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Current and future trends in topology optimization for additive manufacturing

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Abstract

Manufacturing-oriented topology optimization has been extensively studied the past two decades, in particular for the conventional manufacturing methods, e.g., machining and injection molding or casting. Both design and manufacturing engineers have benefited from these efforts because of the close-to-optimal and friendly-to-manufacture design solutions. Recently, additive manufacturing (AM) has received significant attention from both academia and industry. AM is characterized by producing geometrically complex components layer-by-layer, and greatly reduces the geometric complexity restrictions imposed on topology optimization by conventional manufacturing. In other words, AM can make near-full use of the freeform structural evolution of topology optimization. Even so, new rules and restrictions emerge due to the diverse and intricate AM processes, which should be carefully addressed when developing the AM-specific topology optimization algorithms. Therefore, the motivation of this perspective paper is to summarize the state-of-art topology optimization methods for a variety of AM topics. At the same time, this paper also expresses the authors' perspectives on the challenges and opportunities in these topics. The hope is to inspire both researchers and engineers to meet these challenges with innovative solutions.

Keywords: Additive manufacturing; Topology optimization; Support structure; Lattice infill; Material feature; Multi-material; Uncertainty; Post-treatment

Contents

1. Introduction

Topology optimization, as a structural design method, has experienced rapid development in the past few decades, and dedicated reviews can be found in [1–3]. Different from size and shape optimization, topology optimization, as a freeform material distribution scheme, enables the creation, merging and splitting of the interior solids and voids during the structural evolution and therefore, a much larger design space can be explored, and superior structural performance can be expected compared with size and shape optimization.

Because of the expanded design space, the gained topological design has often been criticized for being too organic, which poses challenges during the construction and postediting of the associated CAD model. It is difficult to guarantee that a topologically optimized design to be manufacturable and aesthetically acceptable (deviates from what conventionally a mechanical part would look like). Often engineers will perform an “interpretation” step in which the organic shape is simplified into standard geometries and rebuilt from typical CAD primatives. Unfortunately, sizable optimality is often lost in this step. To address these issues, significant research has been carried out on manufacturability-oriented topology optimization, under both the density-based [4] and level set [5,6] frameworks. Related literature surveys can be found in [7,8]. Targeting conventional machining and injection molding, the length scale issue [8–14], no-undercut restriction [15,16], and feature-driven design [17] have been the primary focus. Solutions have been proposed to resolve these issues, but not all of them are mature enough for industrial application.

Different from conventional manufacturing methods, additive manufacturing (AM) is a rapidly developing technology which has the potential to transform next-generation manufacturing. Widely-used AM techniques range from Fused Deposition Modeling (FDM) and Stereolithography (SLA) for plastic printing to direct metal laser sintering (DMLS) and electron beam melting (EBM) for metal printing, to name a few. AM processes rely on layer-by-layer material deposition or solidification, which eliminates the geometric complexity restriction to a large extent. Furthermore, in AM, manufacturing efficiency and fabrication cost are not sensitive to geometric complexity. Therefore, AM can easily fabricate freeform design from topology optimization, and many of the manufacturability related issues discussed in the last paragraph are eliminated.

Despite these advantages, AM has its unique limitations which should be addressed when developing an appropriate topology optimization algorithms. As mentioned in [18], the lack of AM-friendly topology optimization solutions was a serious bottleneck. It has been over six years since the review paper by Brackett et al. [18] was published. Since then, some of the problems have been addressed, while some have been targeted, e.g., topology optimization with material anisotropy [19,20], self-support design [21–24], and porous infill design [25,26]. At the same time, new issues have arisen which are still under investigation. This perspective article summarizes the state-of-art in topology optimization for AM, and more importantly, discusses the remaining issues in depth and proposes potential solutions. We hope this paper would inspire researchers and engineers working in this exciting field.

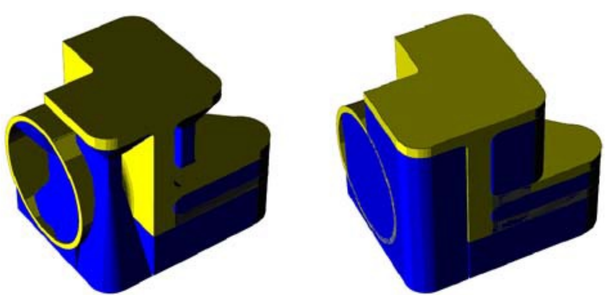
Note that topology optimization for bio-mechanical AM is not covered in this paper since a related literature survey was recently published [27]. In addition, feature size control is not covered, as it has been widely discussed in many recent publications [8,18], and length scale control techniques are well developed.

2. Support structure design

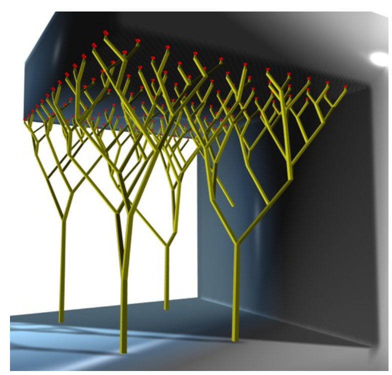
For many AM processes, supports are needed to ensure that large overhang areas can be successfully built. Printing the support can slow down the process and entails post-processing to remove the supports. It is estimated that 40%-70% of an AM product cost is expended for removal of support structures. Furthermore, the support material may be inaccessible and extra weight will be added to the final AM part in an undesirable manner. Although using dissolvable materials for support structures can somewhat solve the problem, it is still a challenging issue in many cases, especially for those manufacturing processes that can only handle single material, such as DMLS and SLA, or when the design contains self-enclosed cavities [25]. Therefore, it is important to design slimmed support or totally eliminate the need for supports.

2.1 Support slimming

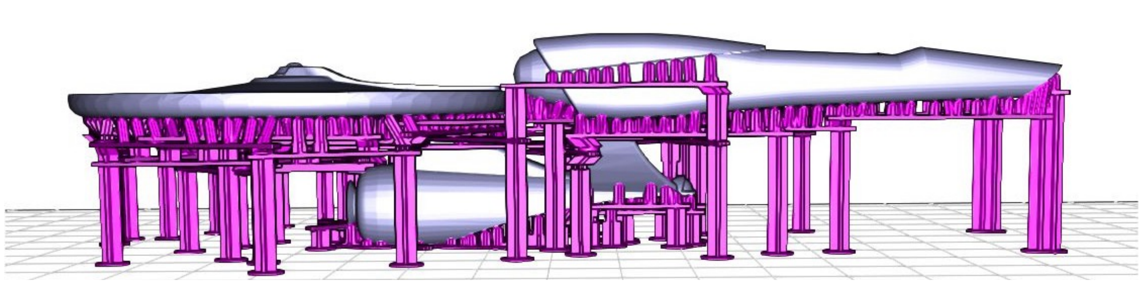
So far, several structural patterns have been used to slim down the support, including the sloping wall structure [28], tree-like structure [29,30], bridge-like scaffold [31], and repetitive cellular structures [32,33], which form lightweight support subjected to the well-defined part geometry and build direction. Hu et al. [34] developed a shape optimization based support slimming method, which slimmed the support by varying the part shape. Optimization of the build direction would also effectively reduce the support material consumption [35,36]. An orientation optimization framework that considers multiple factors in optimization was investigated in [37], where the optimizer is constructed by a training-and-learning approach. For topology optimization, work was conducted by Mirzendehdel and Suresh [21], which transformed the part design into a multi-objective topology optimization problem. A balanced objective function was proposed by concurrently considering the support material volume and structural compliance. A novel 'support structure topological sensitivity analysis' was proposed for the topology optimization implementation. However, their formula based on placing the self-supporting demand as 'soft' constraints cannot completely avoid the need for support structures.



(a) Comparing slope and straight wall supports [28]



(b) Tree-like support [29]



(c) Bridge-like support [31]

Figure 1. Slimmed support patterns

Another perspective deserving notice is that lightweight support structure has been achieved through different approaches; however, little attention has been paid to its thermo-mechanical performance, which may cause support failure. Especially for metal printing involved a heat source, where the thermal residual stress can lead to cracking of the support or separation (delamination) from the printing substrate; see Figure 2 for an example. Therefore, support topology optimization subjected to thermo-mechanical constraints is meaningful, and the main challenge is to develop a computationally-efficient thermo-mechanical simulation technique. Current commercially available software tools from AutoDesk Netfabb, Dassault Systemes' Simulia Abaqus, MSC Simufact, and others offer tools to simulate the thermo-mechanically driven build process, but are computationally expensive, even when modeling with a lower fidelity approach (whole or multiple layers added at a time as opposed to tracking the thermal history of the raster in a line by line manner). And the models rarely have easily accessible derivative information, making it infeasible to include them within a topology optimization design loop. A promising approach to decreasing the computational cost is to approximate the residual strains based on the inherent strain theory [38]. The inherent strains causing the residual distortion can be quantified through experiments or small-scale simulation, which is a one-time effort. It is generally a smooth function of the distance from the boundary to the interior [39]. Then, the inherent strain can be applied as the equivalent structural load to achieve fast part-scale simulation, which eliminates the need for the full-fidelity thermo-mechanical simulation, i.e., a reduction from days to minutes. More importantly, the fast simulation results show a good match with experiments; refer to Figure 3 [40]. By performing a constrained stress optimization coupled with fast process simulation, the support structure for a titanium alloy bioimplant has been optimized and printed successfully without cracking on EOS M290 DMLS machine by A. To's group at the University of Pittsburgh, see Figure 2b. Overall, a 45% weight reduction was achieved by the optimized support structure, which would lead to substantial material savings and reduced costs.

