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REVIEW

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Topology optimization methods for additive manufacturing: a review

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Abstract. Topology optimization is widely recognized for its ability to determine the best distribution of material in a structure to optimize its stiffness. This process often leads to creative configurations that produce complicated geometries challenging to construct using traditional techniques. Additive manufacturing has recently received a lot of interest from academics as well as industry. When compared to traditional methods, additive manufacturing or 3D printing offers considerable benefits (direct manufacture, time savings, fabrication of complex geometries, etc.). Recently, additive manufacturing techniques are increasingly being employed in industry to create complex components that cannot be produced using standard methods. The primary benefit of these techniques is the amount of creative flexibility they give designers. Additive manufacturing technology with higher resolution output capabilities has created a wealth of options for bridging the topology optimization and product application gap. This paper is a preliminary attempt to determine the key aspects of research on the integration of topology optimization and additive manufacturing, to outline topology optimization methods for these aspects with a review of various scientific and industry applications during the last years.

Keywords: Topology optimization / additive manufacturing / manufacturing constraints / lattice structures

1 Introduction

Topology optimization is a sophisticated structural design process that can create the ideal structure configuration by using acceptable material distribution to suit certain load conditions, performance, and constraints. In comparison to size and shape optimization, frame optimization is independent of the initial configuration and has a larger design space. Duysinx has explained that in common design problems, the average performance gains (mass or rigidity) vary: between 5 and 10% for dimensional optimization methods, between 10 and 30% for shape optimization, and between 40 and 100% for topological optimization methods [1]. As a result, topological optimization as a structural design method has seen rapid development in recent decades, as evidenced by expert reviews in [2–6]. Since the reference article by Bendsoe and Kikuchi in the late 1980s [7], numerical topology optimization methods have been the subject of much research [8]. It was designed as a common structural design technique for high performance, lightweight structures. It is multifunctional and has been widely employed in Automobile Industry; Yıldız et al. highlighted the significance of these techniques in designing lightweight diesel engine components, pointing towards the sustainable future of the automotive industry [9]. Additionally, Prabhaharan S. A., G. Balaji, and Krishnamoorthy Annamalai delved deep into the numerical simulations for optimizing the crashworthiness of automotive crash-boxes, offering further insights into the safety implications of advanced design techniques [10]. Aeronautics; Calabrese et al. gave insights into its practical benefits by emphasizing its applications in designing machining fixtures for aeronautical thin-walled components, hinting at broader aerospace applications [11]. In the realm of UAVs, Yue et al. explored the optimal design for Vertical-Taking-Off-and-Landing UAV wings using a multilevel approach,

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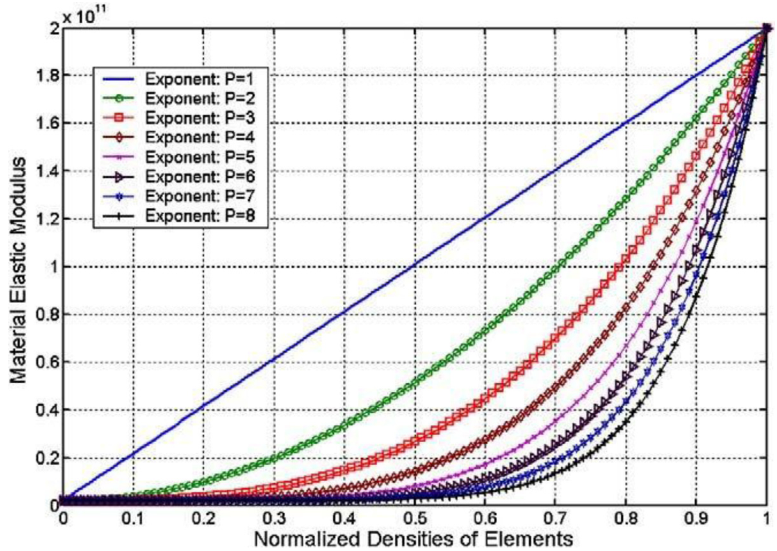

Fig. 1. Effect of penalization coefficient p [42].

further emphasizing the impact of topology optimization [12]. Architecture; Osanov and Guest expanded on the architectural horizon of these techniques by exploring its potential in the development of state-of-the-art materials [13]. Meanwhile, Rokicki threw light on the computational edge provided by these techniques, especially when leveraged with the power of multi-GPU architectures, revolutionizing architectural designs [14], and other fields. Several topological optimization methods have been presented during the last three decades, the most prominent of which being density-based, Evolutionary Structural Optimization (ESO), and level set method (LSM) [5].

The Solid Isotropic Material with Penalization (SIMP) method developed independently by Bendsøe [7], and Zhou & Rozvany [15], the term SIMP was proposed by Rozvany et al. [16]. After discretization of the model, the SIMP approach consists of a distribution of the density of matter in the model under certain constraints in order to determine the most rigid form. Works while maintaining a constant finite element discretization. Each finite element is then assigned a density function $\rho\,(x)$ with values ranging from 0 to 1. A 'zero' denotes a void, while a '1' denotes a solid. Intermediate densities are defined as values between 0 and 1, and they can be viewed as a material mesostructured with holes, as explored by Rozvany et al [2]. Furthermore, the penalization procedure, which is configurable to the designer's preference, is internal to the method and allows for density values close to 0 or 1 [17].

Xie and Steven presented ESO (Evolutionary Structural Optimization) as evolutionary. The ESO approach involves gradually eliminating material from the least constrained locations until the optimal shape is reached [18]. However, like many innovative methods, ESO has its limitations. In certain situations, especially with complex structures or under specific constraints, achieving an optimal solution solely through material removal proves challenging [19,20]. The concept of bi-directional (BESO for Bi-directional Evolutionary Structural Optimization) allows us to overcome this limitation by combining both the AESO method (Addition only ESO) and the ESO method in order to not only eliminate material in weak parts, but also to add more to relieve high stress areas [21,22]. Huang shown the reliability of this approach [23].

The Level Set approach is primarily concerned with the displacement of the border (form edges), i.e., the material-void interface [24,25]. The model is discretized initially, and the starting topology on which the optimization will be based is selected. The speed of the boundary's movement is then estimated by deriving the objective function from the shape. During the optimization process, this speed is employed to move the boundary. The approach is applicable to any objective function or structural model, including nonlinear models [26].

