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ORIGINAL ARTICLE

Generative design of space frames for additive manufacturing technology

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Abstract
A generative design methodology is presented that solves for minimum volume and compliance space-frame systems, with consideration of stress and buckling constraints. The solution space is explored using formal topology optimisation routines. A parameterisation method converts voxelised topology optimisation solutions into skeletonised connectivity representations. An inequality constrained gradient descent optimisation method optimises and defines cross-sectional geometry. This enables fast and automatic solution generation, providing designers with sets of high-performing problem solutions. Skeleton representations provide an inexpensive modelling tool for parallel analysis of physical problems difficult to model using topology optimisation. Geometry is represented using traditional engineering cross-sections with well understood behaviour. This improves certainty in the performance of solutions, simplifying certification processes. The generative design of a structural aerospace bracket for additive manufacture has been used as a case study within this research. A design of experiments produced 360 topology optimisation results, altering input variables and discretisation resolution to identify their effect on solution outcomes and the performance of parameterisation. The proposed method was found to robustly generate high-performing solutions utilising low-resolution topology optimisation. Additionally, 6 high-performing topologies were identified, providing designers with a set of solutions to select from. Limitations on the parameterisation process were identified, with topology optimisation solutions with volume fractions above 0.2 not parameterising successfully, and simulations with a resolution of 5 mm element size and below generating low performing skeletonised topologies.

Keywords Generative design · Topology optimisation · Parameterisation · Shape optimisation · Near-net design

1 Introduction

This research proposes a generative design (GD) strategy which can be used for the near-net design of space frame structures. The proposed strategy can quickly and automatically search the solution space for high-performing solutions and present those solutions to a designer to select from for more detailed design. This allows rapid progression through the conceptual phases of the design process where solution form is selected. The generative design strategy is also an enabling technology for mass customisation; solutions for bespoke designs of the same problem type can be generated by altering the problem definition to suit individual customer requirements. As the solution generation occurs computationally, the lead time required for customised solutions can be reduced when compared with manual methods. Additionally, topology optimisation (TO) solutions are translated into forms which are described using standard engineering shapes, whose performance is well understood. This improves certainty in behaviour, simplifying certification of designs for high-cost performance-critical components such as those used in the aerospace industry.

The method utilises topology optimisation to generate solution forms, and variation of TO input variables allows

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for exploration of the topological solution space. Voxelised TO solutions are then parameterised using image processing algorithms into a skeleton representation of the space frame structure. These skeleton representations provide an opportunity to inexpensively model the performance of topologies generated, particularly for problems which may be difficult or computationally expensive to conduct utilising standard TO techniques. Further shape optimisation is conducted using an inequality constrained gradient descent algorithm, defining cross-section geometry of members within the space frame to minimise structural mass and compliance in a weighted sums approach.

1.1 Generative design

Classically, the design process consists of four phases: problem definition, conceptual design, embodiment design, and detailed design [1]. This process is typically executed manually, and each phase may be iterated until the proposed solution meets all design requirements set out in the problem definition. Manual design methods provide an opportunity for flexible and creative design response; however, these manual methods are potentially limited in accommodating complexity.

Generative design represents an algorithmic approach to the classic design process. Rather than rely on the designer's creative instincts, the solution form is generated computationally by performance-driven algorithms. These algorithms represent "the rules for generating form, rather than the forms themselves" [2]. Approaching the embodiment of a design in this manner provides numerous benefits to the designer. Designer fixation [3], the tendency for designers to focus on past successful problem solutions, and pre-existing forms, can be avoided, leading to potentially novel problem solutions. Many solutions can be evaluated quickly at the early stages of design, providing redundancy in the design process by finding multiple solutions to the design problem which perform highly. Time can be saved in the initial solution generation process by avoiding the evaluation of poor performing solutions. The solution space can then be explored automatically, while still ensuring design constraints and objectives are managed.

Generative design workflows require the use of expert systems. Expert systems are algorithmic constructs that can make decisions comparable to those of an expert in a well-defined area of expertise [4]. This makes them useful for automating the decision-making process for generative design. Expert systems allow the design process to be completed algorithmically and automatically at computational speeds. This results in many more design iterations being conducted than would normally be possible with manual execution. For engineering purposes, we require expert systems which can emulate the decision-making made during the iterative design process (Fig. 1). Two important types of expert systems are required for engineering purposes: generation of form and evaluation of performance.

Generative design methods have the potential to automate the design process in either a *net* or *near-net* manner, where a *net* solution is finalised and ready to manufacture component, whereas a *near-net* solution is close to the final design, but requires additional manual design effort to finalise the solution for manufacture (Fig. 1).

Generative design has found use within architectural, industrial, and engineering design fields for a large range

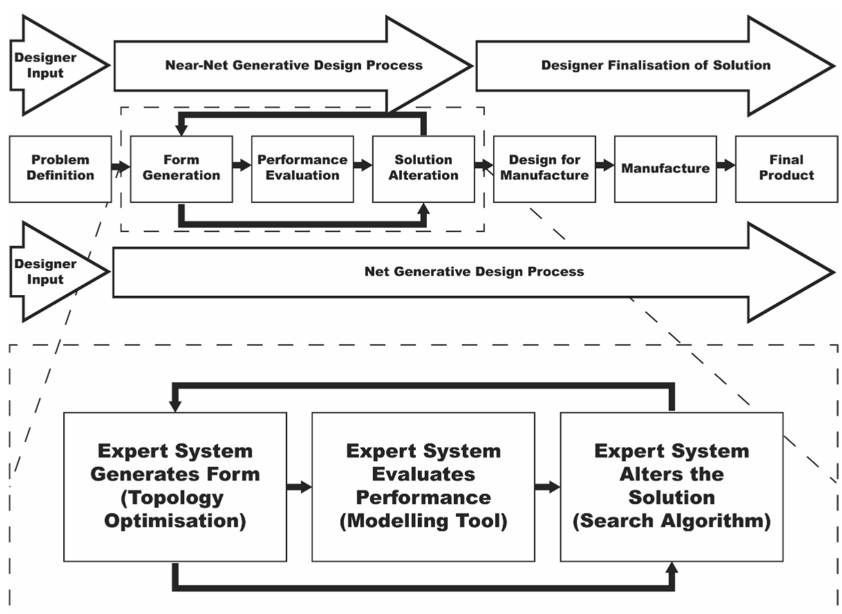


Fig. 1 Simplified workflow diagram of the design process. The difference between a *net* and *near-net* design process is outlined. Inset shows how expert systems can be used to replace portions of the design process

of design problems. GD methods have shown to be suitable for aesthetic product design for perfume bottles [5, 6], desk chairs [5], wine glasses [5, 7], jewellery [5, 8–10], and audio devices [11]. GD has also been used for more technical product designs such as thermal building design [12], structural designs of frames and trusses [13, 14], patient specific implants [15], emergency shelters [16], vehicle wheels [17], heat conducting dendrites [18], and software user interfaces [19].

1.2 The generation of form

The embodiment phase of design is where designers make decisions regarding the physical form of the problem solution. Embodiment design is challenging as "…decisions relating to composition or positioning of components or elements of a design have, in many cases, been guided by instinct, past experience or an educated subjectivity, possibly involving also elements of guesswork (or try it and see) [20]". It is also difficult for designers to foresee the implications of a particular embodiment a priori, where a poor choice of form at the early stages of design can result in sub-optimal design outcomes that are irrevocable due to limited time and fiscal resources. Utilising algorithmic tools to generate solution forms can overcome some of these difficulties, avoiding designer fixation and subjectivity as well as allowing many embodiments to be generated at once, reducing the chance of selecting a poor performing design.

Two algorithmic form generation tools which have found common use for GD are shape grammars (SG) and topology optimisation (TO). Shape grammars were introduced in 1971 by Stiny and Gips [21] as a method of form generation which applies transformation rules to shape primitives. By altering the order of operations of primitive selection and transformation rules, new forms can be generated in a structured manner. Shape grammars are capable of generating complex shapes from simple rules, however are mostly used for aesthetic design applications [5, 7–9, 21, 22].

Topology optimisation is another method for form generation that is inherently performance driven [13, 15, 17, 18, 23]. This makes it particularly useful in engineering applications where performance is the critical design objective. One approach to TO is material distribution methods. These methods attempt to optimise material distribution within a defined design domain by minimising some objective function, typically compliance assessed with finite element method (FEM). Examples of material distribution methods which have found widespread use are Bi-directional Evolutionary Structural Optimisation (BESO) [24] and Solid Isotropic Material with Penalisation (SIMP) [25]. Alongside these methods, ground structure [26] and level-set methods [27] have also found popular use as form generating tools. These methods are technically robust but may result in local optima and difficulties exist in their technical implementation for net design outcomes**.**

Dugré et al. present a case study for the use of TO in the design of pressurised stiffened panels for aerospace application [28]. They note the challenges in the use of TO for design, specifically that TO solutions are heavily reliant on input variables as well as loading and boundary condition definitions. Additionally, they can only be considered local optima within the design problem solution space. These researchers recommend TO be used as an exploration tool for engineers, to gain a broad understanding of possible solutions within the solution space. It is also difficult to model the complexity of a design problem within the constraints of TO, and many design considerations must be considered by the engineer outside of the solutions typically generated. Problems may consist of multiple loading cases, failure modes, or design objectives that may be challenging or impossible to incorporate into a single TO routine. Gu makes similar statements in his analysis of challenges present in the use of TO for structural aerospace design [29]. Comments are made on TO solutions local optimality, difficulties in accommodating complexity of real design requirements, challenges in manufacturability, and subsequent subjective user interpretation. Mukherjee et al. discuss the impact of computational cost of high-resolution topology optimisation on the uptake of the tool in industrial applications, while reviewing the work that is being done with in the literature to combat these challenges [30]. Fiebig et al. comment on the challenges of using TO within the automotive industry [31], noting difficulties in accommodating design complexities as well as manufacturing requirements, alongside the translational requirements from voxelised TO solutions to parametric CAD representations.