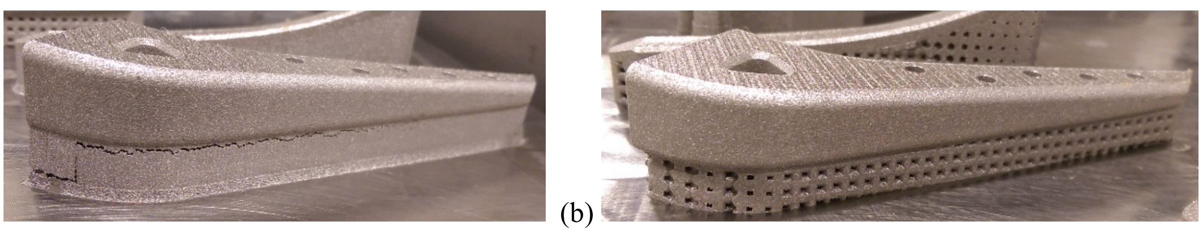
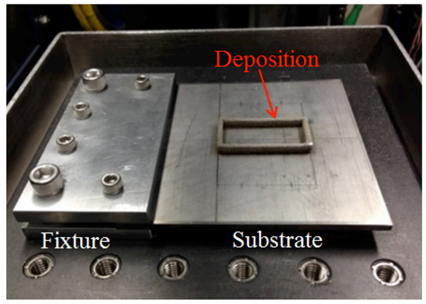
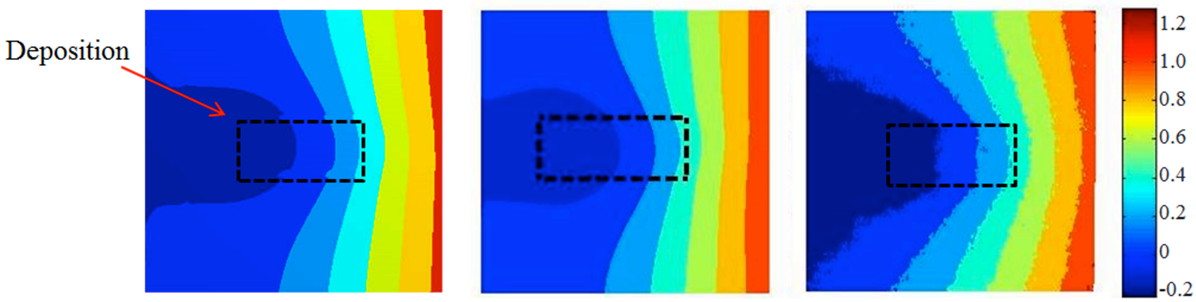
(a) (b)


Figure 2. Support structure design optimization for a part made by the laser metal AM process: (a) Part built with a generic, un-optimized support has cracks, and (b) part built with an optimized support structure remains intact.



(a)



(b) (c) (d)

Figure 3. Vertical residual distortion (unit: m) of (a) the LENS deposited five-layer contour by (b) detail process simulation, (c) inherent strain method, and (d) experimental measurement [40]

2.2 Overhang-free topology optimization

A more appealing topic is to develop the overhang-free topology optimization, i.e., totally remove the need for support. Here, the overhang-free indicates that all overhang angles are larger than the minimum self-supporting angle. A simple way to achieve the overhang-free design is through posttreatment; e.g., Leary et al. [41] added materials to the topology optimization result to remove the overhang-free violations, which is effective even though the optimality achieved by the topology optimization process is compromised. A more rigorous way to address the overhang-free requirement is by tailoring the formulation of the optimization problem. Brackett et al. [18] proposed the conceptual idea to iteratively linearize the structural boundaries, measure the lengths and orientations, and penalize the support-required overhang segments. Gaynor and Guest [22] realized the overhang-free design through an additional layer of design variable projection; see Figure 4, where the minimum self-supporting angle was embedded in the projector. Langelaar [42,43] proposed another density filter which achieves a similar overhang-free effect compared to [22]. A limitation of the density filter-based method is that the extra-layer of projection increases the sensitivity-related computational cost, as commented by the same authors [43,44]. Recently, Qian [45] used the density gradients to check the undercuts and overhangs and applied Heaviside projection to form a global constraint. Mass and Amir [46] developed a two-step approach to improve the printablity: first optimizing a discrete truss-based model to address the self-support requirement and then performing the continuum topology optimization with the discrete design as the start. Advantage of this approach is the obviously improved printability without major change to the continuum topology optimization algorithm.

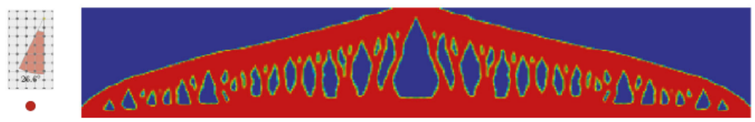
Comparing these techniques, it is noted that those produced by Langelaar are mesh dependent because the overhang angle is explicitly tied to element aspect ratio. Gaynor and Guest [22] presented a method based on design variables, which need not be tied explicitly to the mesh at all, i.e., a mesh independent method. This allows for easy adaptability to any prescribed minimum self-supporting angle, build direction or arbitrary unstructured mesh. It should be noted both schemes have been recently incorporated into commercial software: Gaynor and Guest [22] into Altair Optistruct and Langelaar [42,43] into Simulia's Tosca. It is encouraging to see TO for AM algorithms being incorporated in commercial codes – this exemplifies the strong pull from industry for better "design for AM" capabilities.

The MBB beam designed for the typical "rule of thumb" 45 degrees overhang constraint was printed on a 3D Systems ProX 300, which is a production level DMLS platform with a build volume of 250x250x300 mm^3. The 2D topology optimization, which was optimized to build in two directions – top down and bottom up – was extruded in the third direction to create a 3D part for printing. The parts were positioned on the plate in three orientations – coincident to powder recoating direction, 45 degrees to recoating direction and perpendicular to recoating direction. As seen in Figure 5, the part failed when the print orientation coincided with the recoating direction, which was not expected, as 45 degrees was thought to be a safe design, as it followed the rule of thumb 45-degree overhang rule. However, through this print validation of the topology optimization, it was found that the printable overhang angle was not uniform for all orientations. Here, the processing-driven thermally-induced distortions resulted in roller impact in a particular orientation. Since the raster pattern and other processing parameters (laser power, speed, etc.) were kept uniform for all printed parts, it is presumed the distortions were similar during print. It is therefore hypothesized that the interaction of the recoating roller was part orientation dependent, making the printable overhang angle orientation dependent. As such, this information must be acknowledged and fed back into the topology optimization algorithm, therefore completing the feedback loop from design to manufacturing, back to design.

In summary, overhang-free topology design has been achieved through different approaches. Given the limitations, the optimized topology is drastically changed compared with that of the conventional topology optimization, and the acceptance by general engineers is still questionable. And the topology depends heavily on the prescribed build direction. Other than that, there is still space to further enhance the computational efficiency and stability, e.g., eliminate the need of fine-tuning the control parameters.

a Solution with minimum self-supporting angle of 26.6 degrees, $f = 109.53$, $f_{\eta=0} = 103.42$.

b Solution with minimum self-supporting angle of 45 degrees,, $f = 116.11$, $f_{\eta=0} = 108.38$.



c Solution with minimum self-supporting angle of 63.4 degrees,, $f = 174.69$, $f_{\eta=0} = 158.95$.

Figure 4. Overhang-free topology optimization with various minimum self-supporting angles (26.6, 45 and 63.4 degrees) [22]

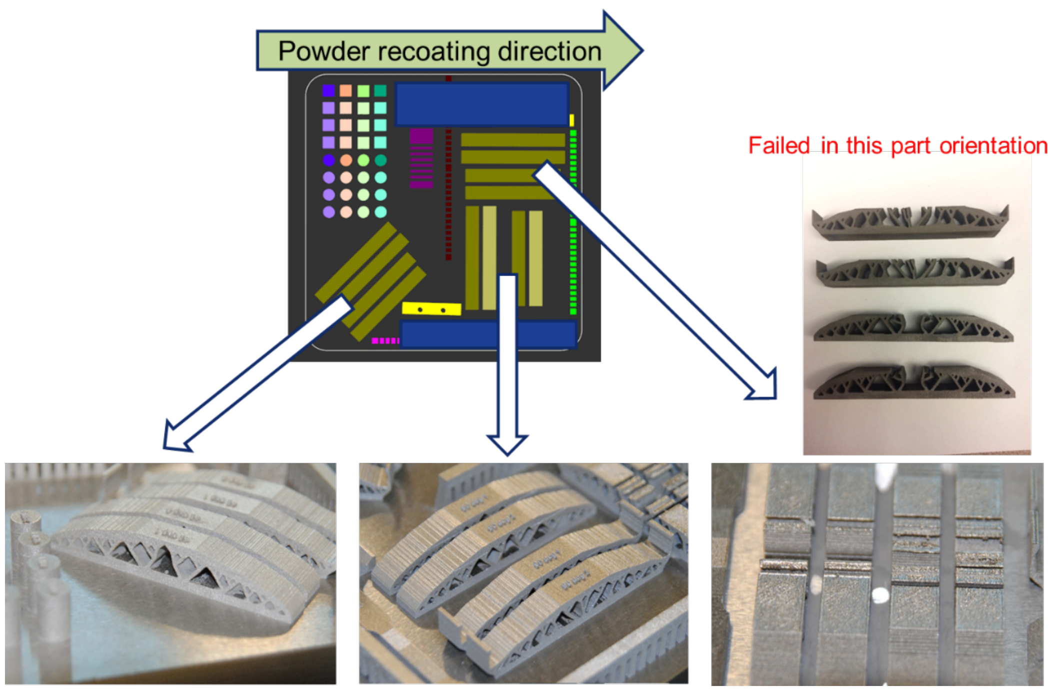
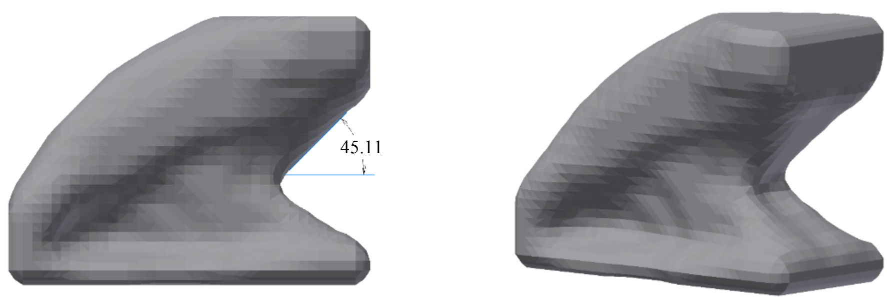
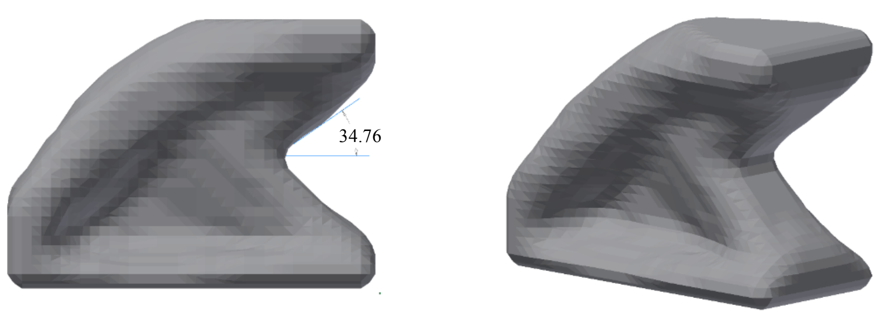