The topological optimization challenge is the production of complicated geometries that standard machining methods are incapable of achieving. As a result, additive manufacturing (3D printing) must be integrated, which only partially fulfills the full potential of topology optimization.

3D printing, often known as additive manufacturing, is a technique used to create a wide range of complicated structures and geometries using three-dimensional (3D) model data. Printing consecutive layers of materials that are produced on top of each other is used in the procedure, Charles Hull is specifically credited for inventing the Stereolithography (SLA) method in 1986 [27]. 3D printing, which employs a range of procedures, materials, and equipment, has grown through time and has the potential to revolutionize manufacturing and logistical operations, many additive manufacturing techniques have emerged, Molten deposition modeling (FDM) [28,29] is the most common, and it primarily uses polymer filaments. Additionally, additive manufacturing of powders by

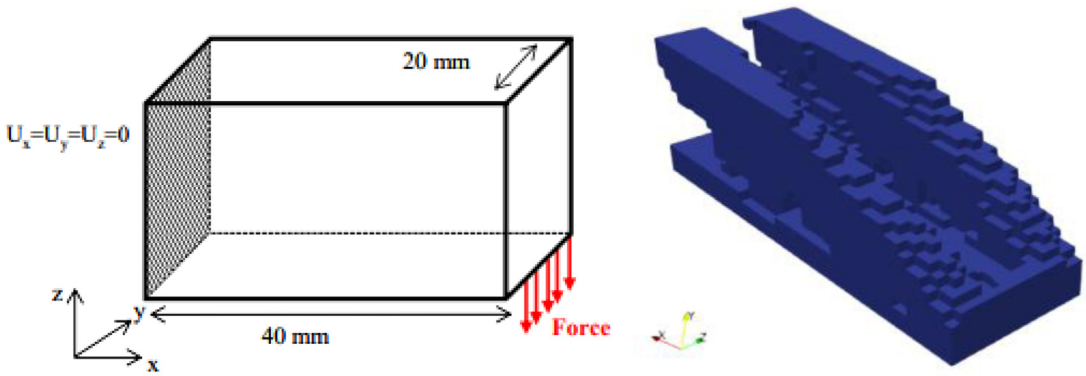

Fig. 2. Part geometry obtained with the topological optimization algorithm by the SIMP method [43].

selective laser sintering (SLS) [30], selective melting by laser (SLM) [31], or liquid binding in three-dimensional printing (3DP) [32], as well as inkjet printing, contour crafts, stereo lithography, energy deposition direct (DED) [33], and laminated object fabrication (LOM) are the main additive manufacturing methods [34]. additive manufacturing materials cover metal, polymer, composite, biomaterial, etc. additive manufacturing parts range from micro-nano components to multi-meter structures [27]. It is distinguished by a variety of advantages, including more freedom in the design of the geometry of the components, particularly because manufacturing costs are relatively independent with the complexity of the parts [35].

Topology optimization is an effective strategy for additively manufactured products with a lightweight configuration, which is why there is interest in integrating topology optimization with additive manufacturing methods, as well as creative. This viewpoint article covers the present state of the art in topological optimization for additive manufacturing as well as the direction of ongoing research in this subject.

2 Topology optimization method

Bendsoe and Kikuchi's reference paper in the late 1980s [7], as well as Sigmund's fundamental studies [36], have set the groundwork for topology optimization techniques today. The most major topology optimization methods are described as follows: density-based method, Evolutionary Structural Optimization (ESO), and level set method (LSM) [5]. Where Ole Sigmund and Kurt Maute offered an overview, comparison, and critical assessment of various methods, their strengths, shortcomings, similarities, and dissimilarities, as well as suggestions for them [37].

In this paragraph, we will define the idea of all topology optimization methods and examine the benefits and drawbacks of each method (Tab. 1.2.3).

2.1 Solid isotropic material with penalization method

Soon after, the topology optimization homogenization technique was proposed [38,39]. Bendsoe suggested the SIMP (Solid Isotropic Material with Penalization) approach's fundamental notion [40], although the name "SIMP" was invented later by the author and first used in a paper by Rozvany et al [16]. (SIMP) is an abbreviation for Solid Isotropic Material with Penalization. It is occasionally referred to as the density method, however the name "SIMP" is now widely used. After discretization of the model, the SIMP technique consists of a distribution of the density of matter in the model under specific constraints in order to determine the most rigid form. The SIMP technique employs a fixed discretization of finite elements. Each finite element is then assigned a density function $\rho\ (x)$ with values ranging from 0 to 1. A 'zero' signifies the emptiness, whereas a '1' denotes a solid. Values between 0 and 1 are known as intermediate densities, and they might be understood as a material mesostructured with holes, as Rozvany discusses [2]. Consider the original geometry, which represents a mechanical construction constructed of a certain isotropic material filling a volume V; the porosity in the geometry will be redistributed. To continue to the optimum material distribution, each element of the mesh is allocated a distinct fictional material based on its density. As a result, element densities can be understood as design factors and utilized to tune the performance of a certain design. (Where 0 denotes absolute absence of substance and 1 denotes solid stuff).

Given a solid ($\rho\,(x) = 1$) with the material attribute of Young's modulus indicated by E_0, the Young's modulus of elements with intermediate densities is given by $E_e = E_0 * \rho_e$, where the index "e" represents a specific element.

Knowing that in practice, intermediate densities are impossible to obtain.

This is why a mechanism to penalize intermediate densities must be introduced. The penalization has the effect of making the contribution to the overall stiffness of the intermediate density elements lucrative in order to avoid the creation of microstructures within. The relaxation of the optimization problem, which allows for a continuous distribution of matter density between 0 and 1, does not allow for discrete outcomes, highlighting the significance of the penalization factor p [41] (Fig. 1).