1.3 The parameterisation problem

Topology optimisation solutions, particularly for density-based homogenisation methods, are represented using discrete voxel domains. In order to utilise these TO solutions in part creation, they must first be translated into a parametric form such as traditional solid constructive geometry computer-aided design. There are a number of different methods for this parameterisation process that have been proposed within the literature, all generally focused on smooth boundary representation for manufacturing purposes.

One common approach to the parameterisation problem is the use of boundary representation using splines (B-splines). The works of Chirehdast et al. [32] and Papalambros et al. [33] are examples of early B-rep TO smoothing in 2D and expanded to 3D cases [34–37]. In more recent examples of B-spline parameterisation, the TO process has been coupled to the control points of the B-spline allowing for parametric representations directly from the optimisation process

[38–40]. A similar process is the use of isolines or density contours [41–43]. A contour is extracted from the topology optimisation solution at a particular density value to represent the component boundary.

An alternative parameterisation technique is the use of simple parametric features such as lines, arcs, or polygons for boundary representation. Larsen et al. [44] and Lin et al. [45] fit points from TO boundaries to pre-defined polygon templates. Lin et al. [46] expand upon this idea further by utilising a neural network for hole polygon identification. Chou et al. [47] use the pixels at boundaries of holes to fit straight line segments, creating polygons. Yi et al. [48] investigate the curvature and roundness between extracted boundary points to fit lines, arcs, circles, and fillets to TO solutions.

A method which has also found common use in 3D boundary surface representation, which does not fit with the method categories previously discussed, is the marching cubes algorithm [49]. This algorithm has found success in use for reconstruction of parametric CAD solution from 3D topology optimisation solutions [50].

The last category of parameterisation techniques are skeletonisation methods. These methods use the geometric skeleton of the solution to reconstruct solution geometry rather than the boundary of the topology optimisation solution. Bremicker et al. [51] discusses this approach, by fitting straight lines to the skeleton of topology optimisation solutions to generate truss or frame like structures. Nana et al. [52] utilise a similar technique, skeletonising 3D TO solutions, and fitting straight line segments to the skeleton, utilising these to model beam elements for sizing of the system with the finite element model. These techniques are what the authors have drawn upon for the parameterisation method proposed within this paper, a novel algorithm which automates the translation of skeletonised solutions into connectivity definitions. This connects topology optimisation solutions to inexpensive FEM analysis, reducing computational cost of analysis when compared to higher order modelling required of boundary representations of TO solutions.

1.4 Additive manufacturing

Additive manufacture (AM) is defined as the "process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies" [53]. AM technologies are increasingly relevant to commercial production, with many different manufacturing methods available for use with a variety of engineering materials. Of particular interest to the manufacture of space frame structures, as designed within this research, are metal additive manufacturing (MAM) methods. For thorough reviews on MAM technologies and processes, the reader is kindly referred to Cooke et al. and Çam [54, 55].

Additive manufacturing provides a unique opportunity for the application of structural optimisation in light-weighting. Design tools such as TO generate solutions with improved strength-to-weight ratio; however, the associated structures are often challenging for traditional manufacturing. If designers are to manufacture these optimised structures additively, then design for additive manufacturing (DFAM) considerations must be an integral aspect of the design process.

In their review of design and structural optimisation in AM, Plocher et al. suggest that GD schemes are appropriate for these DFAM challenges [56]. They report the following essential needs for the successful application of GD technologies in industrial design environments [56]:

- A means to "…streamline the digital workflow for the industrial application."
- The "…necessity to provide users with the tools to select from a range of solutions…"
- An ability to "…provide solutions that capture the trade-off between performance and economy."
- The requirement for smooth boundary representations of TO solutions.
- Utilisation of computational resources effectively, particularly those tied to simulation resolution.
- Computationally inexpensive modelling and associated DFAM tools.

This research directly addresses these identified challenges to the application of both structural optimisation and GD in AM for light-weight structures. Specifically, form generation is approached with the intent to utilise low-resolution TO simulation to minimise the computational cost required to effectively search the solution space; a range of problem solutions are thereby identified for evaluation and selection by designers; skeletonised parametric representations of TO solutions provide a computationally inexpensive modelling tool for designers to evaluate solution performance; this includes a range of physical problems not compatible with other methods as well as DFAM considerations such as overhang angle and minimum feature size; additionally, shape optimisation is utilised to generate solutions with smooth boundary representations utilising common engineering cross-sections. This reduces the overall level of optimality for a solution at the added benefit of increased certainty in behaviour.

Leary makes note of the importance of GD techniques in enabling mass customisation outcomes for AM, stating that "Generative design methods provide an enabling opportunity to accommodate the design effort necessary for a mass-customization philosophy without the infeasibly large design cost or opportunity for design error associated with manual design [57]". Additive manufacturing becomes economically competitive with traditional manufacturing processes when production variation is high, and production volume is low, i.e. when there exist distinct permutations of a particular product design.

The generative design methodology presented within this research can be utilised to achieve such mass customisation outcomes. As the design process is automated and algorithmic, alteration of the initial inputs to the design process can allow for redesign of a product with distinct variations according to the needs of individual customers. This in turn reduces the design effort required, reducing lead times in the early stages of design, and improving the economic competitiveness of mass customisation.

2 Methodology

The proposed methodology is comprised of four major phases (Fig. 2). Initialisation is where the user specifies the rules for the design process; this phase can be altered to enable mass customisation outcomes. Topology optimisation is where the solution space is explored for unique topological outcomes; this phase allows exploration of the solutions space while avoiding designer fixation. Parameterisation is where the TO solution is translated to a skeleton representation that allows computationally inexpensive modelling. Shape optimisation is where geometry of the part is determined; this phase allows for the TO solution to be represented through commonly used engineering shapes that exhibit well understood behaviour. It is also this phase which can be used to model the solution for physical problems which are expensive or difficult to conduct with TO, in the case of this research, stress, and buckling analysis (Table 1).

2.1 Initialisation

The initialisation phase is used to establish the mathematical parameters associated with the generative design process (Table 2). Decisions made during this phase directly effect the design outcomes that will be achieved. Designers select the orthogonal bounding box and resolution of the design

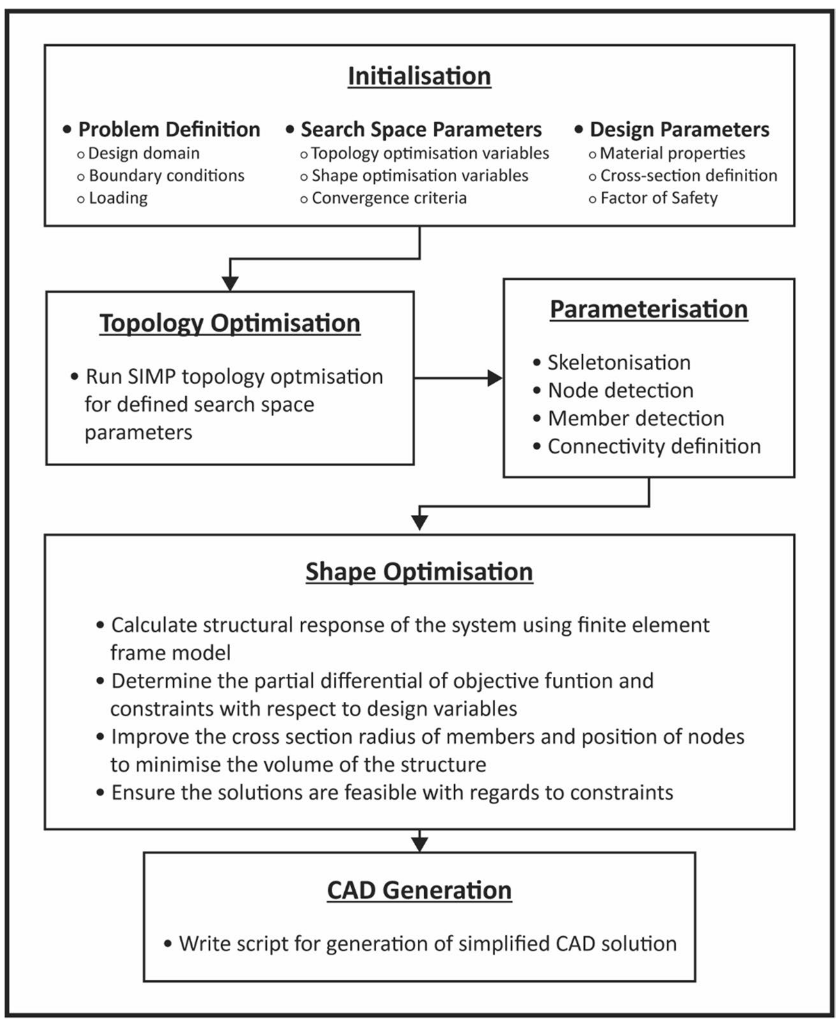


Fig. 2 Workflow diagram for generative design process

Table 1 Nomenclature

Variable	Variable definition
G	Objective function
w	Weighting term
V	Total structure volume
V_o	Structural volume at initial state
C	Total structure compliance
C_o	Compliance at initial state
ρ	Material density
l_i	Length of member i
l_{oi}	Length of member i at initial state
m	Total number of members
K_i	Local stiffness matrix of member i
u_i	Local displacement matrix of member i
$\sigma_{i_{VM}}$	Von Mises stress of member i
S_Y	Material yield strength
F_{os}	Factor of Safety
F_{ic}	Axial compressive load of member i
F_{icb}	Critical buckling load of member i
r_i	Radius of member i

domain discretisation. Position of loading and boundary conditions are specified alongside the topology optimisation settings at which form exploration will be conducted. Material properties are also defined for modelling purposes.