Figure 5. Topology optimization for 45-degree overhang (self-supporting), printed on a 3D Systems ProX 300 in 17-4PH Stainless Steel. The entirely self-supporting design succeeded in two of the three orientations, failing when aligned with the powder recoating direction.

It is worth noting that all these methods are developed under the density-based topology optimization framework. With the level set framework, Mirzendehdel and Suresh recently introduced the support volume topological sensitivity based on the surface angle and combined it with performance sensitivity for support structure optimization [21]. In a recent contribution, Allaire et al. [24,47,48] proposed a new physics-based approach for overhang-free topology optimization. Based on the layer-by-layer characteristics of the AM process, a new mechanical constraint functional is defined to aggregate the compliance of the intermediate shapes during the AM process of the structure, where each intermediate shape is fixed at the bottom and only subjected to gravity. Very importantly, the authors compared the proposed mechanical functional with the angle violation based geometric functional where the dripping effect of the latter was pointed out as a limitation even though the associated computational cost was cheaper. As an alternative solution, Liu and To [49] developed an overhang-free level set topology optimization method, where each level set function corresponds to a printing layer (or a bundle of layers with the same cross-section shape) and a novel multi-level set interpolation was proposed to constraining the spatial relationship of consecutive printing layers to avoid the overhang features. Then, the optimization problem can be solved similar to other multi-level set topology optimization problems [50–53]. Besides the layer-by-layer idea, Guo et al. [23] realized the self-support design through two explicit approaches: constraining the bar component angles of the MMC (Moving Morphable Components) method [54] and using self-support B-spline void representation of the MMV (Moving Morphable Voids) method [55]. This work developed a unified problem formulation where structural topology and build orientation can be optimized simultaneously for the first time. And some theoretical issues associated with self-support design (which are important for checking the effectiveness of different numerical solution schemes) was discussed for the first time. Very recently, Zhang and Zhou [56] developed a polygon feature based approach under the level set framework, where the polygon-featured holes were constructed through side-based or triangle-based Boolean operations of the basic side features. Shape of the polygons was optimized for shape and topology evolution and the overhang-free constraint was satisfied by controlling the side inclination angles. The dripping problem was solved through local modifications by merging intersecting polygons.



(a) Overhang-free topological design with the minimum overhang angle of 45.11 degree



(b) Freeform topological design with the minimum overhang angle of 34.76 degree

Figure 6. Overhang-free topological design through level set method

2.3 Remarks

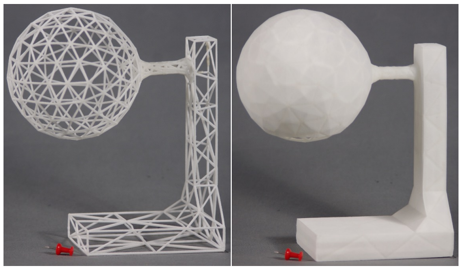
Comparing the support slimming and overhang-free topology optimization methods, they are equally significant from the authors′ perspective. Support slimming has the advantage that the component topology optimization is not or only weakly affected by the support design and therefore, high structural performance could be achieved; however, extra materials and printing time are needed, and the light-weight support structure risks failure due to the thermo-mechanical load. Comparatively, overhang-free topology optimization totally eliminates the need for support, where materials and printing time are saved; however, the structural mechanical performance is to some extent compromised. In practice, it would be useful to take advantage of both techniques to design parts that contain mainly self-supporting members, but strategically place sacrificial support material in regions where said placement would allow for significant improvement in part performance. And it may be useful to design support structures using the overhang-free topology optimization algorithms. In this way, the topology optimization could be formulated to minimize thermal distortions in the printed part while also minimizing the support material, resulting in supports that look similar to the branching supports seen in Figure 1b. In summary, these two techniques are complementary, and their coexistence provides alternatives to design engineers.

3. Porous infill design

3.1 Porous infill optimization

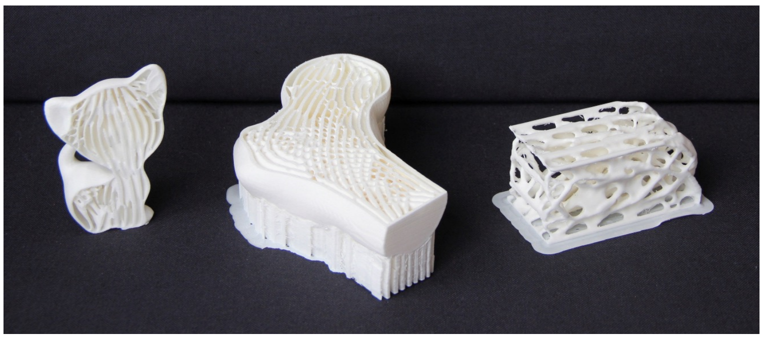
Because of the layered manufacturing process, it is unnecessary to stick to the solid infill when designing mechanical components; instead, porous infill can be a good alternative as it demonstrates key advantages in high strength to relative low mass, good energy absorption, and high thermal and acoustic insulation compared to its solid counterpart [57]. Therefore, diversified methods have been developed for topology optimization of the porous infill, and a brief literature survey is conducted in this section.

A simple approach is to use truss model to perform the infill [58–61]. The diameters and nodal positions of the struts can be effectively optimized with discrete topology optimization methods, such as the ground structure optimization [60,62]. In addition, the principal stress method [63,64] and the moving morphable component (MMC) method [65], which stemmed from conventional continuum topology optimization, can also be applied to design a similar type of porous infill. On the other hand, the self-support constraints were not considered [61] and support in dissolvable materials has to be built [66], which makes this approach only suitable for polymer printing. Other than that, printing defects widely exist in this type of lattice infill. Because of the layer-by-layer printing process, the struts are not perfect cylinders; instead, staggered boundary profile is produced and the defect is magnified with a reducing diameter [67–70]. This issue has been well known, but not yet been addressed in topology optimization to date. Ignoring these defects would cause the design performance being over-estimated.

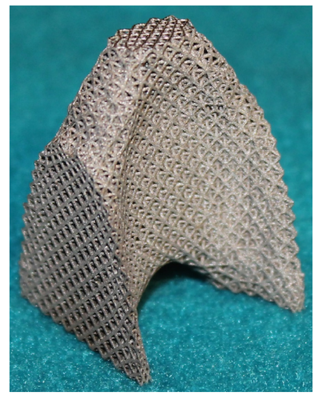


(a) Truss/beam infill [62]

(b) Variable-density periodic lattice infill [20]



(c) High-resolution voxel-based porous infill [26]



(d) Conformal lattice infill [71]

Figure 7. Different types of porous infill for AM

An alternative is a wall-like infill, such as the honeycomb-like [66] and grid-patterned interior [72,73] structures. To realize topology optimization of the wall-like infill, high-resolution topology optimization is necessary to generate the numerous local details. Wu et al. [74] developed an overhang-free infill optimization method, which adaptively filled the part interior by the self-supporting rhombic cells subjected to the stiffness and stability criteria through high-resolution computing. Additionally, Wu et al. [26] recently performed high-resolution voxel-based topology optimization and realized porous-type infill by adding local material fraction constraints, which is a novel attempt to generate porous infill through single-scale topology optimization. The numerical designs gained from [26] is a mix of both walls and trusses, where the former is preferred from the viewpoint of solid mechanics but the latter has better functionality (e.g., allowing interaction of the solid structure and surrounding fluids) and manufacturability (e.g., providing paths for removing the trapped powders). Generally, by increasing the minimum feature size, the structure tends to have more truss members.