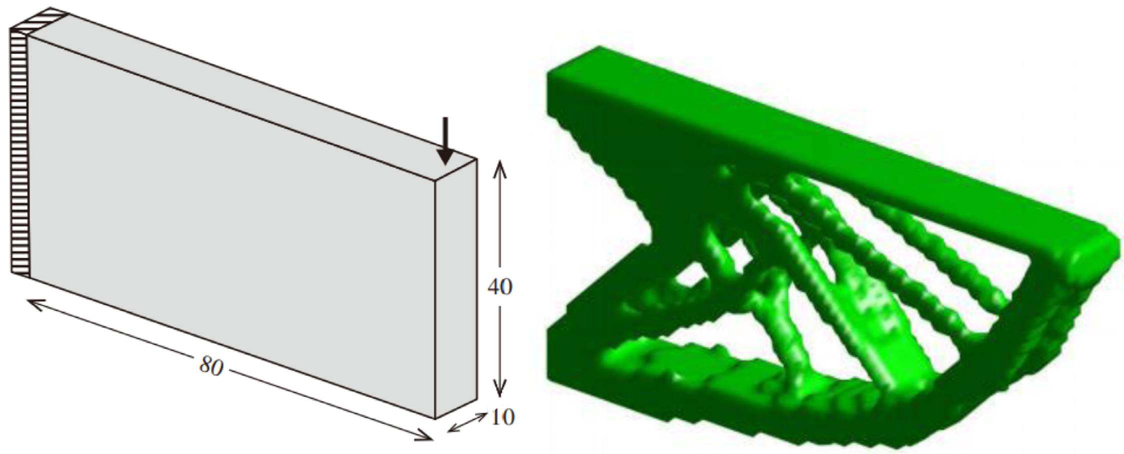

Fig. 3. Part geometry obtained with the topology optimization algorithm by the BESO method [47].

Thus, the fundamental equation which characterizes a SIMP approach with the incorporated penalty factor is given as follows (Fig. 2):

$$E_e = E_0 * \rho_e(x)^p \tag{1}$$

$$V = \sum_{e=1}^{N} \rho_e(x) * V_e \tag{2}$$

with:
E_e : The virtual Young's modulus of the element e.
E_0 : The real Young's modulus of the material
ρ_e : The density of the element e.
p : The penalty coefficient.
V : The total volume of the material.
V_e : The volume of the element e.

2.2 Evolutionary structural optimization method

Xie and Steven introduced the evolutionary structural optimization (ESO) method in the early 1990s [18,20]. The ESO method was originally proposed from a simple and empirical concept that a structure evolves towards an optimum by slowly eliminating (hard-kill) the elements presenting the weakest stresses, that is, by eliminating ineffective materials for a structure. The stress field of a loaded structure may be easily calculated using a numerical simulation approach, such as the most frequently used finite element method, Yang et al approximated the strain energy of the elements empty by linearly extrapolating the field of displacement [21]. For optimal material use, an evenly distributed stress field in the structural domain is expected. Low stress materials are expected to be inefficiently utilized and are thus phased out based on a rejection criterion determined by the local stress level [44].

The elements that contribute the least are chosen based on the coefficient of rejection RR (Rejection Ratio), which is the quotient of the stress within each element and the maximum permissible stress of the structure. If no element meets the rejection criterion during an iteration, a state of equilibrium is attained.

$$\sigma_{VM} \leq RR.\sigma_{MAX} \tag{3}$$

with:
σ_{VM} : Von Mises stress.
σ_{MAX} : maximum von Mises stress of the whole structure.

The rejection rate can then be increased according to a defined evolution rate ER.

$$RR_{old} = RR_{new} + ER \tag{4}$$

Then, until the required optimum is attained, finite element analysis and element removal are repeated. As a result, the technique gets its name. Components deleted using this approach, however, cannot be reintegrated into the model, therefore ensure that the final design is adequately represented by elements. To overcome this limitation, OM Querin proposed combining the AESO method (which is an inverse method to the original ESO algorithm, namely the additive ESO) and the ESO method in order to not only remove the material in the parts with little stress, but also to add it to relieve the areas of high stress [45]. Whereas (BESO) is an abbreviation for Bidirectional Evolutionary Structural Optimization [46].

BESO allows for both material removal and addition, allowing for the final optimum to be attained regardless of how the starting design parameter is set (Fig. 3).

$$\sigma_{VM} \leq RR.\sigma_{MAX} \qquad \text{Elimination of elements} \tag{5}$$

$$\sigma_{VM} \geq IR.\sigma_{MAX} \qquad \text{Addition of elements} \tag{6}$$

2.3 Level set method

In 1999, Sethian introduced the concept of the level sets method [48]. The primary idea behind the Level Set method is to reduce material where stress is minimal and add material in areas with high stress. A specific rate of removal is applied.

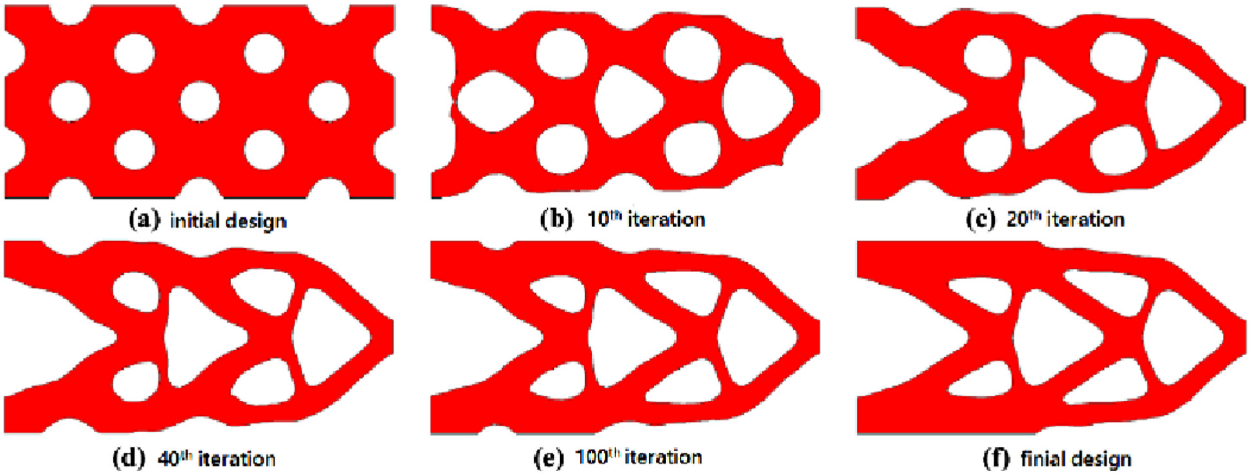

Fig. 4. Topological optimization by the level-set method [50].

