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Review

Recent advances and future trends in exploring Pareto-optimal topologies and additive manufacturing oriented topology optimization

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Abstract: Topology optimization (TO) is a powerful technique capable of finding the optimal layout of material and connectivity within a design domain. However, designs obtained by TO are usually geometrically complex. Such complex designs cannot be fabricated easily by conventional manufacturing methods. Therefore, additive manufacturing (AM), a free-form manufacturing technique, is extensively coupled with TO. Like most techniques, AM has its own limitations. Consequently, a range of additive manufacturing oriented topology optimization (AM oriented TO) algorithms were proposed to generate the topologies suitable for AM. Due to existing trade-off relationships in AM oriented TO, investigating multi-objective AM oriented TO seems essential to obtain more practical solutions. This paper provides a review on the recent developments of MOTO, AM oriented TO, and trade-off relationships that exist in AM oriented TO. This review paper also discusses the challenges and future trends in these topics. It is hoped that this review paper could inspire both academics and engineers to make a contribution towards bridging together MOTO and AM.

Keywords: additive manufacturing; multi-objective optimization; support structure minimization design; self-supporting topology; topology optimization; trade-off relationships

1. Introduction

Topology optimization (TO) represents a group of computational approaches for determining the optimum structural configuration within a given design domain, such that a specific objective or multiple objectives, subject to constraints can be satisfied [1–3]. Initially, TO was proposed to tackle mechanical design problems, whereas nowadays it has developed into a powerful technique used to determine a structure for a great variety of other physical disciplines, for example, fluids, acoustics, electromagnetics, optics, and their combinations [4]. A range of numerical approaches were proposed to implement TO, such as the homogenization method [5, 6], Solid Isotropic Microstructure with

Penalization Method (SIMP) [7], level-set methods [8–10], evolutionary structural optimization algorithms [11, 12], moving morphable components (MMCs) based methods [13–16], moving morphable voids (MMVs) based methods [17–19], elemental volume fractions based methods [20–22], and the method using the floating projection [23, 24].

Additive manufacturing (AM, also known as 3D printing) is a free-form manufacturing technique that is capable of fabricating components in an additive way [25–28]. The additive manufacturing technique was first patented 30 years ago [29]. AM technologies are gradually becoming more widely available on the market in the last few years. The better-known AM technologies include Fused Deposition Modeling (FDM), Stereolithography (SLA), PolyJet, Selective Laser Sintering (SLS), Selective Laser Melting (SLM), and Direct Metal Deposition (DMD). As distinct from the conventional subtractive manufacturing technique, AM has the ability to fabricate highly complicated components due to its additive nature [30–35]. As a result of adopting AM, the manufacturing cost may be reduced in some cases [36, 37]. Additionally, various categories of material such as plastic, resin, metal, and concrete can be utilized as the base material in AM technologies [38–40]. Hence, AM is extensively employed in numerous manufacturing divisions, including automotive, medical, and aerospace sectors. Although there are a range of AM technologies available, the high machine cost and the sizes of existing AM machines limit the application of AM technologies to large components [41]. In addition, products manufactured by AM technologies do not always satisfy all performance requirements, including fatigue resistance, porosity, and surface roughness [42]. Therefore, substantial work is being done to make AM technologies more efficient, precise, reliable, and powerful.

Although TO and AM have developed rapidly independent of each other, the integration of these two techniques is attracting scholars' attention for the following reasons [37, 43, 44]:

- In most cases, designs obtained by TO are geometrically complex. Therefore, machining, injection modeling, and casting oriented TO methods had been developed. By contrast, AM has a much larger design freedom, meaning that the full potential of TO can be realized, and the geometrical complexity is no longer the main factor affecting the fabrication cost.
- As the manufacturing cost of AM technologies is directly proportional to the usage of materials, innovative and light-weight designs achieved by TO could be employed to achieve cost reduction.

TO has great potential to fully exploit the significant benefits provided by the increased design freedom offered by AM. In recent years, the integration of TO and AM shows great potential in designing and manufacturing biocompatible orthopaedic implants with desired mechanical properties and minimal side effects on patients in clinical applications [45]. However, topological designs obtained in TO are not always suitable for AM, because AM still suffers from a range of design limitations despite it offering more freedom than traditional manufacturing techniques. Firstly, the minimum manufacturable component size is inevitably controlled by the characteristics of corresponding AM technologies, like the nozzle diameter in FDM and the beam width in laser sintering [46]. As a result, optimized designs with tiny features are not manufacturable in AM. Secondly, as the structures in AM are fabricated layer-by-layer, each part of components to be fabricated has to be sufficiently supported to prevent component distortion. High bending stresses are generally one of the main reasons causing the above issue. Thirdly, the inclination angle of the downward facing (overhang) surface of the components obtained in TO should not be more than a threshold value relative to the build direction. Otherwise, components would deform or warp, resulting in failure of the fabrication. Typically, the well-accepted value of the minimum overhang angle is approximately 45° with respect to the horizontal axis [47–49]. Additional support structures and self-supporting or support-free structures are two effective ways to overcome overhang angle limitations [32, 50–53]. Finally, enclosed voids are generally not allowed in AM due to the inability to remove unmelted powder and support structures from these voids.

AM oriented TO methods had been proposed via considering some of the aforementioned manufacturing constraints. Single-objective AM oriented TO methods are well-developed. The single-objective optimization problem (SOOP) is merely a special case of the multi-objective optimization problem (MOOP). However, objectives to be optimized are generally conflicting, so only a subset of objectives can be optimized simultaneously. Unlike finding a single solution, the aim of multi-objective optimization (MOO) is to obtain a set of non-dominated solutions (i.e., Pareto-optimal solutions), or at least a subset of it [54]. The set of all non-dominated solutions is called the Pareto set, and the corresponding set of objective vectors is called the Pareto frontier. Similarly, the aim of multi-objective TO or AM oriented TO is to find a set of Pareto-optimal topologies based on two or more conflicting objectives. Multiple optimization objectives should be considered in AM oriented TO to assist designers to obtain trade-off, light-weight, and ready-to-manufacture solutions.