2.2 Topology optimisation

The TO method used within this work is the solid isotropic material with penalisation (SIMP) method, in particular the open source MATLAB script top3d [58]. The solution space is explored by altering the topology optimisation variables (Table 2) with a desired design of experiments (DOE) (Table 5).

2.3 Parameterisation

Parameterisation is used to create a connectivity representation of the topology optimisation solution. This is done through the use of image processing algorithms. The parameterisation process has three phases: skeletonisation, node detection, and member detection.

Error checks are implemented within the proposed algorithm to ensure: TO solution threshold is not an empty set or multiple solid bodies; boundary conditions and load nodes

Table 2 User defined input variables selected during initialisation

Variable	Variable definition
Topology optimisation variables	
Design domain	Array describing x, y, and z dimensions of design domain
Scaling factor	Fraction used for scaling design domain to lower resolution
Voxel domain	Array of voxel density at the size of scaled design domain
Volume fraction	Desired final volume as a percentage of original domain volume
Penalty factor	Used to steer density values toward binary values
Filter radius	Used to smooth density values
Eo	Young’s modulus of void like material
Emin	Young’s modulus of solid material
Nu	Poisson’s ratio
Load	Position (both Cartesian and voxel), direction and size of applied load
BC	Position (both Cartesian and voxel) and direction of applied boundary conditions
Max iterations	Maximum number of iterations to run optimisation for
Convergence Threshold	Threshold value used to determine solution convergence
Parameterisation variables	
Threshold	Value of density, used for binarisation
Shape optimisation variables	
Min/max radius	Bounding minimum and maximum radius of cross-sections
ρ	Material density
E	Material Young’s modulus
G	Material shear modulus
Yield Stress	Material yield stress
FoS	Factor of safety for design
Load	Magnitude of applied load

are located on skeletonised structure and no nodes are disconnected from the skeleton. The skeleton is also assessed in terms of symmetry and non-symmetric solutions are rejected.

2.3.1 Thresholding and skeletonisation

Parameterisation begins with a thresholding of the TO solution such that the greyscale voxel array representing local density is binarised using a user specified threshold value.

After thresholding, skeletonisation is completed using the medial axis transform [59] to reduce the binary voxel array to a one voxel wide skeleton (Fig. 3).

2.3.2 Node detection

The node detection process is conducted algorithmically (Table 3) resulting in voxels defined as branchpoint, load or boundary condition nodes (Fig. 4)

2.3.3 Member detection

Member detection is conducted following node detection and skeletonisation (Fig. 5). The algorithmic process is outlined in pseudocode in Table 4. Once the connectivity and node positions have been defined, a symmetry check is conducted on the solution and skeletons which are found to be non-symmetric are rejected.

2.4 Shape optimisation

Shape optimisation is conducted using a gradient descent method. The ADADELTA [60] algorithm is used for the search process, and the method of gradient summation is used for managing constraints [61]. The objective function uses a weighted sums approach to minimise total solution volume, V, and compliance, C. Volume and compliance are normalised to compensate for large differences between the values. Von Mises stress is constrained to be lower than material yield strength divided by a factor of safety. For any member with a critical slenderness ratio, the compressive axial load is constrained to be lower than the critical buckling load. Cross-section radius is constrained between an upper and lower bound. The length of each member is constrained for ± 10% of the original member length. This is outlined in Eqs. 1 to 7; variable definitions are outlined within Table 1.

$$\text{Minimise } G = w_1 V/V_o + w_2 C/C_o \tag{1}$$

$$V = \rho \sum_i^m l_i \pi r_i^2 \quad i = 1, \ldots, m, \tag{2}$$

$$C = \sum_i^m \boldsymbol{u}_i^T \boldsymbol{K}_i \boldsymbol{u}_i \tag{3}$$

$$\text{Subject to } \sigma_{i_{VM}}\left(r_i, \delta_j\right) < S_y/F_s \quad j = 1, \ldots, n, \tag{4}$$

$$F_{ic}\left(l_i, r_i, \delta_j\right) < F_{icb} \tag{5}$$

$$r_{il} \le r_i \le r_{iu} \tag{6}$$

$$0.90 * l_{io} \le l_i \le 1.10 * l_{io} \tag{7}$$

2.4.1 Finite element frame model

To determine the response of the system at any optimisation iteration, a finite element frame model is used. Members consist of a 2-node 3D frame element type with each node having six degrees of freedom [62]. The Von Mises stress of each element is used as a yield criterion

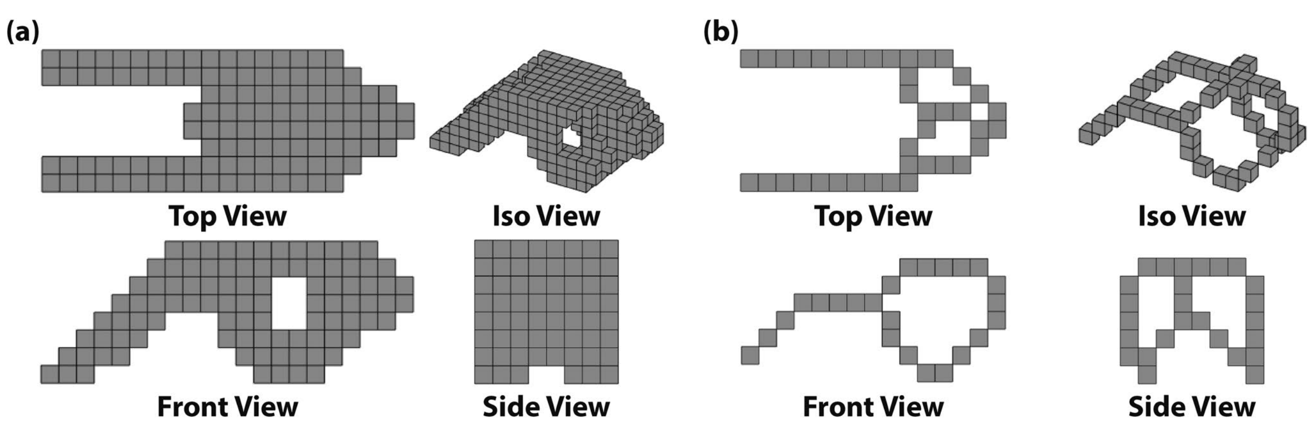


Fig. 3 **a** Binarised voxel topology optimisation solution. **b** Skeletonised solution after medial axis transform is applied

Table 3 Node detection algorithm

Node Detection	
1.	Determine index of nearest solid voxel to original boundary condition position
2.	Determine index of nearest solid voxel to original load position
3.	**For** each solid voxel within the skeletonised solution **do**
4.	Sum the number of solid voxels which are within the 26-neighbourhood of current voxel (inclusive)
5.	**If** number of voxels within neighbourhood (inclusive) ≥ 4 **then**
6.	Assign current voxel as a branchpoint voxel
7.	**End if**
8.	**End for**
9.	Create set of node voxels from branchpoint, load and boundary condition voxels
10.	Label node voxels based on 26-neighbourhood connectivity.
11.	**For** number of labels **do**
12.	Assign each voxel with the same label number to a node group
13.	Determine final node position values by averaging the position of all node voxels that belong to current node label
14.	**End for**
15.	Determine which nodes belong to boundary conditions and loads
16.	Move the boundary condition and load nodes to application location
17.	Scale node positions back to desired units and original design domain size