This will be a percentage of the greatest starting stress below the material to be removed and above the material to be added. The rate of boundary movement and the closed stress contours along which new holes are made are determined by the rate of removal [49]. The design's limit is determined by the level assembly function's zero level contour $\varphi(x)$ and the structure is defined by the domain where the level assembly function takes positive values [37] (Fig. 4).

$$\rho = \begin{cases} 0 : \forall x \in \Omega : \varphi < 0 \\ 1 : \forall x \in \Omega : \varphi \geq 0 \end{cases} \tag{7}$$

3 Topology optimization considering additive manufacturing constraints

The topology-optimized structure can barely be directly additively manufactured due to the manufacturing accuracy of 3D printing equipment. As a result, imposing additive manufacturing restrictions in topology optimization is critical. Overhang restrictions, length scale constraints, and connection constraints are examples of typical additive manufacturing constraints [51].

3.1 Length scale constraints

3.1.1 For SIMP method

The emergence of checkerboard patterns, or areas of alternating solid and void components, in the final solution is a common issue for density-based topological optimization. The checkerboards are not optimum; instead, they are the product of numerical instability [52,53]. One of the most effective approaches to remove mesh dependence is to limit the design space such that the original continuum problem may be solved [54]. By setting a minimum length scale on elements in the final topology, design space may be constrained. Because local features smaller than the scale of physical length are forbidden, topologies independent of the mesh and without checkerboard are obtained [55]. Density filtering is an effective approach for restricting the minimum length scale, in which a regularized Heaviside step function developed by Guest et al assures a minimum length scale on the solid phase ($\rho = 1$) and the empty phase ($\rho = 0$) [55]. To increase its performance, Sigmund integrated the new morphology-based filters with Heaviside's filters [56]. The gray transition zones between the solid and empty sections are a drawback of this approach, however this problem has since been reduced by other projection methods [57]. Zhang proposed an approach that does have the capability to give complete control of the length scales of an optimal structure in an explicit and local way [58]. length scale control is achieved with help of a structural skeleton. A variation of this concept of the minimal length scale for subsets of a convex domain was presented by Linus Hägg [59]. In the context of SIMP topology optimization, Yang examined several gradient operators [60]. It was established that the Prewitt operation, when the boundaries were modified, could compute the density gradient with greater precision. Giulio Costa also presents an understandable approach for controlling the minimum length scale in a topology optimization algorithm based on the density of NURBS [61].

In this work, Xuanpei Rong proposes a technique for optimizing structural topology with control of the minimum length scale of real phase and vacuum phase materials, which are formed by adding measurements of coordination design variable filtering, multiple phase coordination projections, and an adaptive weighted 2-norms aggregation constraint function [62].

3.1.2 For level set method

Guo guaranteed the length scale within the context of the level set technique by restricting the value of the distance function signed at the points of a structure's skeleton [63]. Qi Xia created a conceptually and numerically computationally easy approach for regulating the minimum / maximum length scale in structural topology optimization based on sets of levels [64]. Guo's work set

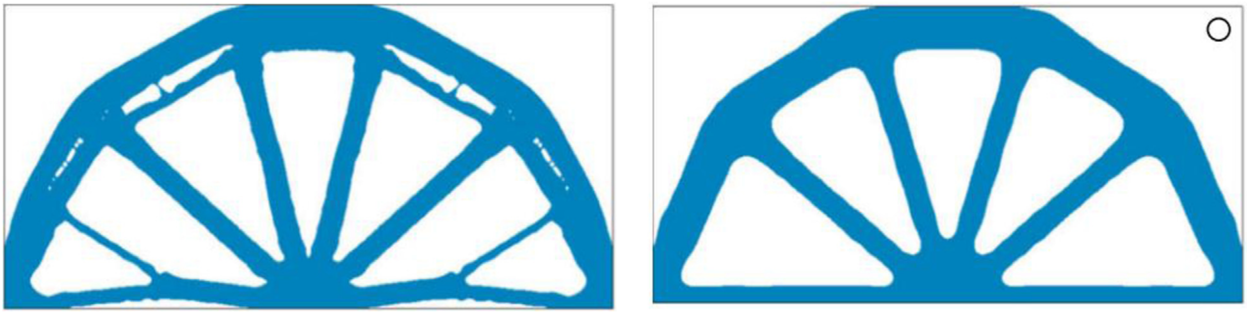

Fig. 5. (a) No length-scale constraint, (b) with length-scale constraint [69].

the groundwork [63]. Weisheng Zhang has proposed a technique based on the MMC framework for controlling the minimum length scale in topology optimization in a direct and explicit manner [65]. Rixin Wang offers a technique for imposing a minimal length scale in topological optimization utilizing mobile morphable components (MMC) and an efficient connection state control (ECS) approach based on the virtual component backbone (VCS) [66]. Jikai Liu developed a novel technique [67].

Unlike earlier techniques that applied a single lower limit to the whole design domain, this novel method divides the topological design into band-shaped components depending on the connection requirement, followed by the lower bound. The length scale may be controlled piecewise and dynamically depending on the real-time status of each component, and its efficacy would be demonstrated by numerical examples.

3.1.3 Remark

The level set and density techniques for topology optimization are frequently seen as two quite separate approaches, with two competing research streams operating in tandem with minimal overlap and knowledge exchange. Andreasen believes that this idea is incorrect. It builds an optimization strategy of the set of levels of the net interface using a simple cut element technique employing many of the fundamental elements used in density-based optimization for length scale management. The only significant difference, we discovered, is in the finite element and sensitivity analysis [68] (Fig. 5).

3.2 Enclosed voids constraints

The limitation of closed voids stated as the solid structure is easily connected in mathematics. for instance, Powders that are not sintered by the laser serve as a support material throughout the SLS process and must be removed after fabrication. As a result, removing the powder or support structure from the component after it has been produced is a severe limitation. When a component has a totally closed vacuum, there is no way to retrieve the unmelted powder and supporting structure from the vacuum once the part has been completed.