A computationally more efficient approach is to perform variable-density lattice structure optimization [27,75–79], i.e., lattice units in prescribed base shape are selected to periodically fill the part interior where an optimal lattice density map will be derived through optimization. Because of the periodicity, computational homogenization can be applied to avoid full-scale simulation and the validity has been verified through extensive experiments and detailed finite element simulations [77,80]. Because of the fixed base lattice unit shape, material properties can be quantified *a priori*, instead of doing it iteratively. Both of the features significantly reduce computational cost. Recently, this approach has been extended to perform AM heat conduction design [81,82]. On the other hand, since the lattice unit type must be prescribed beforehand, the design space is restricted. An apparent observation is that the lattice unit details cannot freely change to account for the varying directions and magnitudes of the principal stresses, which make them only sub-optimal. In some cases, solid topology optimization results with the same material consumption could perform even better in stiffness and strength [83]. Other than that, conformal lattice infill has rarely been studied, while the nonconformity may leave many lattice units being cut across in the middle during post-processing. This could cause damages to both the appearance and mechanical performance. An exception is that Robbins et al. [71] reconstructed the lattice topology optimization result by deforming the lattice base shapes to fit the hexahedral mesh elements. However, the impact of the conformal reconstruction on the mechanical performance was not discussed. Even though there exist some limitations, variable-density lattice infill optimization is popular in the industry because i) it is computationally efficient; ii) the organic shapes from solid topology optimization are still not widely accepted; iii) AM lattice infill can always be made self-supported when their bridge span is chosen properly.

Compared with the variable-density approach, two-scale topology optimization enlarges the design space by concurrently optimizing both the macro and micro-scale material distribution, i.e., base shape of the lattice unit cell no longer has to be prescribed. Both homogeneous [84–91] and heterogeneous [92–98] lattice infill have been studied through the two-scale optimization. It has the issue of high computational cost, where the affordable design domain size is often limited, and local dis-connectivity occurs where the joining units cannot be physically connected. Attempts have been made to address these issues, for example, through parallel computing [92,93,97] for the former and imposing material variation constraints [97,99] for the latter. In addition, geometric modeling of such complicated structures is also a computational bottleneck. Efforts have been made by Wang and others [100,101] to conduct highly parallel algorithms running on many-core GPUs to improve the efficiency. An alternative two-scale optimization approach is to pre-establish a lattice material database and perform the topological design accordingly [102,103]. Since the database can have different unit cells corresponding to the same property, the local dis-connectivity issue can be partially addressed by picking up the best-fit unit cells by minimizing the boundary material mismatch across the adjacent cells.

Another future exploration direction is the so-called free material optimization (e.g. [104,105]). In this optimization, the macro-material physical properties are directly optimized instead of macro-density of usual topology optimization. This method was utilized in the design of fiber orientation angle of carbon fiber composites [106] and could now become a strong tool for AM lattice design.

3.2 Lattice material optimization (meta-material optimization)

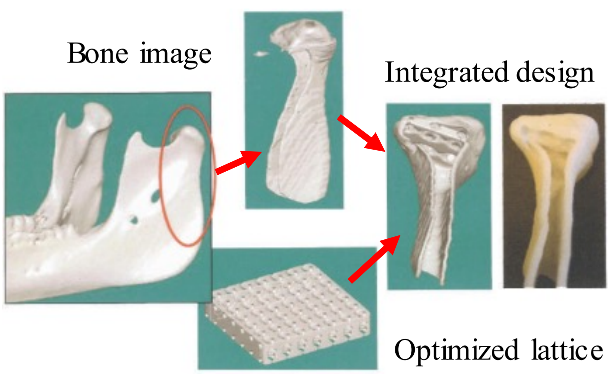
As discussed in the last sub-section, porous or lattice infill is a characteristic structure that could be fabricated only by AM. Aside from the part-level optimization, exploring novel lattice shapes itself is an important research topic of topology optimization and AM.

Even before AM became a major research field, the design of microstructure was an active research field in topology optimization. Their main scope realizes extraordinary effective physical properties through lattice shapes such as the one close to theoretical limits [107,108], negative Poison's ratio in elastic problem [109], negative thermal expansion [110], and acoustic negative bulk modulus [111]. However, their common issues were the lack of fabrication method for such small-scale complicated structures.

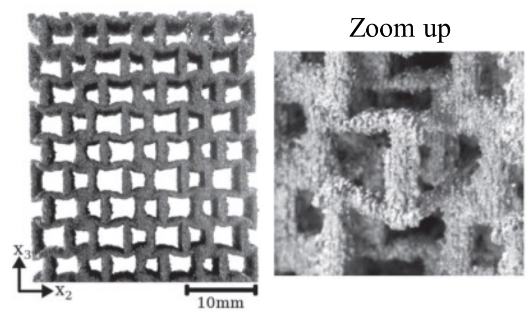
Although some special fabrication technique realized them [112], they needed to wait for AM technology to be sufficiently advanced for easy and precise fabrication.

Through early tries of AM fabrication [113], Hollister [114] performed the first utilization of the topology-optimized lattice in real-world application by AM technology. He developed an optimal lattice shape scaffold in tissue engineering adjusting macroscopic stiffness and permeability of lattices to human bones. Following that work, some lattices with extraordinarily effective physical properties were realized by AM as shown in Figure 8, in association with AM technology improvement and commercialization of sophisticated devices. Schwerdtfeger et al. realized negative Poisson's ratio by metal electron beam melting approach [115]. Andersen also realized a negative Poisson's ratio whose value reached -0.5 by Nylon selective laser melting approach [116]. Clausen et al. realized control of Poisson's ratio even in large deformation region considering geometrical nonlinearity [117]. Utilizing multi-material photopolymer AM, Takezawa et al. realized negative thermal expansion [118] and large positive thermal expansion [119]. The study on basic physical properties of thermal conductivity, stiffness, and strength are still active even recently [120–124].

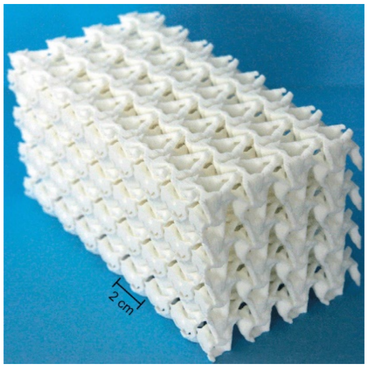
Aside from these successful results, we also need to reconcile with some pessimistic data. Specifically, severe performance reduction, by more than 50%, of AM lattice from topology optimization simulation results has been observed [120,121]. To utilize topology optimized lattice in real-world applications, the study of the reason behind the reported negative results should be examined carefully.



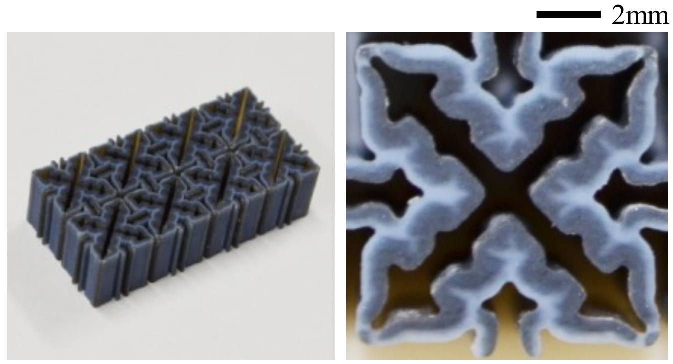
(a) Tissue engineering scaffold lattice design [114]



(b) Negative Poisson's ratio lattice by electron beam melting [115]



(c) Negative Poisson's ratio lattice by Nyron selective laser melting [116]



(d) Negative thermal expansion lattice by photopolymer multi-material AM [118]

Figure 8. Examples of AM lattice designed by topology optimization.

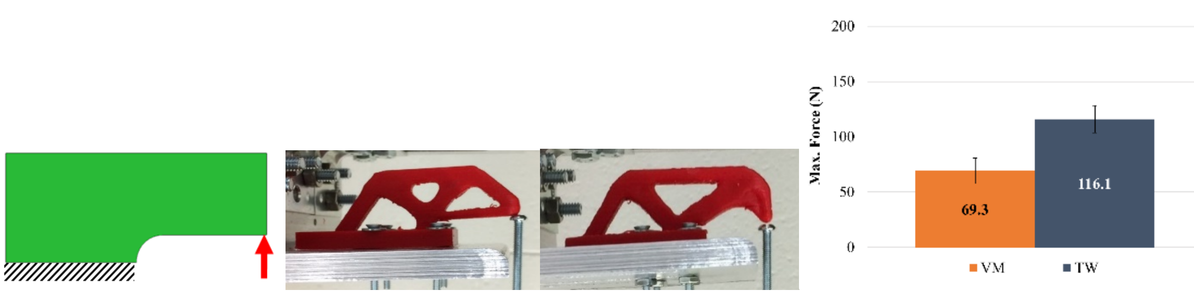
In summary, lattice material design itself still has much room for improvement through large-scale computation for more complex shape, optimization considering nonlinear mechanics, and optimization of 3D multi-material lattice. To improve these technologies, we must also address the issue of avoiding support structure discussed in Section 2. In lattice scale fabrication, support structures are difficult to remove if they are inside the lattice. Utilization of overhang-free topology optimization discussed in Section 2 and support free or easily removable support AM technology would help their improvement.

4. Material feature in AM

4.1 Material anisotropy

AM-induced material anisotropy is widely known [19,125]. Although efforts have been made to reduce the anisotropy [83], it generally cannot be totally avoided and therefore, should be carefully addressed when designing-for-AM. A thorough study of this topic can be found in [20], while we briefly revisit the problems and also presented some updated perspectives.

AM-induced anisotropy manifests itself in two ways: (1) Anisotropic constitutive properties relating stress and strain, and (2) directional strengths. In [126], the latter was addressed by replacing conventional von Mises stress criterion [127] with the Tsai-Wu stress criterion. They demonstrated, through simulation and experiments, that the Tsai-Wu criterion leads to better topologies by accounting for AM-induced anisotropic strength (see Figure 9). As one can observe in Figure 9, the Tsai-Wu based topologies outperform the von Mises based topologies by 65%.



(a) (b) (c) (d)

Figure 9: Accounting for anisotropic strengths in AM: (a) problem formulation, (b) optimal topology of 50% volume fraction obtained using isotropic von Mises stress criterion, (c) optimal topology of 50% volume fraction obtained using anisotropic Tsai-Wu stress criterion, and (d) force required to induce failure for the two topologies.

