (sometimes called support constrained TO).[20], [23], [25]

While that approach was algorithmic, researchers are also using machine learning to identify and avoid problematic geometries. An AI classifier could potentially flag regions of a generated design that would need support, and then a generative model could adjust those regions (by adding material or changing angles) to eliminate the unsupported spans. Though at a nascent stage, such constraint-aware generative design is a promising direction to reduce the gap between theoretically optimal designs and those that are printable.[2], [20], [25]

It is worth noting that verification and validation remain important when AI creates a design. Engineers often loop back to high-fidelity FEA or print tests to ensure the AI-driven design meets all requirements. For example, after an AI tool generates a lightweight bracket design, the design might be simulated for stress under load and also checked for thermal distortion using a calibrated model. Only after passing these simulation checks, it would be cleared for physical printing. This iterative loop is essentially a form of digital twin concept: the AI suggests a design, simulations (the digital twin of the process) predict its behavior, and the design is refined accordingly. As AI tools mature, this loop may tighten, with AI models increasingly taking on the predictive roles of simulations in real-time. Ultimately, the integration of AI with simulation and manufacturability considerations aims to produce robust, print-ready designs. By embedding knowledge of material behavior, process physics, and machine constraints, AI-driven design tools can output solutions that require minimal manual tweaks or trial-and-error, thus streamlining the path from digital design to physical part.[10], [26], [27]

5 Conclusions

AI-driven design tools in metal powder bed fusion span deep learning networks, generative models such as GANs and diffusion models, and reinforcement learning agents. These tools augment human engineers in exploring complex design spaces while balancing multiple objectives. In AI-driven topology optimization and generative design, machine learning enhanced topology optimization can reduce computational effort by learning from simulation data. Studies report that GAN-based solutions can generate optimized structures in one shot, and convolutional neural networks can achieve one-step topology optimization by learning the relationship between design inputs and optimal material layouts as surrogates for the FEA solver. Ensuring physical realism and generality remains an ongoing challenge.

Reinforcement learning learns optimal design decisions through trial-and-error interactions with a simulation environment, and it has been used to treat topology optimization as a sequential decision process while considering thermal constraints. Researchers also ensure AI-generated designs remain feasible for PBF manufacturing by incorporating process constraints. These constraints are support requirements and minimum feature sizes into generative algorithms, integrating an AM knowledge base into the optimization loop to respect support angle and orientation constraints, and by trimming unsupported overhangs during lattice optimization so the resulting geometry is self-supporting and printable without extensive support material.

For AI-driven design tools to be practical in metal PBF, they must integrate with physics-based simulations and account for manufacturing realities. Many approaches use datasets generated by FEA or analytical models to train AI models and create hybrid methods that combine data-driven learning with engineering knowledge. In this setup, AI does not replace simulation but augments it. Once trained, the model can rapidly predict outcomes such as stress distribution or effective modulus without running a full simulation for every design tested. Physics-informed AI is presented as an active research area that embeds physical laws into machine learning, so predictions respect principles such as equilibrium and conservation, supporting physically valid AI-generated designs.

AI is also increasingly used to predict and compensate PBF-specific distortions and defects at the design stage, since thermal cycles can lead to residual stresses and part deformation. One reported approach combines Gaussian process regression with an inherent strain simulation method to estimate distortions and offset the CAD geometry, so that printed parts more closely match intended dimensions. Verification and validation remain important when AI creates a design, so engineers loop back to high-fidelity FEA or print tests, forming an iterative loop described as a digital twin concept where AI suggests a design, simulations predict behavior, and the design is refined. Advances have been validated for metal PBF through simulation benchmarks or printing experiments, indicating a maturing synergy between AI and additive manufacturing in real engineering fields.

Moving forward, AI can expect to play a larger role in integrated design for additive manufacturing platforms. This includes algorithms that concurrently optimize part geometry, process parameters, and material distribution using multi-agent or hybrid AI systems, generative models conditioned on higher level functional requirements, reinforcement learning extended to optimize sequences of manufacturing steps, and more explainable models that improve trust and adoption in industry.

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