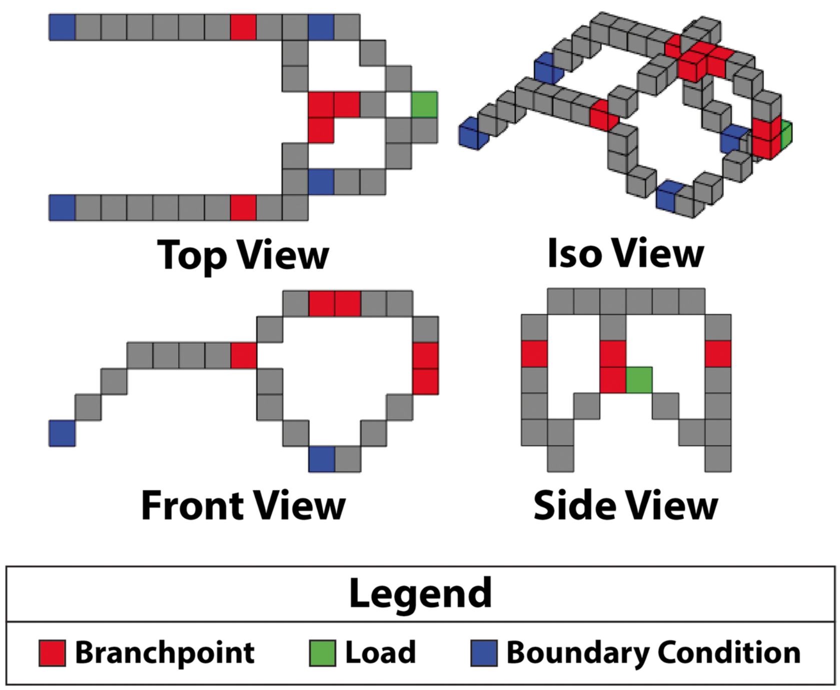


Fig. 4 Node detection results

and compliance is evaluated utilising the element stiffness matrix and displacements. Representation of the TO solution in this form allows for fast evaluation of structural performance for a range of physical modelling problems, stress, buckling and compliance being relevant within this work. The speed of the iterative search algorithm during shape optimisation is improved, compared to higher order models.

3 Case study

The proposed design methodology has been applied to the redesign of an extant aerospace bracket manufactured with billet machining (Fig. 6). Billet machining is an established method for safety–critical structural aerospace applications. For these applications, the manufacturing opportunities (high material removal rates, certified billet

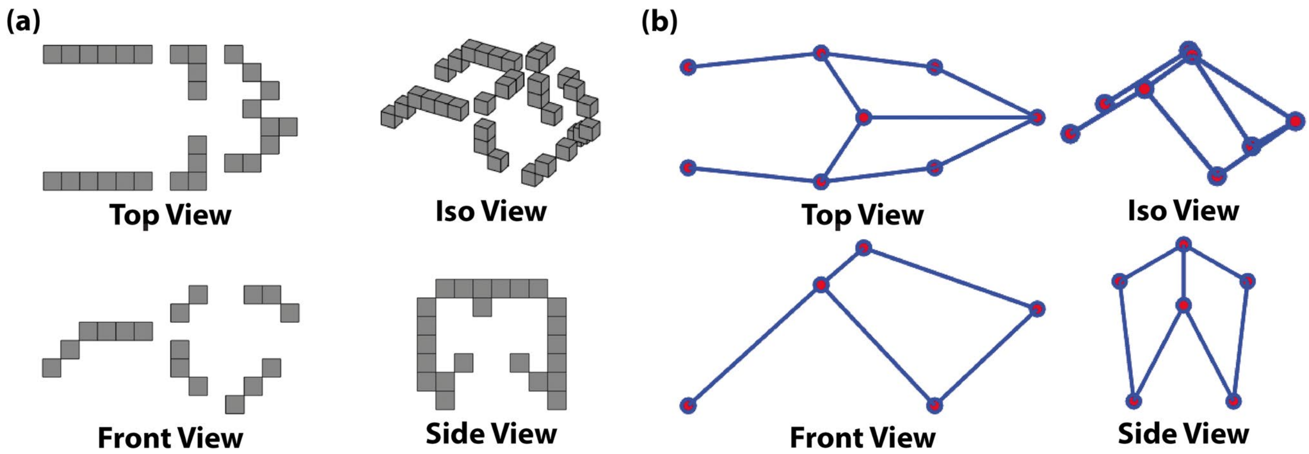


Fig. 5 **a** Structures that remain after removing node voxels from the skeletonised solution (line 1 of pseudocode). **b** Final member connectivity definition

Table 4 Member detection algorithm

	Member Detection
1.	Create member array by removing node voxels from skeletonised solution
2.	Label structures within member array based off 26-neighbourhood connectivity.
3.	Create connectivity matrix size (number of node voxels, number of member labels)
4.	**For** each node voxel **do**
5.	Find 26-neighbourhood of node voxel in the member array
6.	**If** neighbourhood contains a labelled voxel **then**
7.	Set connectivity of node voxel and member label to 1
8.	**End if**
9.	**End for**
10.	**For** number of node labels **do**
11.	sum connectivity rows whose node voxel belongs to current node label number
12.	**End for**
13.	**For** each column in connectivity matrix **do**
14.	Set member connection as two node labels with values of 1
15.	**End for**

input material) and challenges (line-of-sight material removal, low utilisation of input material) are well understood. The inherent benefits (increased material utilisation, increased geometric flexibility) and challenges (optimisation of topology, certification of as-manufactured structure) are less well understood and are therefore effective targets for the proposed design methodology.

3.1 Topology optimisation design of experiments

Topology optimisation solutions result in local optima, and alterations to the input variables for TO can generate new

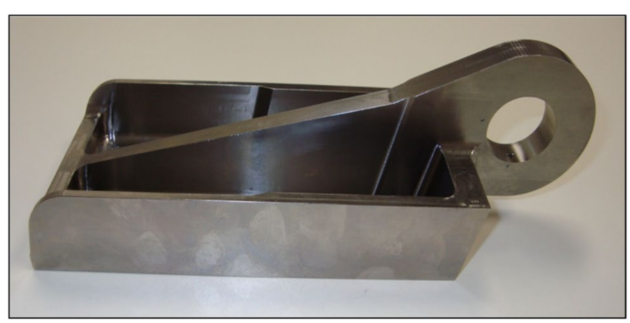


Fig. 6 Original design for aerospace bracket

Table 5 Input variables for topology optimisation search

Variable	Levels	Number of experiments
Discretised resolution (1 element = x mm)	3 to 10 mm in 1 mm increments	8
Volume fraction	0.1 to 0.3 in 0.05 increments	5
Penalty	3.0 to 4.0 in 0.5 increments	3
Filter radius	1.5 to 2.5 in 0.5 increments	3
Total number of experiments		$8 * 5 * 3 * 3 = 360$

Table 6 Dimensions of the original aerospace bracket; bounding box, boundary condition, and load locations

Feature	X-dimension (mm)	Y-dimension (mm)	Z-dimension (mm)
Bounding box	210	75	80
Boundary condition Locations	12, 12, 137, 137	12, 63, 12, 63	0, 0, 0, 0
Load location	189	37.5	49

solutions to the same loading problem (Section 1.2). A full-factorial DOE is conducted whereby the input variables, volume fraction, penalisation factor, and filter radius, are altered at 5, 3, and 3 levels, respectively. Additionally, TO is conducted at 8 different design domain discretisation resolutions (Table 5).

The intent of the DOE is twofold. Alteration of TO input variables provides a means for searching the solution space for unique topological solutions to the problem. The results of this search process can be used to evaluate the capacity for the generative design process to generate unique solutions to a given design problem. Investigation of different discretisation resolutions allows the performance of the tools to be evaluated with regard to computation resources required for solution generation. The behaviour of the parameterisation process is altered depending on the resolution of the design domain, and the ability for the generative design strategy to produce high-performing solutions at low-resolution is quantified within Section 3.3.

3.2 Problem definition

The TO design domain (Fig. 7) is determined as a bounding box whose dimensions are measured from the original aerospace bracket (Table 6). Boundary conditions are located at fastener positions and the applied load located at the centre of mating cylinder (Table 6). This bounding region is then discretised into elements for topology optimisation and loads and boundary conditions are located at the closest node to their original position. Boundary conditions are defined at node location as a displacement constraint in all orthogonal directions, and a load of 10kN in the negative z-direction is applied at nodal location. For topology discretisation with an even number of elements in the y-direction, the load is applied at the middle node, and for an odd number, the load is split and applied at the two nodes on either side of the middle element. Simulation is conducted using material properties for AlSi10Mg as outline in Table 7, with a safety factor of 1.5 applied.

3.3 Parameterisation outcomes

The success of the parameterisation process is dependent on a number of factors, particularly the properties of the topology optimisation solution. Of the 360 topology optimisation simulations conducted, 152 of these were successfully parameterised using the proposed method in Section 2.3. Figure 8 displays the number of successful parameterisations for each of the different TO resolutions investigated. The proposed parameterisation method is more successful for lower resolution TO simulations. For example, simulations parameterised with a success rate of 67%, 58%, 64%, 56%, and 64% for element sizes of 10 mm, 9 mm, 8 mm, 7 mm, and 6 mm, respectively. Conversely, resolutions of 5 mm element size and below performed poorly with only 18%, 9%, and 2% successfully parameterised TO solutions generated respectively.