Regarding the anisotropic constitutive properties, it can be either build direction- or raster direction-dependent where the former is more evident for most AM processes. Therefore, optimizing the build direction has attracted the early attention and effective improvement of mechanical performance [128–130] has been observed. Besides, concurrent build direction and topology optimization problem is trivial to solve, for example, through continuous orientation optimization [131,132]. A major challenge lies in multi-build direction AM (refer to Figure 10), where the part is printed in multiple directions [133–136], and material properties in each build area would be different. Even though multi-material topology optimization [50,51] can readily solve this problem, how to customize the algorithm to facilitate the AM process planning remains a tough problem. For example, see Figure 11: the related process planning is difficult in the case that each color corresponds to a different build direction.

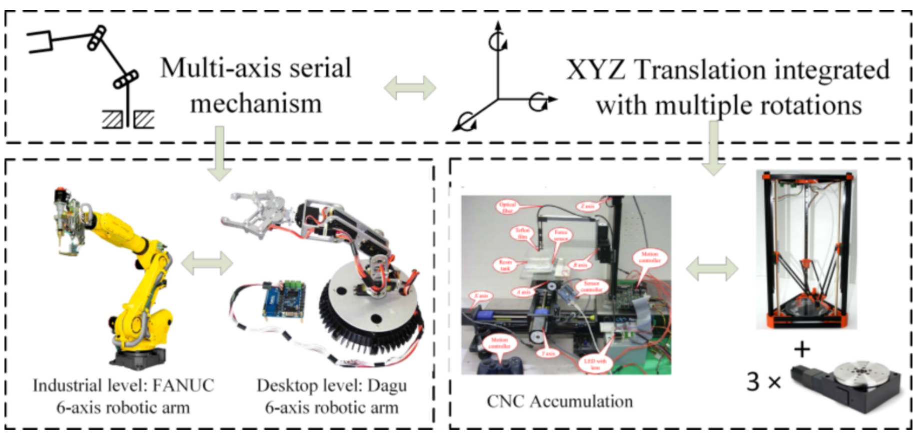


Figure 10. Alternative mechanisms to achieve multi-axis extrusion [133]

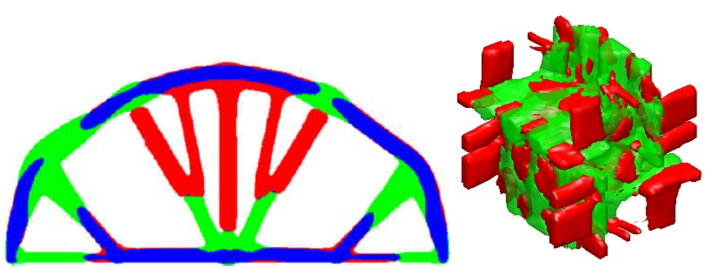


Figure 11. Multi-material topology optimization through the "color" level set method (left) [50] and the reconciled level set method (right) [137]

Investigation on the raster direction optimization is less focused, since the raster direction-dependent material anisotropy is obvious mainly for the filament extrution-based process. Smith and Hoglund [138] explored the raster direction optimization and realized the optimized printing paths into real parts.

However, a limitation is that the raster directions are treated as discrete orientation variables without considering the tool path continuity. Liu and Yu [139] performed the concurrent raster direction and topology optimization by building the continuous contour-offset tool paths and also addressed the continuous tool path design for fixed geometries through the radial basis function (RBF) fitting and level set modeling. Limitations of treating the raster directions as discrete variables were revealed, i.e., the sharp path turnings reduce both the printing efficiency and quality. Recently, Dapogny et al. [140] performed a even more thorough study on the tool path-integrated topology optimization where a couple of tool path patterns were comparatively evaluated and the full sensitivity result is given other than the simplified version in [139].

Various tool path patterns have been applied to AM [141], including the zig-zag, contour-offset, hybrid, and medial axis-based, and each alternative has its unique characteristic from the perspective of manufacturing efficiency and quality. Selection of the specific path pattern significantly affects the derived structural performance, but an in-depth study on this topic is still lacking. Numerical results presented in [139] compared the zig-zag and contour-offset path patterns. Future studies on topology optimization with the hybrid, medial axis-based, or even more complex path patterns are still ongoing.

4.2 Microstructure control via topology optimization

A possible future direction is to utilize topology optimization to control microstructure (e.g., micro-porosity, grain size) distribution in laser or electron beam powder bed AM processes for metals. In most commercially available systems, there is very limited user control over changing process parameters (e.g., scan power, speed) dynamically during the build process. Assuming that the process parameters must be fixed, due to the local geometry changes in a complex design, the melt pool size also changes during processing, which leads to spatial variation in the microstructure. This is usually undesirable as underheating or overheating from local geometry change could cause the formation of microscale pores detrimental to structural integrity, particularly to fatigue life. Although one cannot expect topology optimization to control microstructure precisely, there is still a great opportunity to reduce its deviation from the designed microstructure. One way to achieve this is by controlling the thickness of local geometric features such as beams or struts in topology optimization, which has been addressed in prior methods to satisfy manufacturability requirements. The key challenge, however, is the long simulation time in performing a part-scale AM process simulation to predict the melt pool size and microstructure. Hence we suggest that further research be conducted to develop more efficient process simulation models to gain a deeper understanding of the process-microstructure relationship, which in turn, may enable a robust topology optimization method for controlling microstructure. The optimization method also probably needs to consider the limits on how fast the scan power and velocity can be changed.

5. Multi-material and nonlinear topology optimization

5.1 Multi-material topology optimization

Multi-material structural design through topology optimization can be traced back to the 1990s. Sigmund and his colleagues [142,143] applied multi-material topology optimization to design extreme material properties, and Bendsoe and Sigmund [144] summarized the rules of multi-material interpolation under the density-based framework. Gaynor et al. [145] implemented both this scheme and a new alternative multi-material scheme in conjunction with a robust min-max topology optimization scheme to design multi-material compliant mechanisms [142]. This work highlights the importance of incorporating material properties, as the design changes rather significantly with varying material options. Recently, Watts and Tortorelli [146] proposed a new multimaterial scheme easily adaptable to "n-materials" by implementing a smooth thresholding scheme to specify the volume fraction of each material. This scheme helps eliminate the nonlinearity issues seen in Bendsoe and Sigmund's material interpolation scheme when going beyond three materials. Kennedy [147] applied the DMO (Discrete Material Optimization) for multi-material interpolation and more importantly, employed the full-space barrier method to address stress constrained problems without constraint aggregation.

Under the level set framework, Wang et al. [50,148] proposed the 'color' level set method (CLSM) for multi-material topology optimization, which was later widely followed. In the CLSM, the materials are indexed by using the different sign combinations of n level set functions. In this way, those n level set functions can represent at most 2^n materials. An alternative method is the piecewise constant level set method [149,150], in which different values of the level set functions split the design domain into different areas. Reconciled level set method (RLSM) is employed for topology optimization of NPR (Negative Poisson's Ratio) metamaterials. The RLSM was first introduced by Merriman, Bence, and Osher [151,152] for modeling multiphase flow and was later applied to multi-material topology optimization of smart energy harvesters [153] and metamaterials [137]. RLSM retains the features of CLSM in multi-material representation and the convenience in specifying arbitrary design velocities on each level set function. In addition, RLSM offers a more straightforward and convenient way to set up multi-material topology optimization than CLSM, since each individual material is uniquely represented by an independent level set function. An alternative level set method to eliminate the overlapping area of the level set functions was developed by [154] where the strategy of filling the overlapping area with an artificial weak material was proposed. Interestingly, length scale control on multi-material topology optimization was achieved with this method. Recently, Wang et al. [51] proposed the MMLS (Multi-Material Level Set) method also based on sign combinations of multiple level set functions. Technical merit of the MMLS is the removed redundant material areas because n level set functions are utilized to represent n+1 material phases.

The classic approach to multi-material topology optimization is to minimize compliance or stress while imposing two sets of constraints: (1) a total volume constraint, and (2) individual volume-fraction constraint on each of the material constituents. The latter, however, can artificially restrict the design space. Instead, in [155], the compliance and total mass were treated as conflicting objectives, and the corresponding Pareto curve was traced; no constraint was imposed on the material composition. Consequently, a series of Pareto-optimal multi-material designs were obtained.

Even though widely studied, the multi-material topology design solutions were not physically realized due to a lack of an effective manufacturing method in the past. AM now provides a robust approach to fabricating multi-material components, regardless of the complexity of the interface distribution. A few topology optimization results have been realized into real products through multi-material AM [137,145,156]. On the other hand, it is still an issue to improve the numerical analysis accuracy around the interface areas [157] and reflect the actual behavior of printed materials [158,159].

Another point worth mentioning is that producing part in functionally graded material is enabled by AM and there are different topology optimization approaches readily designing this type of structures [160–164].

5.2 Nonlinear (multi-material) topology optimization

Up to now, most topology optimization studies have been focusing on linear elastic structural systems. This popularity primarily stems from the simple and efficient implementation in both structural finite element analysis and sensitivity analysis. However, linear elasticity inherently lacks the capability of predicting the accurate structural performance under extreme working conditions, in which the structures often behave nonlinearly. In this scenario, the optimized linear elastic designs can perform poorly after entering the nonlinear regime. Besides, other than the structural stiffness (or compliance), other important quantities required in performance-based design phases, such as plastic work, damage and fracture, or buckling load, may not be calculated making the linear elasticity assumption. As the products by AM often represent a porous structure such as lattice or cellular structures, which tend to show irreversible inelastic deformation and occasionally exhibit local buckling even under a moderate loading, optimal design considering nonlinear structural response is also an important topic in AM.