The critical review of AM oriented TO methods is crucial to attract more scholars and engineers to work on this field. Liu and Ma [37] reviewed not only conventional manufacturing oriented TO methods but AM oriented TO methods. Liu et al. [55] summarized the TO methods for six AM topics: Support structure design, porous infill design, material feature in AM, multi-material and non-linear TO, robust design incorporating material and manufacturing uncertainties, and post-treatment. Meng et al. [56] reviewed current topology optimization methods, the cutting-edge additive manufacturing techniques, and successful applications of the combination of these two directions. This paper attempts to provide a comprehensive review on the recent advances and future developments in exploring Pareto-optimal topologies and AM oriented TO. The remainder of this review paper is structured as follows:

Section 2 focuses on the recent theoretical investigations on the weighted-sum and equality constraint methods used to generate acceptable Pareto frontiers.

Section 3 summarizes the state-of-art AM oriented TO methods from support structure minimization design, self-supporting structure design, determination of the optimal build orientation, feature size control, and unsupported or self-supporting enclosed void design.

Section 4 is devoted to the review on trade-off relationships existing in AM oriented TO.

Section 5 discusses the challenges of integrating MOTO with AM oriented TO and presents the recommendations for future research.

Section 6 presents concluding remarks.

2. Methods of exploring Pareto-optimal topologies

The main idea of multi-objective topology optimization problems (MOTOPs) is to transform a MOTOP into a series of single-objective problems, generating a set of Pareto-optimal topologies through solving these single-objective problems individually. Typically, implementations of weighted-sum and equality constraint methods are based on this idea. Weighted-sum and equality constraint methods cannot generate a set of Pareto-optimal topologies independently. Therefore, they must be applied on the basis of existing TO platforms.

2.1. Weighted-sum methods

Zadeh [57] commenced initial research on the weighted-sum method, which is a traditional but effective way to tackle MOOPs. The typical statement of the weighted-sum method is given by Jubril [58]

$$\min_{x\in\mathbb{X}} / \max_{x\in\mathbb{X}} : \sum_{i=1}^{N} w_i f_i(x) = w_1 f_1(x) + w_2 f_2(x) + \cdots + w_N f_N(x) \tag{2.1}$$

where $f_i(x)$ is the ith objective function, w_i is the weighting factor of the corresponding objective function $f_i(x)$, and $\sum_{i=1}^{N} w_i = 1$ and $w_i > 0, i = 1, \cdots, N$.

The weighting factor w_i represents the relative importance (preference) of the corresponding objective function $f_i(x)$ [59]. By varying the corresponding weighting factors of objectives, Pareto-optimal solutions are obtained separately until an acceptable Pareto-optimal set is obtained.

The above weighted-sum method without any normalization scheme is suitable for the MOTOPs with the optimization objectives having the same order of magnitude [60, 61]. However, the magnitudes of diverse objectives may be not comparable in real optimization problems. To avoid this issue, objectives should be normalized when the weighted-sum method is used, which is an effective way to ensure the equivalence of all objectives. A method termed compromise programming was proposed based on the concept of normalizing objectives. In reality, compromise programming is a category of multiple criteria analytical method termed the "distance-based" method, which identifies the best solution as the one in the available set with the minimum distance from an ideal [62]. For an optimization problem, the normalized distance function introduced in compromise programming is given by

$$d_{i,nom} = \begin{cases} \dfrac{f_i(x) - \min f_i(x)}{\max f_i(x) - \min f_i(x)}, & \text{for a minimization problem} \\ \\ \dfrac{\max f_i(x) - f_i(x)}{\max f_i(x) - \min f_i(x)}, & \text{for a maximization problem} \end{cases} \tag{2.2}$$

where $d_{i,nom}$ is the normalized distance.

Using the compromise programming model proposed by Yu [63], the formulation of combining weighting factors and normalized distance functions is given by Choi et al. [64–66]

$$f_{inom}(x) = \begin{cases} \left[\sum_{i=1}^{N} w_i^p \left(\dfrac{f_i(x) - \min f_i(x)}{\max f_i(x) - \min f_i(x)}\right)^p\right]^{(1/p)}, & \text{for a minimization problem} \\ \\ \left[\sum_{i=1}^{N} w_i^p \left(\dfrac{\max f_i(x) - f_i(x)}{\max f_i(x) - \min f_i(x)}\right)^p\right]^{(1/p)}, & \text{for a maximization problem} \end{cases} \tag{2.3}$$

where p is the parameter reflecting the importance with respect to the deviation of each objective from its ideal value (1 for linear, 2 for squared Euclidean distance measure [67]).

In existing MOTOPs, $p = 1$ is universally adopted to show identical importance of all the deviations of objectives [64, 65]. Particularly, compromise programming is also known as the upper-lower bound normalization method in MOOPs, because it sets a bound on both the maximum and minimum values of the component objective function [58, 68, 69].

Similarly, Proos et al. [70] originally developed another normalization method called the upper bound normalization method, which sets a bound on the maximum value. Based on this idea, the equivalent optimization objective with N normalized component objectives is given by [69, 70]

$$f_{inom}(x) = \sum_{i=1}^{N} w_i \frac{f_i(x)}{\max f_i(x)} \tag{2.4}$$

The upper-lower bound and upper bound normalization methods are the most popular approaches used to normalize component objective functions in plenty of TO problems for multidisciplinary criteria.

Although weighted-sum methods are uncomplicated to comprehend and easy to implement, they all have three common shortcomings when solving general MOOPs [71, 72]:

- Solutions in the non-convex areas of the Pareto frontier cannot be determined despite decreasing the step size of weighting factors;
- Even though a uniform distribution of weighting factors is employed, obtained solutions are generally not uniformly distributed on the Pareto frontier;
- The distribution of the solutions on the Pareto frontier is greatly sensitive to the step size of weighting factors.