3.3.1 Poorly parameterised solutions

When the parameterisation method produces poor solutions, those that would be of no interest to a designer, it is

Table 7 Material properties for AlSi10Mg used in simulation

Material property	Value
Young's modulus	75 GPa
Shear modulus	27 GPa
Poisson's ratio	0.3
Yield stress	260 MPa
Allowable stress	173 MPa
Density	2590 kg/m^3

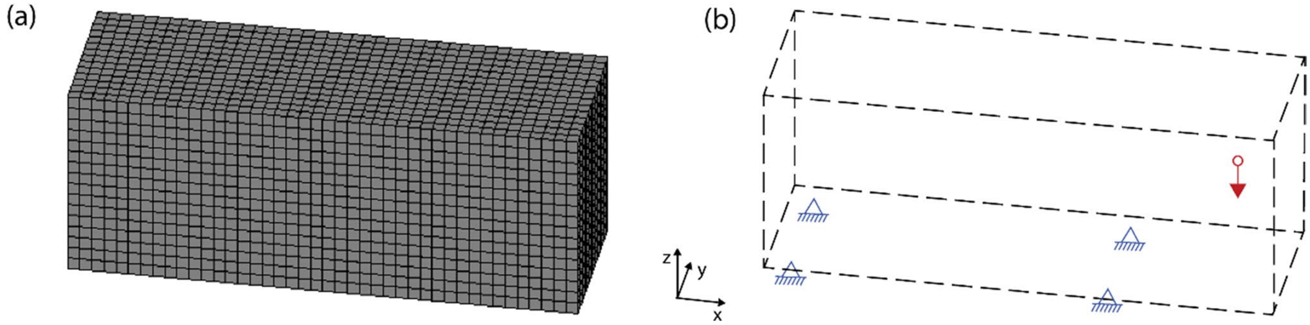


Fig. 7 **a** Discretised design domain. **b** Position of load (red) and boundary conditions (blue) within design domain

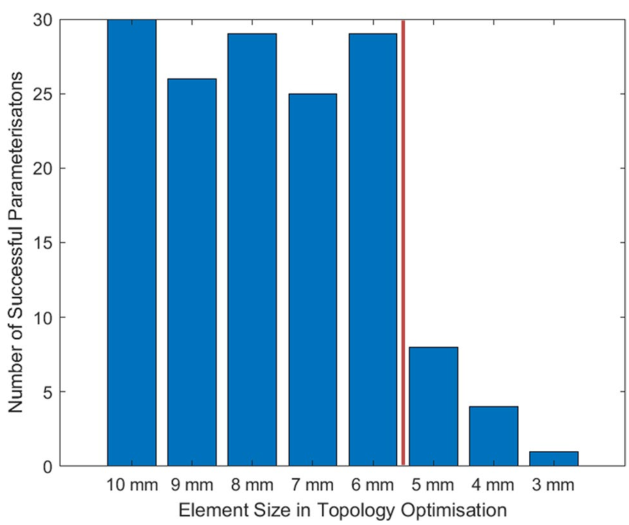


Fig. 8 The number of successfully parameterised topology optimisation solutions for each simulation resolution investigated. For the case study assessed in this research there appears to be a threshold of element size (red line), below which convergence is compromised

due to the medial axis transform of the TO solution. When the voxel TO solution is skeletonised using the medial axis transform, much of the original solution is lost (Fig. 9). The original TO solution in Fig. 9 has a large region of bulk material located around the load application node. The medial axis transform locates the material at the centre of this bulk. The larger the section of bulk material to which the algorithm is applied, the more of the boundary that is lost, making it more difficult for the parameterisation algorithm to identify a connectivity skeleton which accurately represents the topology optimisation solution.

A total of 4 generated solutions encountered this parameterisation problem and are listed in Table 8 with their corresponding topology optimisation settings. All poorly parameterised solutions were conducted at a volume fraction of 0.3 and a filter radius of 1.5. This suggests that the proposed parameterisation technique should be applied to low volume fraction topology optimisation solutions. The closer a TO solution resembles a skeleton-like structure, the more viable the proposed parameterisation technique becomes; these such cases occur at volume fractions of approximately 0.2 or lower, depending upon the problem definition.

Likewise, solutions at higher resolutions tend to parameterise poorly due to the behaviour of the medial axis transform. As the resolution increases, so does the distance in number of voxels between the skeleton and the boundary of the solution. This effect is more pronounced as the proposed method uses skeletons with trimmed spurs (a geometric property of skeletons used to maintain information of the boundary) [63]. As the distance from the medial axis transform to the boundary of the solution increases, the accuracy of the boundary representation reduces. Conversely, low-resolution TO solutions already approximate the medial axis transform quite well, and so the skeletonisation process leads to voxel representations which are more analogous to the original TO solution. This explains the lower number of successful solutions generated at high resolution, as well as the topologies generated being unique.

3.3.2 Effect of resolution on topology of parameterised solutions

Within the 152 successful parameterised solutions, 14 unique topologies were identified; each of these topologies is displayed in detail within the 6. for reference. Topology 4 was produced the most at 43 times (Fig. 10) and for resolutions from 10 to 6 mm element size. No single topology was produced across all topology optimisation resolutions investigated. Topologies 2, 6, 8, 5, and 3 were all produced relatively consistently across multiple (but not all) resolutions. This may be due to the changes made to loading depending on resolution, where resolutions with odd numbers of elements across the y-direction (Fig. 7) required loading to be shared across the two centre nodes, whereas even numbered element divisions had the entire load applied to the centre node.

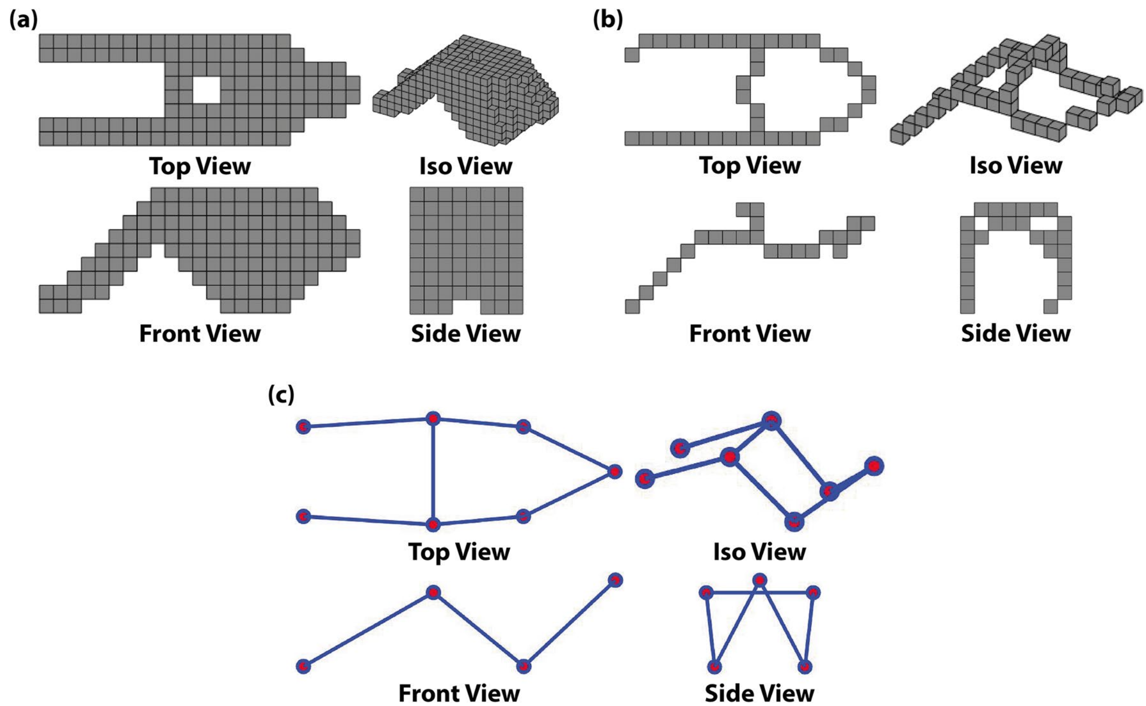


Fig. 9 **a** Voxel topology optimisation solution which parameterises poorly. **b** The medial axis transform of the voxel solution. **c** The final parameterised skeleton solution which does not represent the original TO solution well (Topology 7, 6.)

Topologies 9 to 14 were only generated for higher resolution TO simulations (5 to 3 mm element size). Parameterisation performed consistently poorly at these resolutions, with a low number of total successful parameterisation outcomes (Fig. 8). Visual inspection of topologies 9 to 14 shows that four of these six topologies are not solutions that a reasonable designer would accept. Topologies 9 and 11 have cantilever beam members connecting to the node which the load is applied to, an inefficient use of mass. Topology 14 consists of overly complex connectivity which could be resolved with fewer members. Topology 13 is the least successful parameterisation outcome, with two members acting as zero force members, connecting the boundary condition nodes and not providing any stiffness to the structure.

Table 8 Topology optimisation settings for poorly parameterised solutions

Topology	Resolution	Volume fraction	Penalisation factor	Filter radius
7	9:1	0.3	3.0	1.5
	9:1	0.3	3.5	1.5
	9:1	0.3	4.0	1.5
13	5:1	0.3	4.0	1.5

In addition to these poorly parameterised topologies, topology 7 should also be considered within this set. Generated 3 times for resolution of 9 mm element size, this topology also has multiple zero force members which do not contribute to the stiffness of the structure.