Structural nonlinear responses can arise from geometric and/or material nonlinearity, and topology optimization with such nonlinearities remains challenging so far. For topology optimization with geometric nonlinearity, the main challenge is the mesh distortion issue. This issue is mainly due to the excessive deformation in the low-density elements which causes the tangent stiffness matrix to lose positive definiteness and eventually non-convergence of the Newton-Raphson solver. Several strategies have been proposed in the past two decades to address this critical issue. The important ones include internal nodal forces exclusion scheme by Buhl et al. [165] and Pedersen et al. [166], element removal and reintroduction scheme by Bruns and Tortorelli [167], connectivity parametrization by Yoon and Kim [168], improved nonlinear solver via Levenberg-Marquardt method by Kawamoto [169], element deformation scaling by van Dijk et al. [170], energy interpolation scheme by Wang et al. [171], additive hyperelasticity technique by Luo et al. [172] and the recent DOF removal technique developed under the explicit MMC/MMV–based framework by Zhang et al. [173]. With the mesh distortion issue being addressed, the nonlinear topology optimized results were demonstrated to differ greatly from the linear ones and have improved performance under large deformations. Some important applications in this field include maximization of the critical load of a continuum structure with large displacement by Kemmler et al. [174], consideration of hyperelastic bodies with non-zero prescribed displacement by Klarbring and Stromberg [175] and topology optimization of snap-through problems with the buckling objective function proposed by Lindgaard and Dahl [176].

For topology optimization with material nonlinearity, the customarily studied case is elastoplasticity. As the material is no longer reversible in this case, sensitivity should account for all the previous structural states at each integration point. Thus, the central focus in this topic is on how to derive accurate analytical sensitivity in a computationally efficient manner. In early works, the general formulation of sensitivity analysis was introduced by, for example, these studies [177–184]. Swan and Kosaka [185] first studied continuum topology optimization with elastoplastic materials using the classical Voigt-Reuss mixing rules, while an adaptive topology optimization considering von Mises plasticity based on the SIMP method was introduced by Maute et al. [186], Schwarz and Ramm [187]. Later on, Bogomolny and Amir [188] incorporated topology optimization with the Drucker-Prager plastic model for reinforced concrete design. Kato et al. [189] introduced an efficient approach to reduce the computational efforts dramatically while holding sensitivities highly accurate, in which energy absorption capacity of a structure, under the assumption of von Mises elastoplastic deformation, is maximized. Nakshatrala and Tortorelli [190] proposed a topology optimization framework for energy dissipation maximization subjected to impact loadings wherein the material response was modeled with von Mises plasticity. Wallin et al. [191] proposed topology optimization considering finite elastoplastic deformation and also Zhang et al. [192] introduced an approach assuming anisotropic elastoplasticity based on the adjoint method [184]. Xia et al. [193] adopted BESO method for elastoplastic structure design. Li et al. [194] employed kinematic hardening model based on von Mises plasticity to capture the well-known Bauschinger effect under cyclic loads. Recently, a elastoplastic shape optimization was explored via the level-set method by Maury et al. [195].

Other than elastoplasticity, material nonlinearity also includes material softening (damage) and viscosity. Topology optimization considering damage was first introduced by Bendsøe and Diaz [196] wherein an approximate elastic-damage model was used for designing structures with damage constraints. Challis et al. [197] proposed a level-set based topology optimization method for brittle elastic fracture resistant designs, wherein the fracture is evaluated by the energy release rate of crack propagation. Further attempts have been made to incorporate topology optimization with elastic-damage models for maximizing the stiffness of reinforced concrete structures by Amir and Sigmund [198] and Amir [166]. James and Waisman [199] used an elastic-damage model with constraints on damage and compliance for obtaining minimum weight designs. Kang et al. [200] proposed a topology optimization method to generate cracks insensitive/sensitive designs based on a linear elastic fracture model. In the work recently proposed by Li et al. [201], Li and Khandelwal [202], Alberdi and Khandelwal [203], coupled and uncoupled damage models were incorporated into elastoplastic topology optimization for damage-resistant energy absorption structure designs. Noël et al. [204] extended the elastic-damage model into topology optimization via the level-set method. More recently, Xia et al. proposed a BESO based fracture resistant topology optimization that accounts for the complete fracturing process in quasi-brittle composites [205]. For the ones dealing with viscoelasticity and viscoplasticity, the readers are referred to the references [206–212]. The optimization of discrete structures, like trusses or beams, considering material and geometric nonlinearities were discussed in Choi and Santos [213], Ohsaki and Arora [214], and Ohsaki and Ikeda [215]. However, to the best of the present authors' knowledge, the number of studies on a method of optimization which considers both nonlinear structural response and multi-material is limited [185,188,189]. For a continuous damage model considering single- and multi-material, readers are referred to the studies by Kato et al. [216], Kato and Ramm [217], Amir [218].

Although the studies considering nonlinear structural responses are summarized above, it is still an open question on how to implement these academic methodologies into a practical design for AM in reality. To the best of the authors' knowledge, no optimization software can answer to the demand yet for multi-material design considering nonlinear structural responses. There is also another question regarding how to reduce the computational costs required especially for path-dependent sensitivity analysis, which occupies most of the computational efforts as one extra backward substitution for each load step is generally required to get the corresponding adjoint variable. In a recent paper by Alberdi et al. [219], a unified path-dependent sensitivity analysis framework that can account for various inelastic materials, dynamic effects, large deformation as well as FEA formulations in the context of density-based topology optimization, is proposed. The authors expect the development of useful sensitivity analysis enables to provide a certain accuracy in moderate computational costs.

5.3 Topology optimization of structures with specific functionalities

5.3.1 Topology optimization of structures with embedded functional components

Multifunctional structural systems can be implemented by integrating functional components into the host structures using stereolithography, direct print and other AM technologies [220]. These components may fulfil multiple functionalities, such as load-carrying, electronic circuiting, actuation and structural health monitoring [221].

Topology optimization of structures with embedded functional components may involve special geometrical, mechanical and multidisciplinary requirements to be addressed. First, the layout (position and orientation) of the embedded components, often with prescribed geometries, may need to be simultaneously optimized with the topology of the host structure so as to provide the maximum structural stiffness and to make full use of the usually tight 3D space. Therein, geometrical constraints, including but not limited to non-overlap, shape-preserving and minimum distance constraints among the embedded components, are often to be observed to avoid possible interference of different functionalities [222,223]. Second, interfacial strength issues between the host structure and the embedded components must be considered to maintain integrity of the structure [159,224]. Finally, multi-physics requirements, such as mechano-electric coupling, thermal/ electromagnetic insulation, thermal management and electrical routing, are often encountered in the integrated design of functional structures. Without consideration of these functionality- and manufacturing-related requirements in mind, conventional topology design methods may become less effective.

Apart from abovementioned studies, which address some important issues of component-embedding topology optimization, there are also a few works on layout design of multifunctional components that fully exploit the design freedom of AM. An interesting example was presented by Panesar et al., who developed a topology optimization framework for the design of functional structural systems to be made using multi-material AM processes [225]. Walker et al. performed topology optimization of a wing structure to be fabricated through AM, in which a fuel tank is embedded to act as both a functional component and a load bearing structure [226]. Clearly, combination of topology optimization and AM opens a new path to the design and manufacturing of such integrated multi-functional structures which were not previously feasible.

5.3.2 Topology optimization of multi-material active structures

Conceptual design of active structures, such as piezoelectric actuators and active vibration control structures, have been well studied using multi-material topology optimization formulations [227–229], or integrated optimization of structural topology and control parameters [230,231]. Realizing that piezoelectric ceramics are fragile and actuators with complex geometric shapes are extremely difficult to manufacture, Wang et al. proposed a topology optimization formulation incorporating commercially available regular-shaped PZT actuators into the structure to enable in-plane motion [232]. In general, topological design of active structures is still limited by manufacturing restrictions. However, the emerging 3D printing technology provides many new possibilities of fabricating active structures with embedded functional materials such as piezoelectric materials or shape memory polymers. For instance, state-of-the-art multi-material printers allow precise placement of active materials to form a structure that can be later activated in a controlled manner to change its configuration in response to certain stimulus. This is also known as 4D printing [233]. To take advantage of this capability, Maute et al. introduced a level set-based topology optimization method into microstructural layout design of printed active composites (PACs) [156]. The use of the level set model ensures smooth and well-defined material boundaries, and the optimized designs were verified by experiments (Figure 12). Ge et al. used 3D printers to precisely place shape memory polymers into an elastomeric matrix as intelligent active hinges to enable 4D origami folding patterns, and pointed out a future direction of the folding design based on topology optimization [233]. Currently, developing soft actuators and sensors by means of 3D printing of viscoelastic polymers has also become an interesting topic [234]. It is envisaged that topology optimization may offer an useful design tool to exploit this capability.

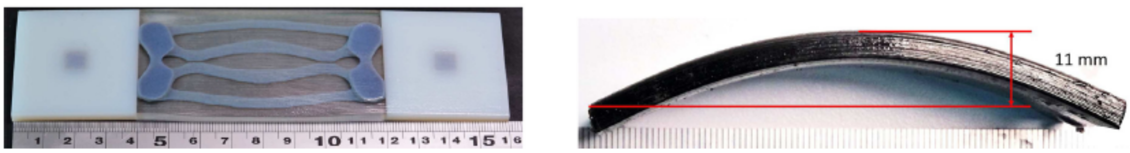


Figure 12. Experimental verification of a printed PAC sample with optimized topology [156]

6. Robust design incorporating material and manufacturing uncertainties

Additive manufacturing introduces a host of uncertainties into the design process, most notably the material and manufacturing uncertainties. The material properties depend highly on raster pattern, build direction, part orientation, and technology dependent processing parameters such as laser power, laser speed, raster overlap for DMLS and bead size, extrusion rate, etc for extrusion-based methods such as FDM, or wire-fed metal AM systems.