Shutian LIU suggested a method called virtual temperature (VTM) in which the structure's voids are spun with a virtual heating material with high thermal conductivity and the solid regions are spun with another virtual material with low thermal conductivity [70]. When there are closed voids in a structure, the maximum temperature value of the structure is quite high. According to this technique, the simply connected stress equals the maximum temperature stress. When temperature is chosen as the scalar field, Quhao Li proposed a method called the virtual scalar field, in which the connectivity constraint can be converted into an equivalent maximum temperature constraint, and the temperature constraint is then easily integrated and implemented and works in routine topological optimization [71]. Based on the level sets technique, Lu Zhou presented a lateral constraint strategy for topology optimization that takes structural connection into consideration [72]. Based on the two-way evolutionary structural optimization strategy, Yulin Xionga developed a solution that removes closed holes by selecting creating tunnels that link the voids to the structural border during the optimization process [73]. To remove closed voids, Chao Wang used the scalar field stress technique based on the Poisson equation. Because the numerical performance of this approach is not well known, he devised an electrostatic model to describe it. It offers an effective constraint scheme that combines density filtering, Heaviside projection, regional measurement, and normalizing approaches to address the method's numerous numerical issues and difficulties [74].

3.3 Overhang constraints

During the production process of additive manufacturing methods, particularly for metals, an extra support structure is necessary to sustain the overhanging areas and prevent the component from collapsing or deforming. These structures use precious raw materials and are eliminated during post-processing. This increases overall material use, fabrication time, and post-fabrication treatment time. To minimize support structures, Kailun Hu suggested an orientation-driven form optimizer [75]. The optimizer may be used to assist designers in optimizing the initial model in order to obtain a more self-supporting form. H. D. Morgan utilized MATLAB software to design a

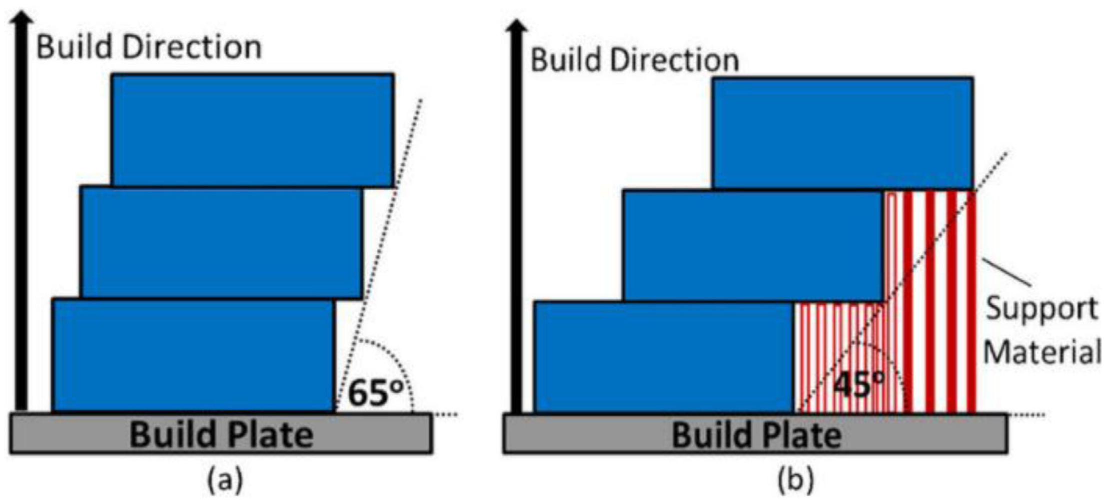

Fig. 6. (a) Overhangs without support material. (b) Overhangs with support material [78].

basic, single-objective optimization approach that was used to identify the optimal part orientation that would reduce the amount of support required during assembly [76].

In terms of topology optimization and taking into account overhang constraints, Andrew T. Gaynor introduced a series of projection operations that combine a local projection to apply minimum requirements in terms of length scale and a projection of the support region to ensure that the side of the element is properly supported from below, with the goal of integrating a minimal self-supporting angle as part of the topology optimization so that the planned components and structures may be produced without the need of supporting materials [77]. Terrence E Johnson presented a projection-based topology optimization methodology for the design of self-supporting structures in 3D, in which you first work on adopting a new overhang mapping scheme that allows precise specification of the authorized overhang angle, and then implement an adjunct to the sensitivity calculations to significantly speed up the calculations [78] (Fig. 6). Yun-Fei Fu demonstrated a smooth design of self-supporting topologies by combining a "solid isotropic material with penalization technique" (SIMP) created on the basis of elementary volume fractions and an existing additive manufacturing filter [79]. Jun Zou was also interested in topology optimization for additive manufacturing while taking self-supporting restrictions into consideration using the “Solid Isotropic Material with Penalization” (SIMP) framework. The suggested technique achieves self-sufficiency through the progressive development of support systems. Furthermore, a directional sensitivity filter is provided to aid in the development of support structures [80]. Minghao Bi also introduced a new method for dealing with overhangs under “Bidirectional evolutionary structural optimization” (BESO), creating self-supporting but structurally efficient designs in which the overhang problem is formulated as a layered relationship and elements whose modification does not create an overhang are chosen as candidates for the element update scheme [81] (Fig. 7).

3.4 Cost constraints

The usage of additive manufacturing, particularly metal additive manufacturing, is expensive, and this high cost significantly limits the technology’s widespread adoption. This is why Jikai LIU presented a metal additive manufacturing-specific method that balances production costs while pursuing improved structural performance through topology optimization. He developed the additive manufacturing cost model for the laser powder bed-based method, and real data is being gathered to validate it. Then, as a constraint, it is incorporated into the Level Set topology optimization problem. As a result, the metal additive manufacturing part may be optimized while keeping production costs to a minimum [83].

3.5 Remark

When all of the additive manufacturing restrictions are included into the topology optimization method, a high-resolution 3D printable structural topology design is produced. For example, Kaiqing Zhang used the SIMP method to optimize an additive manufacturing-oriented structural topology with low overhang and horizontal length control for minimal compliance. In a variety of digital examples and additive manufacturing tests, his technique has demonstrated high efficiency [84] (Fig. 8,9).