Identical with general MOOPs, these three issues of traditional and normalized weighted-sum methods are extremely common in MOTOPs [73–76]. To mitigate these disadvantages, adaptive weighting methods were developed. Izui et al. [73] put forward a weighting method capable of adjusting weighting factors adaptively depending on each solution's position relative to the other solutions in search space. In this method, multiple solutions can be assessed simultaneously within an iteration, and then each solution is updated in a proper direction, as illustrated in Figure 1 [73].

Particularly, Izui et al. [73] utilized the Data Envelopment Analysis (DEA) technique, which was originally employed to calculate the relative performance of decision-making units (DMUs) in a multiple-input multiple-output environment, to assign an appropriate weighting factor to each evaluated solution. Importantly, a single value termed efficiency was adopted to assess the relative performance of DMUs [73]. That is, Izui et al. [73] made use of the critical character of the DEA technique that it is able to assign optimal weighting factors to evaluated solutions based on efficiency. Efficiency of the Mth solution f^M is expressed by

$$\begin{aligned} \min / \max : f^M &= \sum_{i=1}^{m} w_i^M f_i^M \\ \text{subject to : } &\sum_{i=1}^{m} w_i^M f_i^k \geq 1 \quad (\text{for} \quad k = 1, 2, \cdots, K) \\ &w_i^M \geq 0 \quad (\text{for} \quad i = 1, 2, \cdots, m) \end{aligned} \tag{2.5}$$

where w_i^M is the ith weighting factor of the Mth solution, f_i^M is the ith objective of the Mth solution, K is the total number of solutions, and m is the total number of objectives.

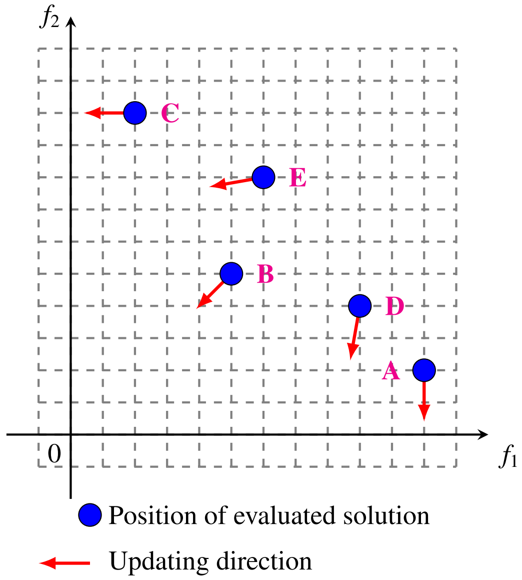

Figure 1. Conceptual scheme of an adaptive weighting method.

Granted that the Mth solution is the non-dominated solution, f^M is switched to 1, and for dominated solutions, f^M is greater than 1. To illustrate this adaptive weighting method, a minimization problem with two objectives is taken as an example. If the Mth solution has a lower value of the first objective f_1^M and a larger value of the second objective f_2^M than the other solutions, a larger w_1^M and a lower w_2^M are assigned to f_1^M and f_2^M on the basis of the DEA technique [73].

Based on the adaptive weighting method proposed by Izui et al. [73], Sato et al. [74] introduced two new techniques (i.e., the distance constraint and generation of new points) to structure a well-distributed Pareto frontier. The distance constraint of the Mth solution [74] is

$$\| f^M - f^k \| \geq \tau_\varepsilon \quad (\text{for} \quad k = 1, \cdots, M-1, M+1, \cdots, K) \tag{2.6}$$

where τ_ε is toleration for the distance constraint.

The new solution is expected to be generated in a relatively sparse area based on two neighboring non-dominated solutions with the Zth longest distance. Initially, Z is set as 1. The generation scheme of the new solution is given by [74]

$$\mathbf{x}_{\text{new}} = \frac{\mathbf{x}_1 + \mathbf{x}_2}{2} \tag{2.7}$$

where $\mathbf{x}_1$ and $\mathbf{x}_2$ are two selected solutions and $\mathbf{x}_{\text{new}}$ is the new solution.

Provided that the newly generated solution satisfies the distance constraint in Eq(2.6), the new generated solution is then added. Additionally, Z and K are increased by one ($Z = Z+1$ and $K = K+1$) for the next iteration. If not, the new solution is deleted.

Sato et al. [75,76] modified the version of the adaptive weighting method proposed by Izui et al. [73] by using a new updating scheme of weighting factors instead of the DEA technique. To illustrate this new updating scheme, the multi-objective minimization problem is taken as an example. If the ith objective of the Mth solution f_i^M is the lth largest among the ith objective of the other solutions, the ith weighting factor of the Mth solution w_i^M is defined as

$$w_i^M = l - 1 \tag{2.8}$$

Afterwards, the weighting factors for each solution are normalized by

$$\bar{w}_i^M = \frac{w_i^M}{\sum\limits_{j=1}^{m} w_j^M} \tag{2.9}$$

where $\bar{w}_i^M$ is the normalized weighting factor.

Figure 1 shows that the value of the second objective f_2 of the solution C is the largest, whereas the value of the first objective f_1 is the lowest. For the solution C, the weighting factor vector $\bar{w}^A = (\bar{w}_1^A, \bar{w}_2^A)$ should be (1,0) based on the adaptive weighting method proposed by Sato et al. [75,76]. The weighting factor vectors of other solutions in Figure 1 can be determined with the same method [61] .