6.1 Topology optimization under material uncertainty

Materials are typically benchmarked for each AM system by building and testing tensile, compression, and other specimens for mechanical characterization, microstructure characterization, and other material property characterization such as hardness testing, surface roughness, void density, and distribution, among others. To account for the material property dependence on feature orientation, these specimens are usually built in various orientations. Once the material properties of concern are quantified, a mean and standard deviation can be calculated for each property. Finally, this material property information can be fed back into the topology optimization algorithms resulting in more robust and reliable solutions.

A few researchers have introduced material uncertainty to topology optimization using either the robust design formulation or the reliability-based design optimization (RBDO) formulation. Asadpoure et al. [235] studied robust optimization of structures under uncertainties in material stiffness through a stochastic perturbation method incorporating second order statistics. Chen et al. [236] employed the Karhunen-Loeve expansion of random fields to incorporate material and loading uncertainty in a level set framework for robust topology optimization. Lazarov et al. [237] introduced the stochastic collocation method to incorporate stochastic material stiffness and geometry into a density-based topology optimization framework. Jalalpour and Tootkaboni [238] presented a reliability-based topology optimization method considering material property uncertainty in continuum domains using second-order stochastic perturbation to evaluate the response statistics. When sufficient samples are not available to permit a precise probability model of the uncertain inputs, non-probabilisic convex models [239] providing smooth bound descriptions of the uncertainties become attractive for acquiring reliable topology optization solutions [240].

It is also possible that geometrical nonlinearities interact with the material property variations and thus aggravate the effects of these uncertainties. To this end, Jung and Cho [241] studeid reliability-based topology optimization for three-dimensional geometrically nonlinear structures in presence of uncertainties of material properties and external loads. Kang and Luo [242] presented a non-probabilistic reliability-based topology optimization method for the design of continuum structures undergoing large deformations.

These approaches become even more necessary in AM since the obtained material properties can vary drastically within a build volume. Interestingly, it has been found that material properties exhibit significant variability even when locking in the machine, feedstock material, and processing parameters. For example, it is common to obtain statistically significant differences in material properties (mechanical, defect distributions, etc.) when simply changing machine operator. While this speaks to the need to develop higher quality and less fastidious AM machines, the engineer must be able to design for the situation. Hence, employing one of the aforementioned approaches (or similar) will help drive toward robust, material aware solutions.

6.2 Topology optimization under manufacturing uncertainty

While topology optimization can design complex "organic" structures, the manufacturing process will always deviate from the design, even if that deviation is minimal. The significant performance reduction of AM parts and lattice materials, for instance as mentioned in Section 3.2, marbe partly attributed to geometric uncertainties arising from manufacturing imperfection. In Guest and Igusa [243], it was demonstrated that if no uncertainty in geometric accuracy of manufacturing (construction) is accounted for in the optimization, the solution to a multimember, pin connected truss in compression is a straight truss with "pivot joints" along the length. However, as can be inferred, with the slightest perturbation of nodal location, i.e., manufacturing tolerance, the optimized structure would buckle on itself. The presented issue is fixed by introducing uncertainty in nodal location to the optimization scheme, resulting in structures with a primary load path along the axial direction but with bracing members to prevent buckling of the structure. This scheme is also implemented in continuum topology optimization in addition to truss topology optimization and showcases the ability to produce structures that are more stable and often introduce redundant load paths (in typical topology optimization, the optimal structures are often statically determinate, i.e., with no redundant members).

To better illustrate the necessity of incorporating manufacturing uncertainty, an example of an optimized gear is presented. This gear, optimized for torsion loading and with a relatively small minimum feature size in relation to the global size of the part, was manufactured through Stratasys Objet Polyjet technology and with FDM. The resulting 2D optimization was post-processed into a 3D geometry through thresholding of the element densities and extruded a certain thickness in the third dimension. After manufacturing, the two gears were scanned on a CT system and analyzed through a post-processing software to perform an "as designed vs. as manufactured" comparison. The gear in the top right of each subplot shows the deviations from the as-designed geometry and the plot below shows quantitative information on the deviations. Interestingly, the distributions vary greatly for the two manufacturing approaches with the Polyjet approach showing a general trend for features manufactured smaller than designed; the FDM approach exhibiting a bimodal distribution, showing features either deviating smaller or larger than designed. It is hypothesized that the Polyjet approach exhibited some shrinkage of the part. The FDM gear most likely ran into the discreteness issue of an extruded bead. Many of the small struts in the gear were likely specified for a ~2.5 beads widths, so the printer had to either place too much material (3 beads) or too little material (2 beads). Hence, the FDM additive manufacturing system's software must perform rounding operations when translating from desired topology to printed topology. While there are currently no continuum topology optimization approaches to design for a discrete set of allowable bead widths – feature must have integer increments of bead width (1 beed wide, 2 beads wide, etc.) – a designer may be able to begin designing for this though some combination of both a minimum and maximum lengthscale. It is noted that minimum length-scale control can guarantee a feature is not smaller than the bead width (or perhaps 2 bead widths), but this length-scale control does not prevent the occurance of non-integer increments of bead width. For example, it is entirely possible to design to a minimum length-scale of 2, but the algorithm can certainly create a feature of width 2.7. A similar situation exists for maximum length-scale control. Future research is necessary to develop algorithms to design for this extrusion-based additive manufacturing situation.

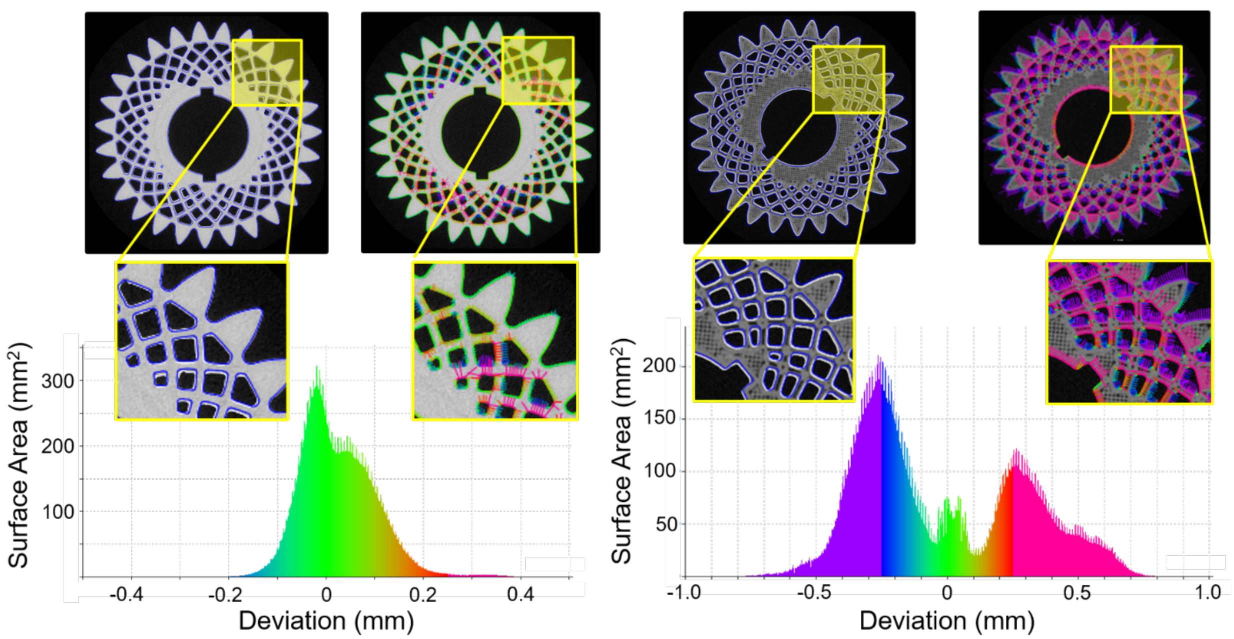


Figure 13. CT scan analysis of a topology optimized gear. The gear on the left was manufactured through a photopolymer inkjet process (Stratasys Polyjet), while the gear on the right was manufactured through fused deposition modeling (FDM).

There has been an uptick in papers approaching the material placement problem. Jansen et al. [244] approached the problem through a density filter-based approach incorporating a random field in the perturbation-altered filter kernel formulation. Wang et al. [245] propose an erosion and dilation projection approach that mimics an under and over deposition of material. This approach is demonstrated on compliant mechanism design, which eliminates the oft-mentioned issue of one-node hinge solutions. This work builds upon a similar formulation proposed by Sigmund [246]. Chen et al. [247] employed a boundary velocity perturbation approach to introduce geometrical uncertainty into topology optimization. In order to treat possible topoligical changes (e.g. breakage of structural members) caused by manufacturing errors in a mathematically more rigorous manner, Zhang and Kang [248] proposed a stochastic level set perturbation model of uncertain topology/shape to characterize manufacturing errors, and integrated this model with the random field-based uncertainty quantification techniques to achieve robust shape and topology optimization results. Recently, Keshavarzzadeh et al. [249] presented a study on density-based topology optimization under manufacturing uncertainty by integrating the non-intrusive polynomial chaos expansion with design sensitivity analysis. Therein, the geometrical uncertainties are introduced with a Heaviside thresholding model.

While the aforementioned approaches tackle robust design for stochastic material placement, there remains a need to develop approaches to tackle material shrinkage during the AM build. In many processing situations, especially DMLS, the rapid heating (melting) and cooling (solidification) of the material results in significant residual stress buildup during the build. After removing parts from the build plate, it is common to obtain parts with significant "spring back" distortions, creating situations where the as-built part is significantly out of design tolerance and thus requires post-processing including heat treating, and in many cases machining. As such, the as-built geometry can differ from the as-designed geometry by an appreciable amount. To counteract this phenomenon, the printed geometry must compensate accordingly to at least eliminate the need for machining – in many cases, topology optimized geometries are inaccessible for post-machining, so these "manufacturing cognizant" smart design algorithms are needed to produce parts which are realistic and achievable with current additive manufacturing processes.