3.6 Effects of additive manufacturing process parameters

Incorporating additive manufacturing constraints within topology optimization enables the direct, incremental fabrication of the optimized structure, due to the precision of 3D printing equipment. However, inevitable variances emerge between digital representations and real printed designs. To detect and mitigate these disparities, it’s crucial to acknowledge and address the associated challenges

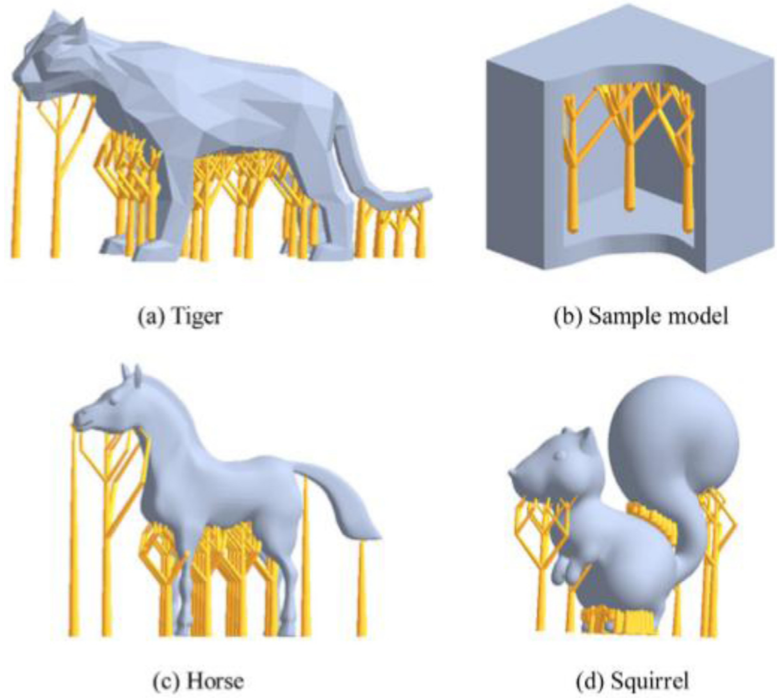

Fig. 7. The support structure of several models was obtained using the method of Yong Zhou [82].

encountered during the various stages of the printing process. In this context, S Guessasma et al. extensively explored the challenges associated with the application of topology optimization in additive manufacturing (AM). Their findings brought to the forefront various concerns. The research emphasizes the importance of thoroughly understanding and revising the constitutive laws that characterize the behavior of materials produced through AM. This emphasis stems from the frequently observed suboptimal adhesion between printed filaments, which impacts the failure mechanisms and the overall performance of the material. Moreover, they posit that the intricacies of microstructures might significantly influence hierarchical structures. Additionally, the potential for customizing porosity in AM becomes particularly notable when considering micro-porosity. The study also sheds light on the fact that topology optimization hasn't yet reached its full potential in systematically addressing process errors in AM. They argue for a tool capable of recognizing the limitations of the AM process and for more granular numerical models that can understand the genesis sites of process-induced defects [85].

A specific branch of research has been dedicated to addressing process errors in AM for topology optimization. Chen et al. detailed a non-planar slicing method for maximizing the anisotropic behavior of continuous fiber-reinforced fused filament fabricated parts using a 6-DOF industrial robot for topology optimization [86]. Jikai Liu et al. offers a detailed numerical and experimental exploration of stress-constrained topology optimization for Fused Deposition Modeling (FDM) additive manufacturing, revealing the influence of FDM process parameters on the structural strength of topologically optimized designs [87]. Mudda Nirish et al. discussed a concept of 3D metal printing of Direct Metal Laser Sintering, Selective Laser Sintering and Electron Beam Melting with application and compares processes with respect to material, process and parameter [88]. Rajit Ranjan et al introduce a new design approach that aids designers in crafting components that are conducive to additive manufacturing. Their research establishes design principles by examining the link between the geometry of the input part and the parameters of the AM process. This strategy showcases a topology optimization-driven design method that empowers designers to produce innovative lightweight designs, seamlessly manufactured through AM techniques [89]. Liang Meng et al offer a review that transitions from the perspective of topology optimization design to additive manufacturing. They emphasize that to achieve high consistency and improved mechanical attributes, the fine-tuning of processing parameters has always been essential. Numerous numerical models have been created in pursuit of this goal. Nonetheless, it's evident that these models can be quite complex for general applications, necessitating meticulously planned experiments to adjust and validate the numerical model in real time [90]. As suggested by S Guessasma et al. it is important to combine topology optimization with artificial intelligence algorithms to ensure that the final design not only meets structural and functional criteria but also is optimized in terms of the processing parameters [85].

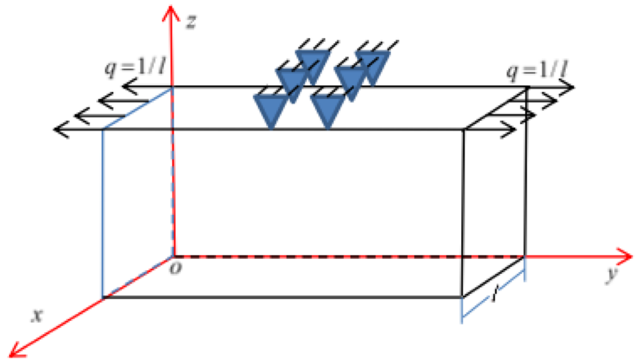

Fig. 8. 3D tensile beam example [84].

4 Topology optimization of lattice structures in additive manufacturing

Lattice structures are characterized as periodic objects, with unit cells that recur and interconnect in three dimensions [91]. They are often made of lattice structures [92] and minimalist surfaces [93,94]. These structures have recently gained importance as a result of advances in additive manufacturing, which are used to try to achieve major goals such as minimizing the number of materials used, minimizing the time required to produce an object, minimizing the amount of energy used, and optimizing the resistance of the object produced while minimizing its weight. Other highly valuable side effects are also made feasible by lattice structures. These properties include energy absorption [95,96], acoustic and vibration damping, high strength-to-weight ratios, and thermal management capabilities [97]. These properties have been successfully used to improve the impact resistance of military vehicles [98], as well as in the medical industry [99,100]. Although lattice structures were previously manufactured using traditional manufacturing methods, the production of such complex objects was severely limited due to the inability to use the traditional manufacturing process to create structures that did not require a labor-intensive assembly process. Researchers can now consistently build lattice structures and change parameterized cell designs because to significant advancements in additive manufacturing [101]. As a result, topology optimization and lattice structures are two essential ways to achieving a lightweight design while fulfilling the required mechanical characteristics criteria. The purpose of this paragraph is to identify the major topics and applications of recent research on the application of topology optimization techniques for lattice structures.

4.1 SIMP method

As stated in the preceding paragraph, the lattice structures has a high stiffness / strength / weight ratio and allows for multi-functional performance. Topology optimization methods, on the other hand, will be able to find the best distribution of lattice structures in order to optimize one or more objectives such as mechanical characteristics. Density-based topology optimization has recently been integrated into a framework for optimizing lattice structures for additive manufacturing. J. Robbins presented an end-to-end design process for the topological optimization method of lattice structures based on conformance minimization (by homogenization), until the realization of a final printed product. His technique works on a global scale, from the topological optimization process through the production of a printable STL representation of the improved part [102].