Superior to the adaptive weighting methods proposed by Izui et al. and Sato et al. [73, 75], Sato et al. [76] introduced a point selection scheme based on the concept of the "crowded comparison" method in the non-dominated sorting genetic algorithm II (NSGA-II) proposed by Deb et al. [77]. The value of the "crowded distance" is used as the indicator to select the non-dominated solutions to be updated in the next iteration. That is, the non-dominated solutions with large "crowded distance" values are selected to improve the distribution of the sparse area on the Pareto frontier. The "crowded distance" of the Mth non-dominated solution is expressed by

$$\mathrm{CD}^M = \sum_{i=1}^{m} \frac{f_i^{M+1} - f_i^{M-1}}{f_i^{\max} - f_i^{\min}} \tag{2.10}$$

where $f_i^{\max}$ and $f_i^{\min}$ are the maximum and minimum values among all non-dominated solutions of the ith objective respectively, f_i^{M+1} is the ith objective of the $(M + 1)$th solution, and f_i^{M-1} is the ith objective of the $(M - 1)$th solution.

Two dimensional search space is taken as an example to illustrate the relative position relationships among the non-dominated solutions used to calculate the "crowded distance", as shown in Figure 2. If f_i^M is the largest or lowest, f_i^{M+1} or f_i^{M-1} in Figure 2 will not exist. Therefore, the item $f_i^{M+1} - f_i^{M-1}$ in Eq (2.10) is replaced with $2(f_i^M - f_i^{M-1})$ when f_i^M is the largest or $2(f_i^{M+1} - f_i^M)$ when f_i^M is the lowest.

However, these adaptive weighting schemes may generate the low-quality Pareto frontiers with local optima (local Pareto frontiers), lacking the improvement in the diversity of the non-dominated solutions. This is because that these schemes are heuristic, which may deteriorate the distribution of Pareto frontiers [78]. Therefore, Sato et al. [78] modified the adaptive weighting scheme proposed by Sato et al. [75] to mitigate this issue through giving more appropriate weighting factors for each initial solution. Specifically, this method consists of two optimization algorithms: obtaining a Pareto frontier approximation and solving a single-objective topology optimization problem (SOTOP). In this method, weighting factors $w^M = (w_1^M, w_2^M, \cdots, w_m^M)$ are adaptively determined by minimizing or maximizing a linear programming problem: $f_L = w^M \cdot \mathbf{x}_{\text{new}}^M$. Specifically, $\mathbf{x}_{\text{new}}^M$ denotes the desired points obtained with Eq (2.7). Therefore, no prior weighting factors need to be provided in comparison with previous schemes. However, the biggest issue is that non-convex optimization problems cannot be well handled because of the nature of weighted-sum methods. Afterwards, Sato et al. [79] proposed a data mining technique for knowledge discovery in MOTO for serviceable structural designs.

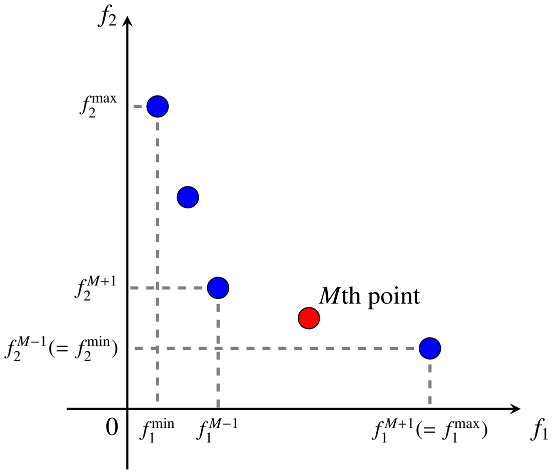

Figure 2. "Crowded distance" calculation.

2.2. Equality constraint methods

Lin [80] presented the equality constraint method used to obtain the set of Pareto-optimal solutions for a general MOOP. The expression of the equality constraint method is

$$\begin{aligned} &\min_{x\in\mathbb{X}} / \max_{x\in\mathbb{X}} : f_1(x) \\ &\text{subject to} : f_2(x) = \alpha_2, f_3(x) = \alpha_3, \ldots, f_N(x) = \alpha_N \end{aligned} \tag{2.11}$$

where $\alpha_2, \alpha_3, \ldots, \alpha_N$ are prescribed values assigned to corresponding objective functions and $\mathbb{X}$ is the constraint set.

Equation 2.11 is called the parametric-equality-constrained single-objective (PECSO) optimization problems related to the multi-objective problem [80]. To implement the equality constraint method, one objective among multiple objectives is selected to be optimized (for example, $f_1(x)$). Next, the other objectives are converted into parametric equality constraints, and prescribed values $\alpha_2, \alpha_3, \ldots, \alpha_N$ are assigned to the other objectives $f_2(x), f_3(x), \ldots, f_N(x)$. Then, the optimal solution of the selected objective $f_1(x)$ is obtained. Finally, this process is repeated many times through altering the predefined values of the other objectives until generating the acceptable Pareto frontier.

In terms of MOTOPs, the equality constraint method is uncomplicated to execute, while the computational cost of this method is high, because each implementation of TO involves plentiful Finite Element Analysis (FEA). To solve this problem, Turevsky and Suresh [60, 81] developed an efficient equality constraint method capable of minimizing a bi-objective TO problem (the compliance and volume case) through assigning a prescribed value to the volume objective automatically. In their study, the compliance was selected as the objective to be optimized, and the volume was transformed into a parametric equality constraint [60, 81]. Additionally, they utilized the fixed decrement of the volume to update the prescribed value of the equality constraint, which is expressed by

$$V(x) = V_i = V_{i-1} - \Delta V \tag{2.12}$$

where V_i is the current prescribed value for the equality constraint of the volume $V(x)$, V_{i-1} is the previous prescribed value, and ΔV is the fixed decrement of the volume.

The introduced method is based on the notion of topological derivatives, and it can directly generate the Pareto frontier [60, 81]. Three crucial definitions and a lemma are given to determine whether a specific topological design is Pareto-optimal or not.