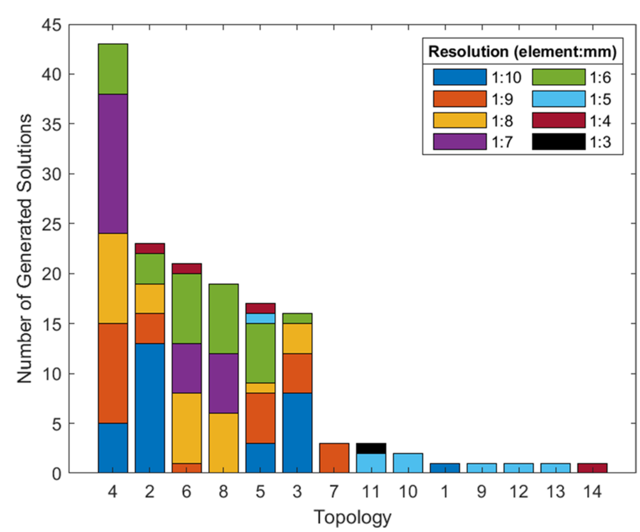


Fig. 10 The number of parameterised solutions generated for each unique topology (6.)

Although the parameterisation method does produce solutions which are poor performing, or poorly represent the topology optimisation solution, successful outcomes are more commonly generated throughout all lower resolution TO simulations.

3.4 Shape optimisation outcomes

Shape optimisation was conducted at a number of different weightings for volume and compliance to investigate their effect (Table 9).

As the objective function is normalised, its value lies between 0 and 1 and is a measure of how improved the optimised solution is from its initial state. The highest performing solution for each topology is outlined in Fig. 11 for each weighting investigated. The majority of solutions optimise more poorly when objective function weighting is skewed towards compliance. Topologies 4, 6, 8, 13, and 14 did not find significant improvement from their initial state across all weightings.

Table 9 Weighting values for compliance and volume for each shape optimisation process investigated

	Volume weighting	Compliance weighting
Shape optimisation 1	0.1	0.9
Shape optimisation 2	0.3	0.7
Shape optimisation 3	0.5	0.5
Shape optimisation 4	0.7	0.3
Shape optimisation 5	0.9	0.1

Across all 14 topologies produced, the lowest objective function values found were either for weightings of 0.9 for volume and 0.1 for compliance or 0.1 for volume and 0.9 for compliance (Fig. 12). Topologies 4, 6, 8, 13, and 14 were found to be able to improve their compliance but not their volume under the constraints applied.

Through the generative design process 14 potential solutions for a designer are generated. As the objective function is normalised, each topology is only comparable to itself through objective function evaluation. To provide a means for selection of solutions for a designer, the total mass and displacement of solution at the load node is compared to one another (Fig. 13). Topologies 1, 2, 3, 5, 7, 10, and 12 (Fig. 14) all performed quite comparably with a range of maximum displacement of 0.042 mm and a range of total mass of 0.076 kg (Table 10). All topologies have very similar characteristics when compared visually, except for topology 7 (Fig. 15) which is an outlier and consists of two cantilever members which ground the entire load applied and five members which are disconnected from the node and act as zero force members. However, this solution was still found to have high material utilisation through shape optimisation. Of the high-performing solutions, topologies 2, 3, and 5 (Fig. 14) were generated consistently across multiple resolutions (Fig. 8), demonstrating the ability for the proposed method to locate high-performing local optima to the design problem. Each of these high-performing topologies provides a good starting point for a designer to continue the design process and ready the solutions for manufacture.

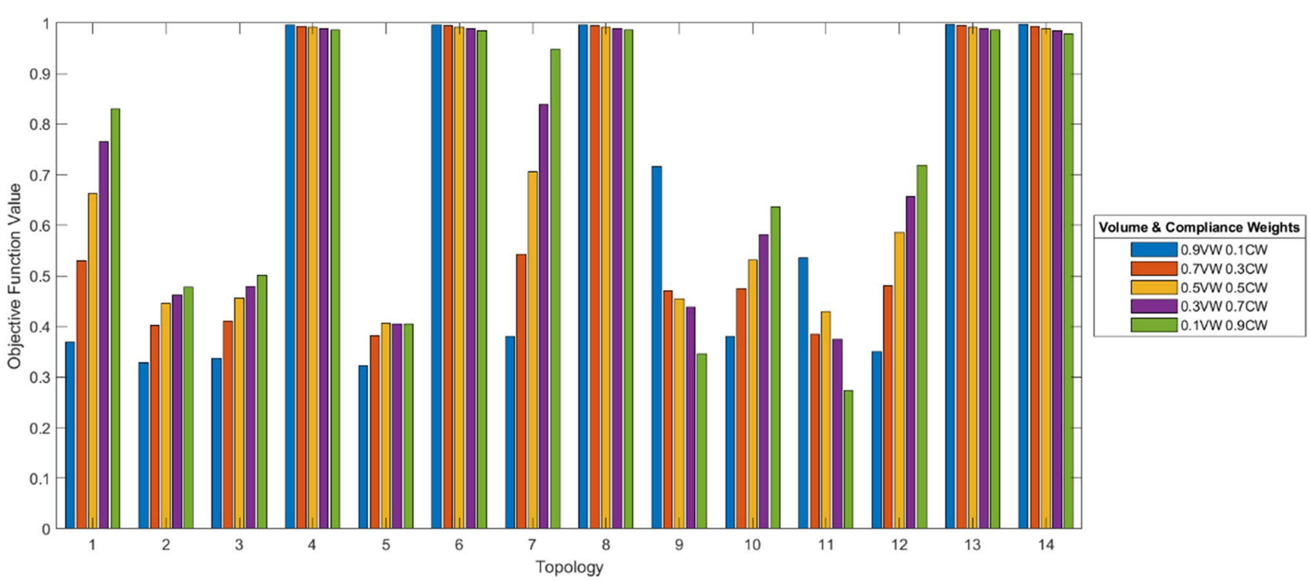


Fig. 11 Minimum objective function value of each topology for different weighting values (VW, volume weighting; CW, compliance weighting)

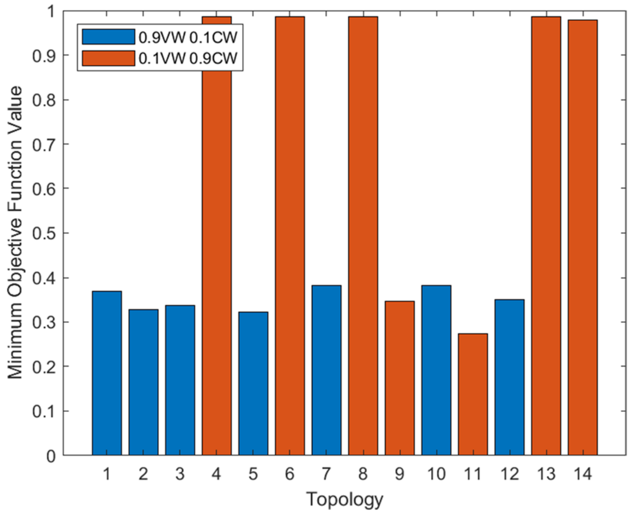


Fig. 12 Highest performing solution for each topology and the weighting at which this objective function value was found

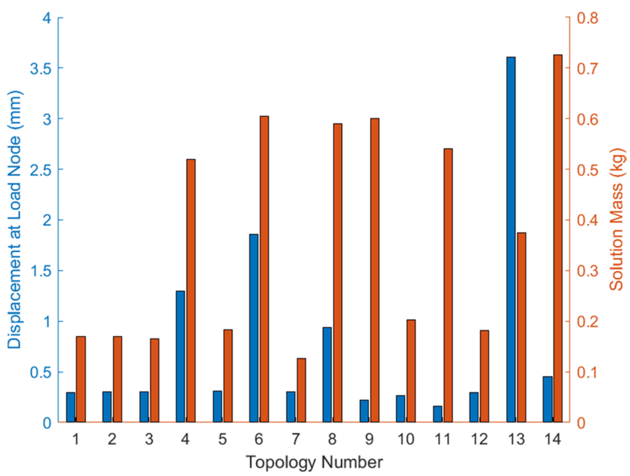


Fig. 13 Displacement at load node and total solution mass of minimum objective function solution for every generated topology

3.4.1 CAD representations of shape optimised solutions

A CAD representation of the highest performing solution for topology 3 was generated manually by utilising the cross-section geometry generated through shape optimisation (Fig. 16). Important part features from the initial aerospace bracket design were added to the skeleton structure.

The CAD solution shown in Fig. 16 strongly resembles the original topology optimisation solution, and maintains its topological intent. Although the resolution of the topology optimisation solution is low, this does not affect the quality of the CAD representation, and solutions useful for designers are capable of being generated without requiring computationally expensive, high-resolution TO.

4 Discussion

The generative design method proposed within this research was successfully used for the automated generation of multiple high-performing space-frame solutions for the case study of an aerospace bracket. The solution space was explored utilising topology optimisation to generate potential solution forms, while avoiding designer fixation. Utilising a novel parameterisation technique, TO solutions were translated to skeleton representations, suitable for use in computationally inexpensive FEM frame models. This allows modelling of the solution for a range of physical problem types, stress, buckling, and compliance analysis being of particular interest within this research. Geometry of solutions was determined through the use of gradient descent shape optimisation search algorithms, using cross-sections comprised of standard engineering shapes. As the behaviour of these shapes is well understood, this provides a level of certainty in the behaviour of the solution, aiding in the certification process. This is of particular importance for safety–critical components such as those in aerospace. Multiple high-performing solutions were generated for designers to select from for more detailed design, providing redundancy in the early stages of the design process by progressing many solutions simultaneously.