Jeroen P. Groen also provided a projection approach based on homogenization that allows for high resolution and manufacturable structures using efficient topological optimization solutions at a coarse scale. He provided a method for relating the coarse scale to the fine scale, allowing control of the projected topology and ensuring a minimal length scale on the properties of solids and voids in the final product [28]. Chuang Wang also presented a topology optimization technique that integrates homogenization theory with the PAMP (Porous Anisotropic Material with Penalization) model to identify the best topologies of lattice structures. It offered new parameters to characterize the microstructure's unit cell models and their non-uniform distribution, avoiding costly repetitive numerical homogenization computations during topology optimization and making structure designs easier to represent [103]. Then, Christian Rye Thomsen used a model based on homogenization theory and a gradient-based topological optimization problem to design periodic cellular materials with maximum strength under compressive load, where the failure mechanism of buckling instability in the microstructure is the strength limiting factor [104]. and Zhirui Fan optimized the fundamental frequency of multi-material lattice structures using a multiscale topological optimization method (a combination of the asymptotic homogenization method, the optimization method for discrete materials based on the Heaviside penalty, the density filter with a projection of Heaviside preserving the volume, and the polynomial penalization scheme). It maximizes natural fundamental frequency while adhering to mass limitations and reduces compliance while adhering to frequency limits [105]. Jun Wu developed a method of designing lattice structures that simultaneously optimizes the topology using the SIMP (Solid Isotropic Material with Penalization) method and

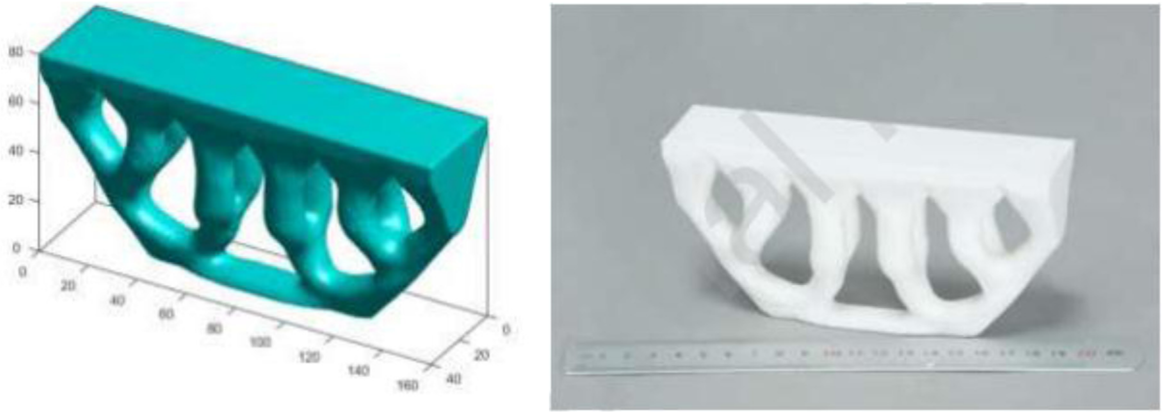

Fig. 9. Tensile beam solution, and additive manufacturing experimental verification [84].

the distribution of orthotropic lattice materials inside the form to maximize stiffness under the application of specific external loads, and takes the optimized configuration from the previous lattice materials [106].

4.2 Level set method

M. Jansen provided a hybrid density formulation for the Level Set topological optimization technique using functional gradient lattice structures generated by additive manufacturing for the Level Set topological optimization method. This technique can optimize the form of the large-scale structure as well as the functional gradient lattices inside this design at the same time [107]. Lin Cheng proposed a solution to a design-dependent lattice and movable element infill optimization problem with boundary conditions by using the level set parametric function to represent the geometry of the moving elements and, as a result, the thermal boundary conditions are applied implicitly. This sort of problem is important in practice, for example, the design of cooling channel systems utilized in various thermal management applications [108].

4.3 Evolutionary structural optimization

For the Bidirectional Evolutionary Structural Optimization topological optimization method M. Yunlong Tang proposes a new design technique for creating periodic lattice structures, then modifies the standard bidirectional evolutionary structural optimization method to optimize the thickness distribution of the lattice uprights [109]. After two years, Mr. Yunlong Tang suggested a technique for developing and optimizing lattice structures to assure the required print quality, using the same method as the prior optimization (Bi-directional evolutionary structural optimization) [110].

4.4 Application

In many domains, topological optimization is used to build lattice structures. For example, A.M. Vilardell proposed a topology optimization technique for the construction of Ti6Al4V ELI lattice structures with stiffness and density near to human bone for implant applications [111]. And S. Mantovani developed three additive manufacturing oriented numerical optimization techniques in the sports car area, with the goal of optimizing components consisting of bulk materials, a combination of bulk materials and graded lattice structures, and integration of solid structures, in lattice and thin-walled [112]. Arun J. Kulangara also presented an application for reducing the weight of a brake pedal using lattice structures, in which the lattice structures are generated on the brake pedal by replacing the region of material, followed by optimization of the lattice structure's topology for a given force acting on it [113].

4.5 Efficiency and performance of derived lattice structures in additive manufacturing

Ajit Panesar et al proposed a number of methods for deriving lattice structures using topology optimization results that are appropriate for additive manufacturing. These structures are assessed in terms of mechanical performance as well as production concerns linked to additive manufacturing design. The following are the results, from a production standpoint; extending lattice size reduces the need for support structures while increasing memory and time. The finite element analysis (FE) findings for the two loading situations considered: anticipated loading and loading variability, give insight into the optimality of the solution and the resilience of the design methods. When compared to structures where this was not the case, lattice strategies that used the results of the finite element analysis proved significantly ($\sim$ 40–50%) higher in terms of specific stiffness. The gradual method has shown to be the most desired in terms of design and production. This has stimulated the realization of complicated lattice geometries by additive manufacturing [114] (Fig. 10,11).