7. Post-treatment

7.1 Post-machining

As discussed in the previous section, AM components deviate from the 'as designed' geometry and suffer from poor surface quality. Hence, if tight tolerances in size, form, and surface finish are required, subtractive machining is necessary to post-process the AM component, which transforms the AM into a hybrid manufacturing strategy [250]. On the other hand, an AM component from topology optimization is often too complex in geometry, which makes post-machining oftentimes more expensive than the AM process itself. Hence, a key point for hybrid manufacturing-oriented topology optimization is to produce machining-friendly topological design and thus to reduce post-machining cost.

Topology optimization for hybrid manufacturing is an emerging topic, wherein little progress has been made. The key issue here is the many violations of the machinability-related design rules [7,8], e.g., interior holes are difficult to access but are often produced by topology optimization. Interestingly, recently, Liu et al. [251] and Li et al. [252] demonstrated a method to eliminate internal voids through introducing an artificial heat assigned to the void regions with zero temperature boundary conditions on the edges of the design domain. The optimization problem is then made slightly more complex with an additional constraint on the material "temperature," thus eliminating internal voids. Note that, there are also other methods to generate internal void-free topological design [15,16,253,254]. The interior void-free topological design ensures the part machinable; however, the geometric complexity-associated post-machining cost is not specifically considered. For instance, 2.5D machining is much more cheaper and efficient than 3D CNC machining [17]. Thus far, the only topology optimization implementation considering the specific post-machining technique was found in [255]. The casting-SIMP (Solid Isotropic Material with Penalty) [256] was used to remove materials from boundary to surface, so that undercut or interior void was avoided. Then, material removals at some pre-selected directions were regulated through 2.5D machining feature fitting, which therefore can be simply post-treated with 2.5D machining. Figure 14 illustrates the topology optimization result where only the side surfaces will be post-machined.

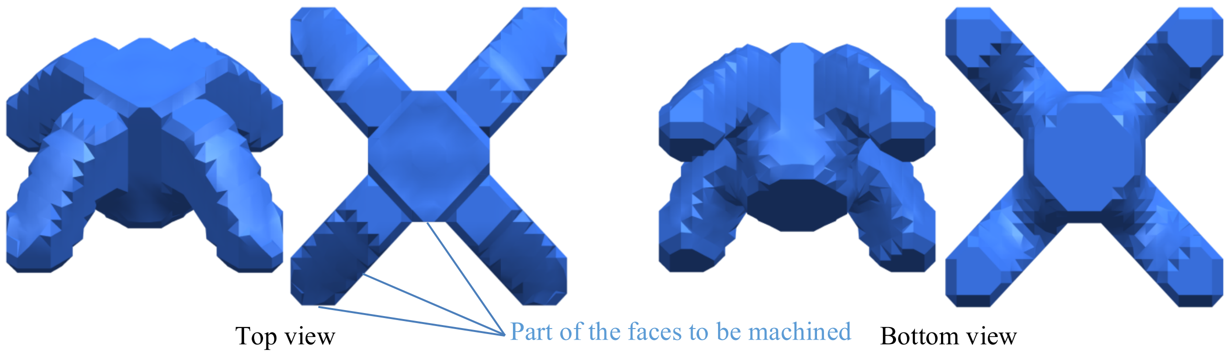


Figure 14. Topological design for hybrid manufacturing [255]

Obviously, more challenges lie ahead in this emerging topic. From the authors' perspective, the following issues on topology optimization for hybrid manufacturing are highlighted below:

i) A limitation remains for the method in [255] that, the casting-SIMP method only supports the material changes in the three axial directions, while for complex parts, inserting machining features through an arbitrary direction is necessary but also technically challenging. The potential solution is to make the problem mesh-independent through, for example, adding auxiliary density fields in a rotated coordinate system and build the connection through density field projection [257,258].

ii) Even though 2.5D post-machining has its advantages in cost and efficiency [17,255], the possibility of 3D freeform post-machining cannot be ignored especially for problems where the structural performance takes priority. In such a situation, it would be meaningful to quantify the manufacturing cost and make it part of the topology optimization problem, so the overall hybrid manufacturing cost could be controlled and balanced with structural mechanical performance. For this task, the main difficulty is to build a cost function derivable on the shape and topology variables. Note that, cost modeling of 3-axis freeform machining is an extensively studied topic.

Other than the additive-subtractive combination, design for product upgrade by removing and adding features is also promising, as AM can add features to an existing component [259]. Topology optimization for subtractive-additive remanufacturing potentially contributes to this topic.

7.2 Post-treatment of graphics

Generally after topology optimization, either the density [260] or level set field [261] needs to be post-processed into a printer-compatible geometric file, e.g., the STL. As a boundary-based geometric model, level set methods not only provide a clear representation of the boundary but also embed higher order geometric information, such as the normal vectors or curvatures. Such information can be utilized to create a seamless connection between the design and fabrication process [261]. This is important in the topology optimization-driven design innovation, where the organic conceptual design often needs post-processing such as CAD reconstruction before it can be manufactured. In level set methods, the external surfaces (boundaries) of a 3D object are defined by the zero level of a continuous 4D level set function. The embedded information can be extracted for STL file generation and further manipulation, which is more suitable for 3D printing, as illustrated in Figure 15. The isosurface, formed by the boundaries of the design, can be transformed to a triangle mesh using Delaunay triangulation [262]. Each triangular facet has three vertices and a normal vector n, implied by the change of the level set function's sign. The data of all the facets must be stored in a file with STL (Stereolithography) format, a standard format widely recognized by the 3D printers and CAD software.

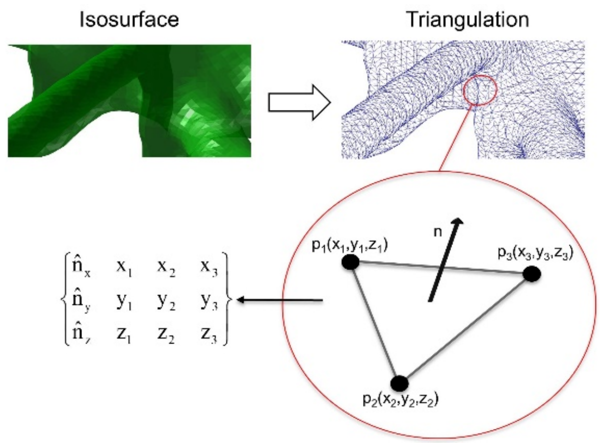


Figure 15. Extraction of geometric information from the level set model [263]

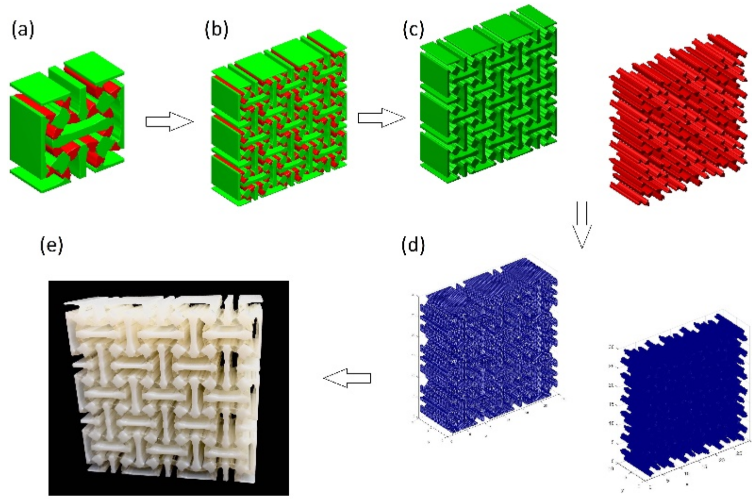


Figure 16. Level-set-based framework for integrated TO and AM [261] . (a) unit cell design, (b) 3x3 structure design, (c) separate design for each material, (d) meshed surface, and (d) 3d printed prototype

Open-source codes are available for generating STL files based on topology optimization results [260,260,261,264]. Wang developed methods in [A1, A2] to extract surface meshes from implicitly represented volumes, and a parallelized algorithm for mesh generation was proposed in [A3]. Compatible meshes for different material regions can be generated by these methods, which is extremely important when fabricating by 3D printers supporting multi-materials (e.g., Stratasys Connex). Another recent trend to fabricate the results of topology optimization in implicit representation is to direct slicing implicit solids, which can avoid the robustness issue when generating the intermediate mesh representation [B1, B2, B3]. In the case that further editing of the topology design is needed, parameterization and creation of feasible CAD models are necessary, and tremendous research efforts have been spent attempting to address this issue [7]. Even so, it still remains to be an open problem; the best practice so far is to generate a neural geometric file in IGES or STEP format, but the related editability is still problematic.

8. Conclusion

In this paper, the authors expressed the perspectives on topology optimization for AM. The status, challenges, and future of several related topics are presented and discussed in depth. In summary, we have seen significant research achievements in the past few years and also the numerous successful printings of the topological designs [77,137,145,156,265–267]. However, research in this field is far from mature. Most of the existing algorithms can be better tuned or developed further – e.g., concurrently optimizing the build direction when performing overhang-free topology optimization. Additionally, many of the algorithms have not been closely linked to or validated by AM – e.g., the heterogeneous two-scale topology optimization algorithm and the robust topology optimization approaches, among others. Furthermore, increasingly more open problems emerge, such as the residual-stress constrained topology optimization for metal AM. In addition, some problems are highly evaluated by industry but have not drawn enough attention from the research community – e.g., the expensive post-machining of the topological designs. All told, we forecast a prosperous and exciting future in topology optimization for AM [268] – the surface has only been scratched.

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