Suresh [82] extended the Pareto-topology-optimization method proposed by Turevsky and Suresh [60, 81] to tackle the compliance and volume case of large-scale 3D problems based on the idea of the equality constraint method. Identical with the method proposed by Turevsky and Suresh [60, 81], the compliance was selected as the objective to be optimized, and the volume was transformed into a parametric equality constraint. In their study, the topological sensitivity field was directly exploited as a level-set instead of the above three definitions and a lemma for the Pareto optimality [82]. The induced domain Ω^τ under different cutting-planes is defined as [82]

$$\Omega^\tau = \{p^\tau \mid T(p^\tau) > \tau\} \tag{2.13}$$

where p^τ is the point where an infinitesimal hole is inserted, τ is the value of cutting-planes, and $T(p^\tau)$ is the domain whose topological sensitivity field exceeds the predefined value τ.

For 3D large-scale problems, the cutting-plane is generalized to the cutting-manifold. The reported method calculates the value of τ for a desired volume fraction to obtain a Pareto-optimal topology, and for generating the Pareto frontier, this process is repeated many times through varying the desired volume fraction automatically until the convergence condition is satisfied. Generally, the updating scheme of the volume is similar to that reported by Turevsky and Suresh [60, 81]. However, if the optimization process diverges because of the large step size, the step size will be controled by an adaptive approach to promote convergence.

Deng and Suresh [83] extended the Pareto-topology-optimization method proposed by Suresh [82] through involving arbitrary constraints and multi-loads. Similarly, Mirzendehdel et al. [84] proposed a strength-based TO method for anisotropic components and explored a non-convex Pareto frontier of the relative strength constraint value in relation to volume fraction percentage based on the Pareto-tracing TO method developed by Suresh and Mirzendehdel [81, 82, 85].

3. Additive manufacturing oriented topology optimization

Conventional manufacturing oriented TO is developed through incorporating the manufacturing constraints for casting, extrusion, sheet-forming, rolling, and forging [37, 86]. AM constraints or filters are incorporated into TO methods to generate the designs suitable for AM [87]. Compared to conventional manufacturing oriented TO, AM oriented TO is still a relatively new research field, allowing room for obtaining better solutions under the condition of satisfying AM limitations. This section mainly focuses on design methods for AM, and therefore post-processing methods for AM (for example, geometry clean-up methods [88]) are not involved in this section.

3.1. Support structure minimization design

For the purpose of providing sufficient support and overcoming the overhang limitation, support structures are inevitably fabricated during the AM process [89]. However, after fabrication, support structures are useless, and they must therefore be removed with the post-treatment operation. Despite the increase in the geometries manufacturable through the use of support structures, the removal of these supports after fabrication leads to a waste of materials, an increase in build time and cost, an increase in the post-treatment cost, and potential pollution by specialized polymers (for example, the medical grade) [52]. Specifically, Hu et al. [90] reported that up to 63.6% of the fabrication time in FDM could be consumed in manufacturing support structures, and Thomas and Gilbert [91] revealed that the post-treatment (clean-up) of support structures accounted for approximately 8% of the total AM cost. Unlike chemical etching and dissolution widely used to remove support structures for polymers, the removal of support structures is tough or even impossible for Electric Discharge Machining (EDM) that is extensively utilized for metallic additive systems [89]. Therefore, support structure minimization is a crucial research direction for AM oriented TO.

Brackett et al. [36] suggested a penalty function on non-manufacturable areas to minimize the use of support structures. Mirzendehdel and Suresh [43] introduced the topological sensitivity of the support structure volume into the Pareto-topology-optimization method proposed by Suresh and Mirzendehdel [82, 85] to generate the Pareto frontiers of the support structure volume with respect to the volume fraction, and the augmented Lagrangian method was exploited to impose the support structure constraint. However, they merely utilized the vertical support structure volume, which is simply the integral of the support length over the boundaries of the surfaces that violate the critical overhang angle, multiplied by an appropriate fill ratio. The method of calculating the amount of support structures is expressed by

$$V_S = \gamma \int_{(\alpha \geq \hat{\alpha})} l_p \mathrm{d}\Gamma \tag{3.1}$$

where V_S is the support structure volume, α is the subtended angle, $\hat{\alpha}$ is the threshold value, l_p is the length of the support structure at the boundary point, and Γ is the boundary.

There are, however, non-vertical support structures in practice. Vertical support structures result in more supports attaching to the part, which is useful if platform space is limited. By contrast, non-vertical support structures could result in more supports attaching to the platform, generating fewer blemishes on the parts. In addition, there are different types of support structure for AM to further slim down the support, for example, the lattice support [92], tree-like support [93], and bridge-like support [94]. New support structure designs are continuously being developed [95, 96].

Ranjan et al. [97] introduced a constraint of generating designs with the minimum support materials into the TO program developed by Liu and Tovar [98], and the results showed that the proposed AM oriented TO method termed DFAM could efficiently reduce the use of support materials in comparison with the conventional one. Panesar et al. [99] proposed five design strategies (i.e., the solid, intersected lattice, graded lattice, scaled lattice, and uniform lattice) to generate the lattice structures that are derived from TO results, and support structure usage of the proposed design strategies was compared. As distinct with other methods, this method utilized different lattice structures to reach the goal of support structure minimization. Recently, Cheng and To [100] developed a support structure optimization framework for part-scale applications where three lattice structures (cubic, cross, and diagonal) are used as support structures, and afterwards the feasibility of the proposed method in reducing the use of support materials was experimentally validated by Cheng et al. [100, 101].

3.2. *Self-supporting structure design*

Compared with introducing extra support structures, designing self-supporting or support-free structures via TO algorithms seems preferable, which is able to reduce the fabrication cost and simplify the post-treatment. Recent years witnessed an increasing interests in developing AM oriented TO methods for self-supporting structure design.

To fulfill the idea of self-supporting structures, Leary et al. [52] incorporated a post-processing method in the density-based method to assure manufacturability of FDM structures without introducing extra support materials, and the implementation of the proposed method is on the basis of altering the support inclination angle and offset thickness [52]. Essentially, the features similar to support structures are added as a part of the component, which is a straightforward way to obtain support-free structures.