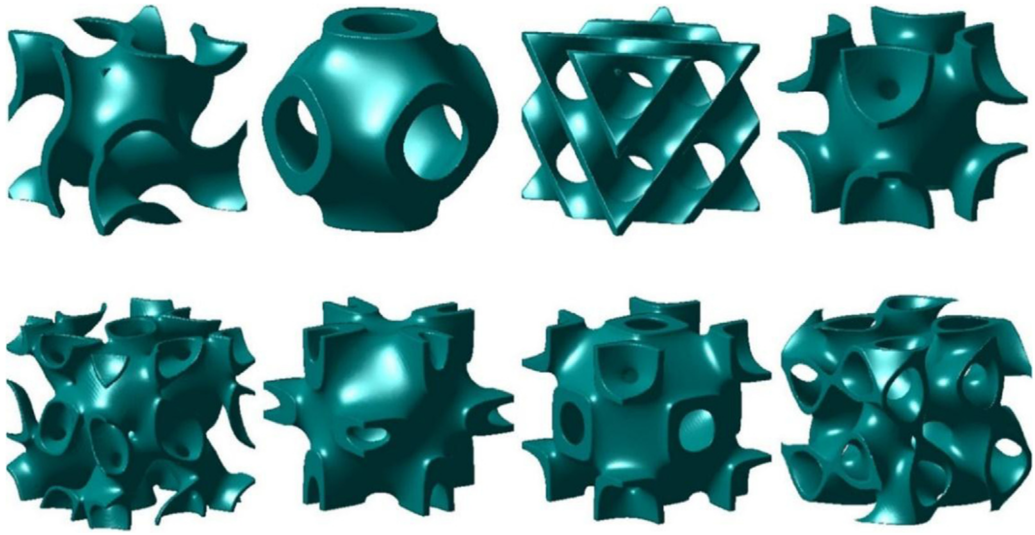

Fig. 10. Examples of lattice structure unit cells [114].

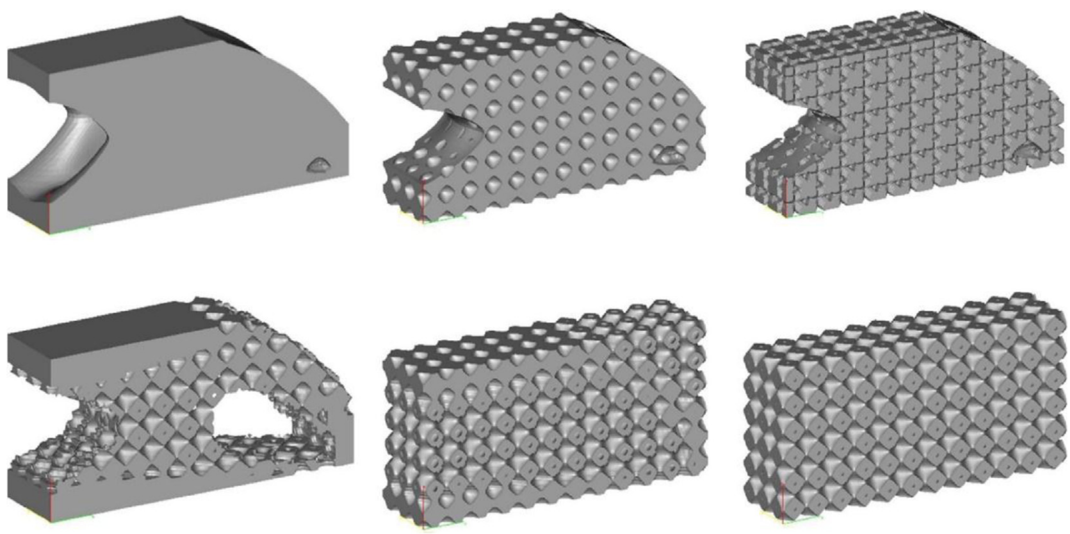

Fig. 11. Topology optimization results for the design of lattice structures in additive manufacturing applications [114].

Table 1. Strengths and weaknesses of SIMP method.

Strengths	Weaknesses
Homogenization is not a prerequisite. Calculation efficiency and Robustness. Adaptation to all design conditions. Conceptual simplicity (no higher math required). Available for all combinations of design constraints.	The dependence of the optimized solution on the type and size of the meshes. Intermediate densities (checker boarder effect). The appearance of local minima.

Table 2. Strengths and weaknesses of ESO method.

Strengths	Weaknesses
Independent of the mesh. Adaptive form. A small progress report and a fine mesh can produce a good solution.	The dependence of the optimized solution on the type and size of the meshes.

Table 3. Strengths and weaknesses of level set method.

Strengths	Weaknesses
Flexibility in topological changes. (It has the potential to simultaneously treat the complex changes in shape and topology of structural boundaries.). Independent of the mesh. Can find variations in shape to design a robust design.	Geometry restricted from existing borders. Inability to generate new holes at points surrounded by solid material.

5 Conclusions

Topology optimization is an effective strategy for additively manufactured products with a lightweight configuration, which is why there is interest in integrating topology optimization with additive manufacturing methods. We have addressed the major features of research on the combination of topology optimization and additive manufacturing in this paper. In recent years, we have witnessed major scientific accomplishments as well as several successful topological design articles.

However, in order to include additive manufacturing design constraints into topological optimization (length scale constraints, closed void constraints, overhang constraints, cost constraints). Methods for fully incorporating additive manufacturing design constraints into structural optimization have yet to be established. Algorithms that take into consideration all of the additive manufacturing design constraints have also not been established, with the exception of Zhang's proposal which incorporates both the overhang constraint and the control constraint of the minimum horizontal length and produced satisfactory printing results [84].

The authors also pay little attention to cost constraints, despite the fact that they are significant part of additive manufacturing design constraints, with the exception of the algorithm proposed by Jikai LIU, which balances manufacturing costs while seeking superior structural performance by optimizing the topology, dedicated to metal additive manufacturing [83].

Furthermore, topology optimization has not fully realized its potential in systematically tackling process discrepancies in AM. Such discrepancies can appear as geometric flaws, volume inconsistencies, or unwanted surface finishes.

Secondly, for the topology optimization of lattice structures in additive manufacturing. Several topology optimization techniques for lattice structures have been developed and are useful for additive manufacturing. However, strong and adaptable manufacturing capabilities are not the only ones that must be fully utilized in order to build precise lattice structures with complicated geometry.

Overall, we believe that additive manufacturing topology optimization has a bright and exciting future, although there is still more work to be done.

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