It was found that the proposed parameterisation technique performs better when both topology optimisation resolution and desired volume fraction are kept low. This is advantageous to the GD process as using low-resolution topology optimisation for form generation reduces the computational cost of the overall generative design process, reducing lead times for product development.

Given that the result of topology optimisation is dependent on the initial conditions defined by the user, it is very difficult to predict which input variables will result in a desirable outcome a priori. Repeating topology optimisation processes many times to determine which input variables are most desirable, while using a high-resolution discretisation, can take a large amount of computational resources and time. This reduces the effectiveness of the tool in time critical environments, a design consideration which is of particular interest in many engineering situations.

The results within this work show that TO does not need to be conducted at a high resolution, with the intent of determining part geometry; rather, topology optimisation can be used in a cost-effective manner to explore potential topologies using low-resolution simulation. These TO solutions can be translated into simple connectivity definitions which are compatible with many common engineering modelling and prediction techniques. These modelling tools can then be used to determine the response of the system for critical design objectives, and optimisation algorithms can be utilised to search for optimal geometric properties.

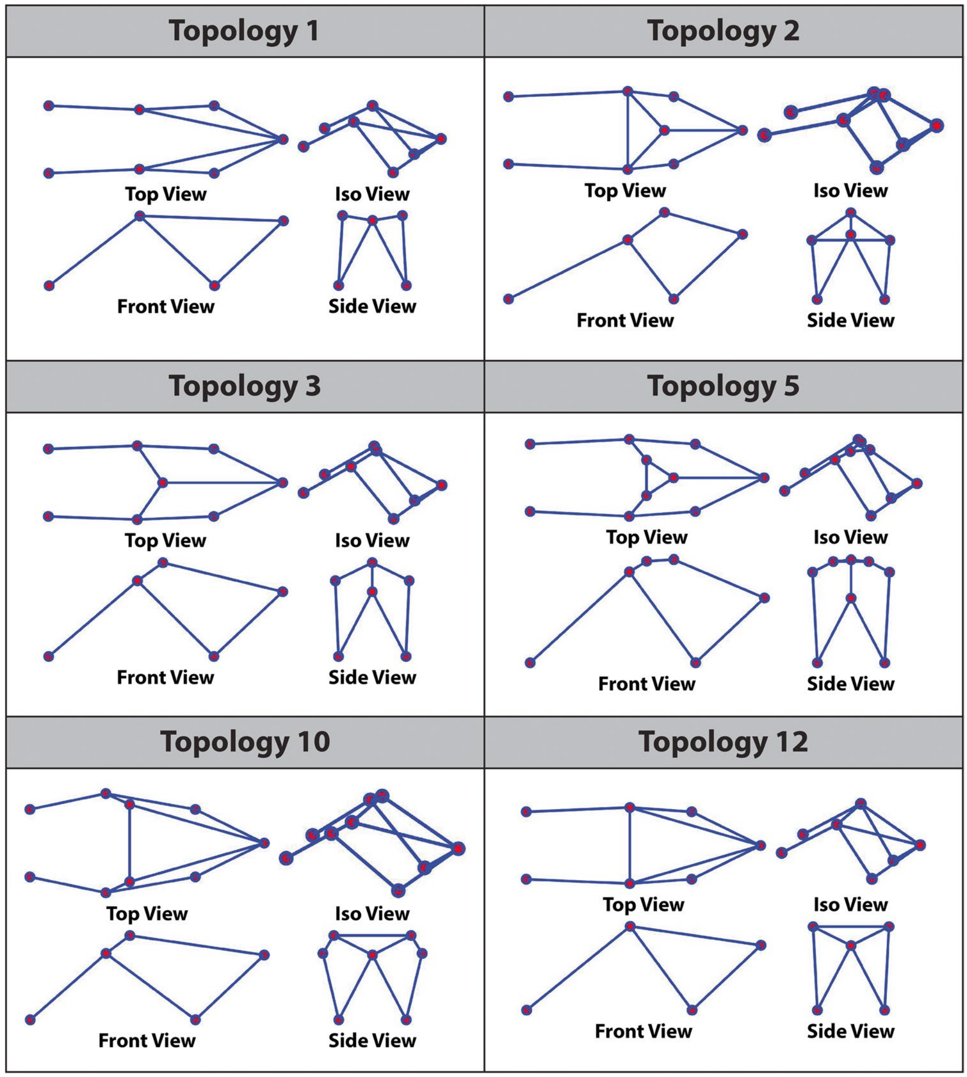


Fig. 14 Topologies 1, 2, 3, 5, 10, and 12. High-performing solutions generated from the generative design process

What TO excels at is informing a material distribution, determining a desirable topology. Using topology optimisation to try and determine final part geometry can be fraught with difficulties and generally requires a lot of manual and time-consuming work on the designers behalf to finalise a solution.

Table 10 Displacement and total mass of highest performing topologies with lowest objective function value

Topology number	Displacement at load node (mm)	Total solution mass (kg)
1	0.296	0.169
2	0.306	0.169
3	0.306	0.165
5	0.306	0.183
7	0.302	0.126
10	0.264	0.202
12	0.296	0.182

Many TO techniques also do not consider the yield stress of the material, or the effect of more complex failure modes such as buckling or fatigue, simply attempting to minimise compliance while achieving a particular volume fraction. For this reason, it is also difficult to have confidence in a TO outcome as to how it will perform when the solution is placed in a working environment.

Utilisation of topology optimisation in this way, not to define geometry, but to determine topology, can also improve the certification process for components designed using topology optimisation. Geometry which is defined through topology optimisation is often very complex, and can consist of dendritic and organic shapes whose geometry is difficult to define in a parametric way. The response to loading of these complex geometries can be difficult to model with a high level of confidence. Using methods akin to those proposed within this paper, the geometric part outcomes are defined using more traditional engineering shapes, whose loading response is more well understood.

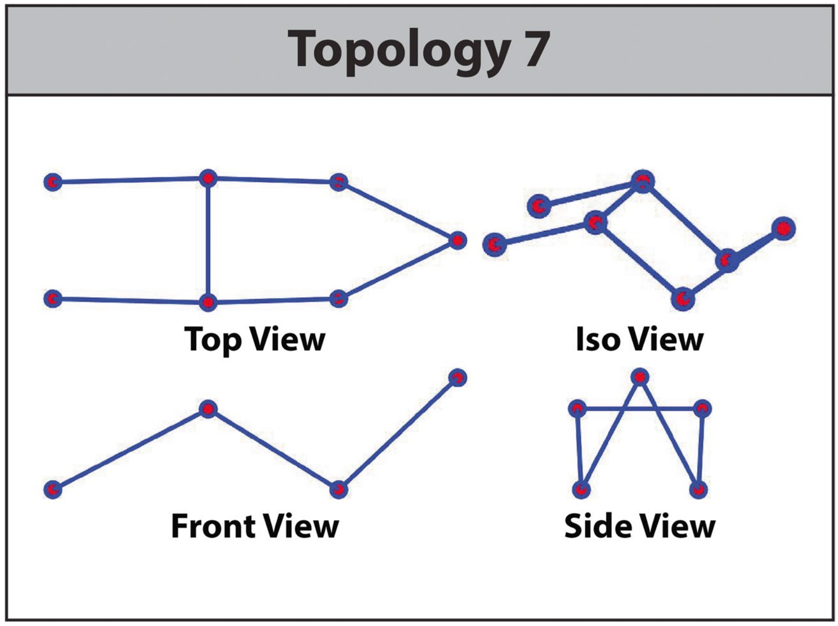


Fig. 15 Topology 7 which performed highly during shape optimisation, but has a geometric realisation which causes 5 members within the structure to act as zero force members