Some geometric overhang restrictions were directly considered in AM oriented TO. Gaynor et al. [102, 103] presented a Heaviside projection-based approach in the optimization scheme to ensure that structural features are sufficiently self-supporting. The basic logic is that a certain structural feature point is not allowed to exist unless it is sufficiently supported by neighboring features [102, 103]. In their study, the overhang angle constraint is imposed via the presented projection-based method rather than an explicit constraint [102, 103].

Similarly, Langelaar [104,105] combined a layerwise nonlinear spatial filtering scheme that mimics a typical powderbed-based AM process. The aim of this layerwise filtering scheme or AM filter is to prevent the optimized designs violating geometrical limitations from AM [104, 105]. However, this method fixed the critical overhang angle at 45°, and the regular mesh has to be used in this method. Afterwards, Barroqueiro et al. [106] improved Langelaar's AM filter by using the softmax function instead of the P-Q max function. Most recently, the effectiveness of Langelaar's AM filter has been experimentally validated by Fu et al. [107,108] with both FDM and SLM. Ven et al. [109] developed an overhang filter based on front propagation, whose role is to detect overhang regions with the anisotropic speed function. The aim of this overhang filter or AM filter is to obtain self-supporting topologies, and the presented filter is able to control the minimum allowable self-supporting angles [109]. Unlike using a structured mesh, this method utilized the unstructured mesh suitable for the initial design domain having holes and curved surfaces. Jimenez et al. [110,111] took advantage of an edge detection algorithm in the image processing field, Smallest Univalue Segment Assimilating Nucleus (SUSAN), to identify and control the inclination of members. Kuo and Cheng [112] proposed a method capable of forming self-supporting topologies using a logistic aggregate function. Most recently, Zhang et al. [113] proposed an approach considering both the overhang angle and hanging feature constraints where the hanging feature and thin component can be successfully suppressed.

The common restriction of density filter-based methods is that the extra-layer of the density filter will greatly raise the computational cost. Allaire et al. [87,114–116] proposed a physics-based method for self-supporting design through defining a new mechanical constraint functional on the compliance of the intermediate shapes during the layer-by-layer manufacturing of a topology.

In addition to density-based and physics-based methods, the deposition path planning-integrated level-set framework was also used to develop self-supporting design methods. Liu and To [117] utilized multiple level-set functions to represent the sliced homogeneous AM part and implemented the self-supporting manufacturability constraint through a novel multi-level-set interpolation scheme for 3D structures. Specifically, two deposition path patterns (i.e., contour-offset and structural skeleton-based path planning) were integrated with TO for properly addressing AM-induced anisotropic material properties. After that, Liu et al. [118] integrated optimal hybrid deposition paths with the shape and TO for FDM under the level-set framework. In comparison with the deposition path patterns adopted by Liu and To [117], the hybrid pattern could result in a better structure and would be closer to practice.

Other than the layer-by-layer manner, the feature-driven method is attracting scholars' attention recently. Guo et al. [53] proposed AM oriented TO approaches capable of forming self-support structures based on MMC and MMV solution frameworks [13, 18], and numerical simulations demonstrated that MMC and MMV based methods were able to fully obey overhang angle constraints for searching optimized structures.

As the intersections of holes in MMV may be prevented by constraints, a recent study from Zhang and Zhou [119] introduced polygon-featured holes and overhang constraints to design self-supporting structures. In their studies, polygon-featured holes are used as basic design primitives, and overhang restrictions are involved into the geometry description [119].

Depending on the experimental results obtained by Fu et al. and Huang et al. [108, 120], it can be concluded that only using the overhang angle constraint is too strict to obtain better solutions. Even though the angle of the overhang is less than the minimum allowable self-supporting angle, the overhang can still be built without any support structures as long as the length of the overhang is less than the maximum allowable length. Therefore, the overhang length constraint should be introduced to exactly determine whether support structures are required. As presented in [43], the overhang length constraint for FDM can be expressed by

$$h(\text{mm}) = \begin{cases} 5 + 40(1 - \alpha/\pi) & 3\pi/4 < \alpha \le \pi \\ \infty & 0 \le \alpha \le 3\pi/4 \end{cases} \tag{3.2}$$

where h(mm) is the overhang length defined by Mirzendehdel and Suresh [43]. Some potential solutions of considering both overhang angle and length constraints in TO had been discussed by Huang et al. [120]. Most recently, Liu and Yu [121] proposed a new method capable of using only the critical overhang angle criterion, or the comprehensive criterion that simultaneously considers the overhang length and angle to obtain suitable self-supporting topologies for different AM processes.

Although self-supporting structures have some merits in comparison with introducing sacrificial support materials, they do have a range of demerits because of their inherent characteristics. Self-supporting structures are significantly different from unconstrained optimized structures, resulting in a different stress distribution. Therefore, the designed self-supporting structures may violate the stress or other performance constraints, and result optimality has to be sacrificed in some cases. In addition, the computational cost of current support-free TO methods is high compared to standard TO methods.

3.3. Optimal build orientation

The build direction is an important parameter that can affect the total material consumed in AM, and the component is support-free for a specific build direction in some cases. As a result, different strategies were introduced into AM oriented TO to find the optimal or a better build direction such that the aim of reducing the total material volume or achieving better performance could be reached. Leary et al. [52] took advantage of three manufacturing parameters (i.e., the volume increase, maximum height, and base width at the plate) as indicators to select the optimal build direction.

Mass and Amir [122] reported that the optimal build orientation of a virtual skeleton (i.e., a truss) cannot ensure the optimal continuum optimization results, meaning that distinct build directions should be examined to obtain the optimal direction for continuum optimization. In terms of the above two methods, the determination of the optimal build orientation is conducted separately from the TO process. Although Langelaar [104, 105] considered several specific build orientations in the AM filter, only topologies with a single build orientation can be obtained. The similar strategy was also adopted by Gaynor and Guest [103], but only upward and downward build orientations were taken into account.

Some algorithms have been formulated to simultaneously optimize the topology and build orientation. Diressen [123] considered the build orientation in the TO stage based on a density gradient method such that the optimal topology and build orientation could be concurrently searched. For diagonal directions, there was, however, some trouble in convergence. Guo et al. [53] incorporated the optimization process of the build orientation into the AM oriented TO approaches proposed by them via defining the angle of the working plane as a design variable. Langelaar [124] considered optimization of the support layout and build orientation simultaneously based on a density-based TO, and the selection of the optimal build orientation is based on the trade-off relationship between the manufacturing cost and performance.

3.4. Feature size control

Due to the limitations of AM, components with tiny feature size are not printable [107]. Even though components with the small feature size are manufactured in AM, they will be easily damaged when support structures are removed. Consequently, a couple of methods had been developed to control the minimum feature size. Guest et al. [125] presented a method of controling the minimum length scale in TO with the projection functions capable of transforming nodal design variables to element-wise volume fractions. Guest [126] employed a circular test region to search the design domain, and a minimum predefined void ratio was used to prevent the sizes of features from being larger than the maximum length scale. Guest [127] proposed a minimum feature size control scheme on multiple phases based on the Heaviside Projection Method (HPM). Zhang et al. [128] proposed an approach capable of controling both maximum and minimum feature sizes with structural skeleton, a concept in mathematical morphology, based on the density-based TO framework. Zhou et al. [129] used a filtering-threshold scheme and geometric constraints to obtain topologies with strict minimum length scale. Zhang et al. [130] developed an explicit method to control the minimum feature size based on the MMC-based framework. Allaire et al. [131] formulated geometric constraints to control local thickness based on a level-set method. A recent study from Hägg and Wadbro [132] proposed the definition of the neighborhood based minimum length scale for subsets of a convex (possibly bounded) domain.

Recently, some minimum feature size control schemes have been integrated with AM oriented TO methods. Leary et al. [52] introduced a parameter called the offset thickness into the proposed self-supporting AM oriented TO method in order to constrain the feature size. Gaynor et al. [102, 103] made use of HPM to obtain the minimum allowable feature size. Qian [133] employed a Helmholtz Partial Differential Equation (HPDE) based filtering to realize the minimal feature size control. Guo et al. [53] argued that the proposed MMC-based method had potential ability to control the minimum feature size because of the publication reported by Zhang et al. [130]. Mohan and

Simhambhatla [134] used the material continuity to obtain topologies with the minimum feature resolution for manufacturing feasibility. Liu [135] presented a piecewise length scale control method for level-set methods where new features of piecewise and dynamic length scale control are provided, showing a more exible manner. Liu et al. [136] introduced the minimum length scale constraints to multi-scale topology optimization for AM on the condition that the unit cell size is defined beforehand. By contrast, the minimum feature size control methods for conventional manufacturing oriented TO are well-established, where ideas could be used in AM oriented TO methods [37, 86].

However, common limitations of minimum feature size control are that it may generate a local optimum topology because of preventing some topological changes, and make the method computationally expensive due to the additional length scale measure and control.

3.5. Unsupported or self-supporting enclosed void design

As TO methods would generate complicated structures, enclosed voids are inevitably formed, resulting in non-manufacturable designs for AM. Therefore, some efforts had been made to tackle this issue. Liu et al. [137] presented a virtual temperature approach capable of formulating the simply-connected constraint in TO, aiming at avoiding enclosed voids. Particularly, the validity of the virtual temperature method has been verified by Li et al. [138]. Guo et al. [53] reported that the proposed MMV-based method was able to implement no enclosed void design, while there is no details about this in their study. Interestingly, the deposition path planning-integrated TO method proposed by Liu and To [117] has the ability to generate self-supporting enclosed void design. Zhou and Zhang [139] presented a side constraint scheme considering structural connectivity to eliminate enclosed voids. Most recently, Xiong et al. [140] proposed a new connectivity control approach through which enclosed voids are eliminated by forming tunnels connecting them. However, this topic has not attracted much attention in this field, and existing methods have not been widely adopted.

4. Trade-off relationships in AM oriented TO

Currently, little research focuses on trade-off relationships existing in AM oriented TO, which are the key in terms of establishing MOTO for AM. Despite lacking systematic investigations, the idea of MOO has been adopted in AM oriented TO. For example, a study from Gaynor and Guest [103] reported four solutions with the minimum self-supporting angle of 45°, which were obtained through altering the allowable volume fraction. Specifically, the optimization objective is to minimize compliance. As the volume and compliance are two conflicting objectives, the strategy mentioned above can be extended to trace the Pareto frontier, and a similar strategy was reported by Saadlaoui et al. [42]. A recent investigation from Langelaar [124] mentioned the importance of establishing the trade-off relationship between the costs related to support materials and performance. Therefore, considering MOOPs in AM oriented TO is essential and rational to attain one or multiple better trade-off solutions. However, this topic is still far from being a mature field.

There are some trade-off relationships in AM oriented TO, and the establishment of trade-off relationships is a crucial step for clearly determining the MOOPs to be solved. In addition, trade-off relationships are important to determine the optimal build orientation in the TO stage [124]. Trade-off relationships that exist in AM oriented TO are summarized based on the papers reviewed in Section 3, and some potential trade-off relationships are also mentioned in this section.

In the case of support minimization design, the relationship between the total consumed material and performance is not well-established. A topological design with a less volume fraction generally requires more total materials to build it than that with a larger volume fraction. However, Mirzendehdel and Suresh [43] argued that the Pareto frontiers of the support volume to the volume fraction were non-convex, meaning that the total material consumption of the topology with a certain volume fraction may be greater than or equal to that with a smaller volume fraction. Therefore, the Pareto frontier of total consumed materials with respect to performance should be explored to assist decision-makers to select a topological design that consumes the minimum materials under the precondition of satisfying performance requirements.

In terms of self-supporting design, the relationship between the sacrificed performance and critical overhang angle defined in TO is not well-established. Although the design with a larger predefined critical overhang angle can be suitable for more 3D printing machines, more performance of that design would be sacrificed. Actually, the above ideas can be proved by the results reported by Gaynor and Guest [103]. With the rise in the minimum allowable self-supporting angle (critical overhang angle), compliance consistently increases, meaning that more performance is sacrificed. Therefore, the Pareto frontier of performance with respect to the critical overhang angle defined in the TO stage should be generated such that decision-makers could select one or more solutions from the obtained Pareto set according to the 3D printing machines that they have.

The minimum allowable self-supporting angle represents manufacturability of a component. For example, for a component with a minimum allowable angle of 90°, all the 3D printing machines can build it with no support structures, whereas for a component with a minimum angle of 35°, less machines can build it. To put it differently, with the rise in the minimum allowable self-supporting angle, manufacturability of a component may increase, but more performance would be sacrificed. Therefore, an artificial parameter of manufacturability should be introduced for self-supporting structure design, which can be defined as:

$$AM_f = \begin{cases} \dfrac{S_{AM}}{90^\circ}, & \text{if } S_{AM} \le 90^\circ \\ \\ \dfrac{180^\circ - S_{AM}}{90^\circ}, & \text{if } S_{AM} > 90^\circ \end{cases} \tag{4.1}$$

where AM_f is the manufacturable factor and S_{AM} is the minimum allowable self-supporting angle where the definition is related to the horizontal axis. Depending on Eq(4.1), the trade-off relationship between the sacrificed performance and manufacturablity can be established.

As the critical overhang angle is machine-material dependent, designers working on a specific AM machine have no choice of using various critical overhang angles. The trade-off between the critical overhang angle and performance is practical only when designers have access to different AM machines. However, some cost factors such as material cost and machine setup cost need to be considered in the selection of AM machines. For a specific AM machine, the trade-off between the build direction and performance is more practical than that between the critical overhang angle and performance.

Furthermore, multiple load cases can be introduced into AM oriented TO algorithms, so trade-off relationships among different loads could be established [60, 141, 142]. Although multiple static load cases had been widely used as numerical examples, dynamic loadings like cyclic and impact loadings should also be considered for the purpose of engineering application. Trade-off relationships related to manufacturing cost and time should be established, because they are important evaluation indices in AM [52, 143].

The above trade-off relationships could be used to bridge together two separate topics: MOTO (discussed in Section 2) and AM oriented TO (discussed in Section 3) for the development of new MOTO methods for AM in the future.

5. Challenges and future trends

MOTO offers opportunities for decision-makers to select one or more compromise topologies through considering distinct trade-off relationships or conflicting design targets. AM oriented TO is a powerful technique capable of considering both the optimal configuration of a structure and its manufacturability in AM. With weighted-sum and equality constraint methods being unable to generate topologies independently, investigations merely focus on generating uniformly distributed Pareto frontiers for existing TO methods. Although there exists a possibility of combining together existing MOTO methods and AM-related constraints, trade-off relationships existing in AM oriented TO are rarely discussed. Therefore, the integration of these two topics is a promising future in achieving the topologies suitable for AM and satisfying multiple design criteria concurrently. Challenges and future directions in integrating these two topics are summarized as follows:

(1) Current MOTO algorithms cannot deal well with non-convex optimization problems despite improving the distribution of Pareto frontiers. As non-convex problems are common in AM oriented TO, efforts should be made to develop new MOTO algorithms capable of exploring non-convex Pareto frontiers.

(2) Some other AM-related restrictions – for example, the length of overhang and removal restriction of support structures – should be introduced to AM oriented TO to synthetically consider the manufacturability in AM, post-treatment, and performance.

(3) Introducing the length of overhang constraint could further enhance the performance of a structure through relaxing some areas that violate the overhang angle restriction but are less than the maximum allowable length. Therefore, the maximum allowable length related to the critical overhang angle, materials, and specific AM techniques should be defined via testing overhang criteria, which would be huge work.

(4) As long as support structures are introduced, the removal of support structures has to be conducted after AM. For 2D cases, every position is accessible such that support structures can be removed easily, whereas there may exist some positions that are impossible to be accessed in 3D cases. Therefore, the limitation of removing support structures should be considered. However, this restriction may worsen the performance of the structure.

(5) Trade-off relationships that exist in AM oriented TO are not well-established. The existing AM oriented TO methods mainly focus on minimizing compliance without fully considering these trade-off relationships.

(6) Some actual AM factors such as manufacturing cost, build time, heat accumulation, and residual stress should also be considered as optimization objectives to obtain more reasonable solutions.

(7) The design process of multi-objective AM oriented TO should be made more robust and physically based, where each step of the way is supported by analysis. In contrast, conventionally, the

design that would satisfy all the requirements and constraints is driven by the intuition of the designer.

(8) The most challenging issue of multi-objective AM oriented TO would be the computational cost. Even for an independent topic, the computational efficiency does not perform well, let alone the integration of these two topics. If the build orientation is simultaneously optimized, the computational cost would increase dramatically.

6. Conclusions

This paper presents a review on the current status of MOTO, AM oriented TO, and trade-off relationships existing in AM oriented TO. Based on literature, it can be concluded that scholars mainly concentrated on the separate investigations on the methods of exploring Pareto-optimal topologies and AM oriented TO algorithms, whereas trade-off relationships existing in AM oriented TO had not been discussed systematically. Despite the lack of detailed discussions, scholars are gradually realizing the significance of considering multiple optimization objectives in AM oriented TO. Finally, challenges and future trends of the integration of these two topics are discussed.

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Conflict of interests

The author declares that there is no conflict of interests.

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