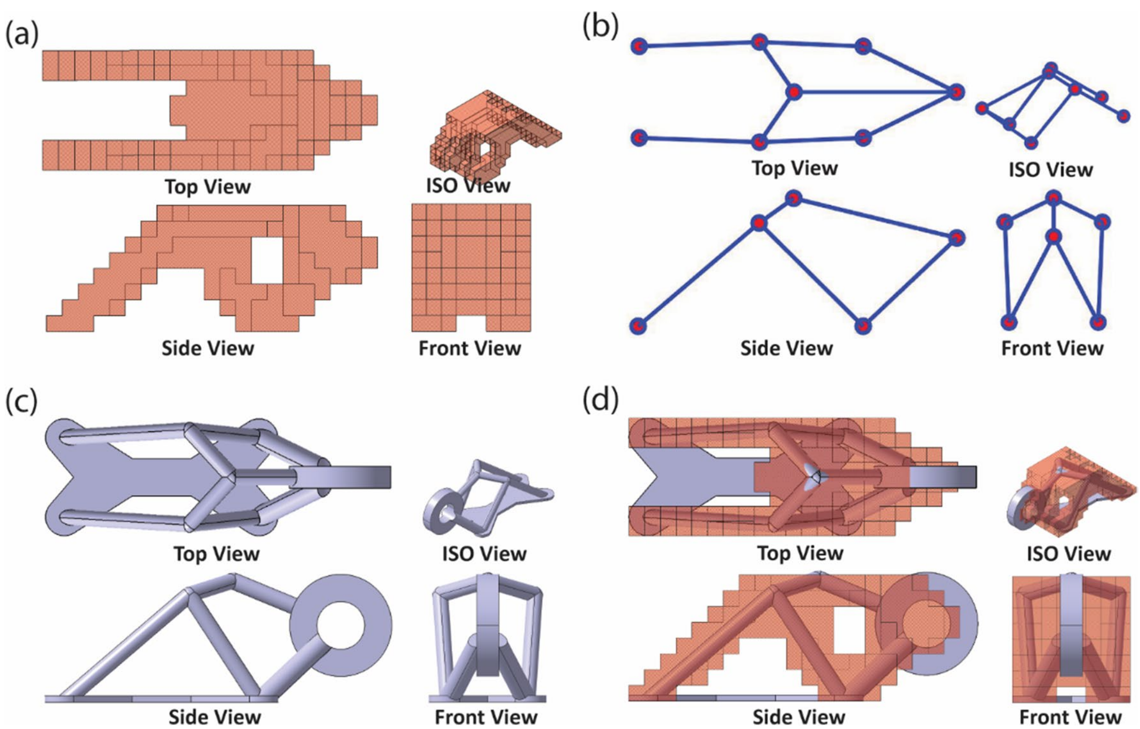


Fig. 16 **a** Voxel topology optimisation solution which generated the highest performing solution to topology 3. **b** The parameterised skeleton representation of the TO solution. **c** The shape optimised CAD representation of the TO solution. **d** Voxel TO solution projected over the shape optimised CAD representation

Although this may reduce the level of optimality of the final problem solution, this reduction comes with the benefit of higher confidence in the performance of the component in working conditions. Alongside this, as design decisions are made algorithmically, the documentation process is simplified.

Additionally, using generative design methods such as those proposed can improve manufacturing outcomes, particularly in additive-manufacturing environments, where the techniques can enable mass customisation processes. The computational cost reduction granted through low-resolution topology optimisation results in reduced lead times for solution generation. Mass customisation can become economically competitive when products with differing individual customer requirements can be progressed through the design process in a short time span. If a generative design system is constructed for a particular problem type in a similar manner as is proposed within this work, the input variables for the problem definition can be altered to meet each customer's requirements. The solution space can then be algorithmically explored, and a set of high-performing design outcomes can be presented to the designer within hours or days depending on the problem type.

5 Conclusions

Critical challenges to the application of TO in industrial environments include local optimality of TO solutions, discontinuous surface geometry, limitations on managing the complexity of multiple failure modes, challenges in accommodating multiple loading cases, and subjectivity in user interpretation (Sections 1.2–1.4). The contribution of this research is the development of a GD methodology which addresses these identified challenges in the use of TO and structural optimisation for the design of AM components.

Generative design techniques have been identified as enabling technologies for DFAM and mass customisation (Section 1.4). The use of GD has the potential to streamline digital workflows, reduce lead times required for bespoke product design, and provide redundancy in design by supplying designers with a set of high-performing solutions from which to select. To provide such benefits to the designer however, computational resources must be managed effectively, such that highly performing problem solutions can be generated in an economically competitive manner.

A GD strategy is proposed which uses TO to generate form, a novel parameterisation algorithm to translate TO solutions into a connectivity definition, and a shape optimisation process driven by a finite element frame model to define and optimise part geometry. The generative design strategy is applied to the case study of the light-weight design of an aerospace bracket.

Performance of the proposed GD method is evaluated through a DOE which investigates the effect on TO control variables as well as discretisation resolution on the GD outcome. Of the 360 solutions generated, 152 successful parameterised outcomes were achieved. The proposed parameterisation technique was found to behave most successfully at low resolutions, and a resolution limit was identified, whereby element sizes of 5 mm and lower had difficulties in parameterising. It was also identified that the parameterisation process did not behave well for TO simulation with volume fractions above 0.2. At these higher volume fractions, the solution consists of too much bulk material, and for the parameterisation process to be successful, TO solutions must resemble frame-like structures. This limitation becomes less relevant when seeking light-weight designs.

Parameterised solutions were sorted into 14 unique topologies, and the highest performing solutions for each topology were compared post shape optimisation. A set of 7 high-performing solutions were identified for designer selection. A CAD representation of the highest performing solution for the preferred topology was created manually for comparison to initial TO solutions, and to display the smooth boundary representations possible through the result of shape optimisation. Both the skeleton and CAD representations of TO solutions were found to satisfactorily maintain the topological intent of the solutions.

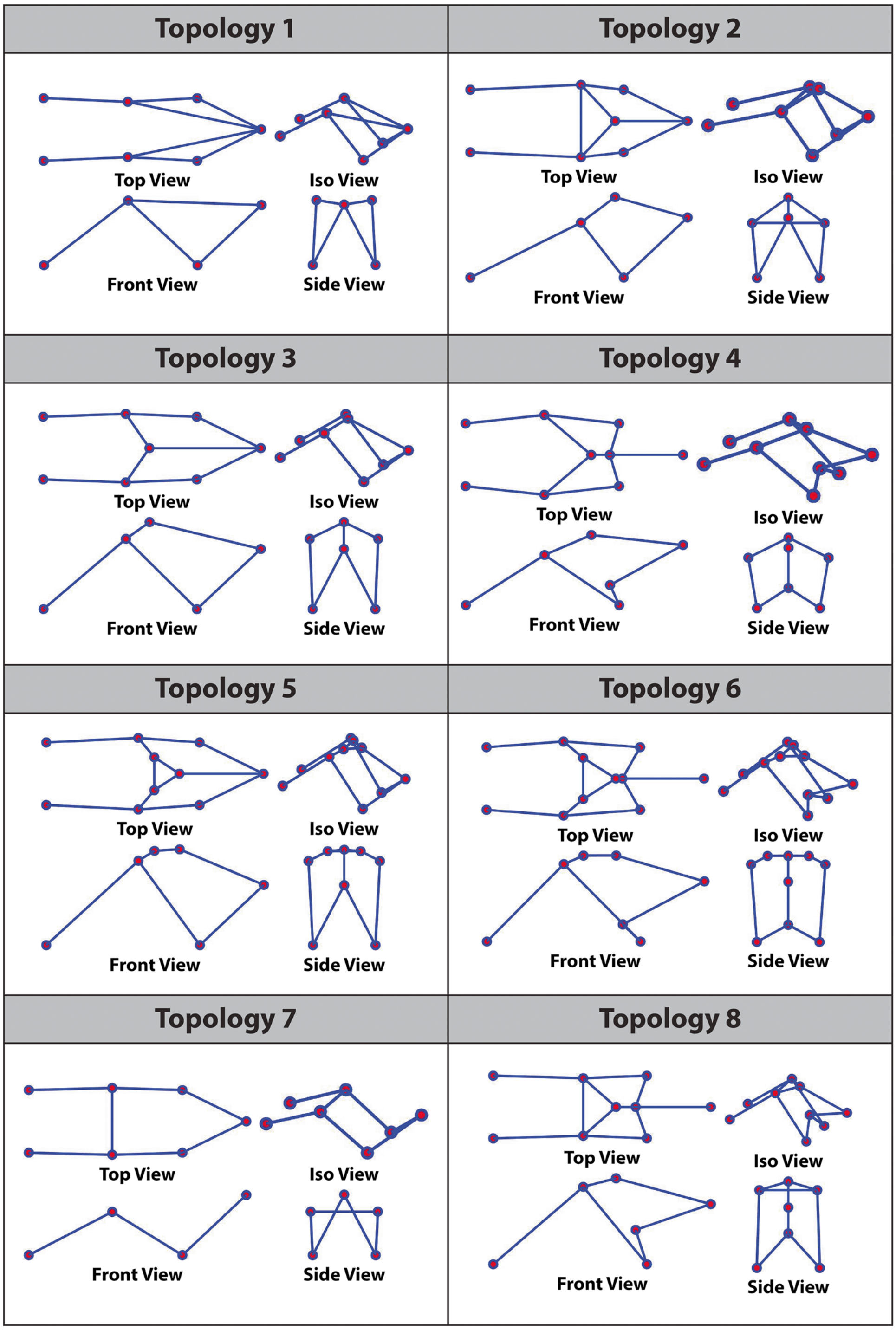
Results confirmed that the proposed GD method can generate high-performing solutions while using low-resolution TO simulation. In this way, the computational cost required for simulation can be reduced, allowing for larger solution space search sizes with available resources. In this way, the local optimality of TO solutions has less effect on the overall outcome. Subjectivity of user interpretation and designer fixation are avoided through the use of algorithmic form generation and parameterisation. Shape optimisation outcomes have also been shown to be suitable for the creation of smooth boundary representations of TO solutions.

Skeleton representations of TO solutions provide a means of low cost modelling of physical problems, such as buckling and stress analysis, which can be difficult or cost prohibitive to manage utilising TO. These representations also provide a means for gaining insight into performance of solutions with regard to DFAM considerations, including overhang angle or minimum feature size for example.

Reductions in overall computational cost improve the speed at which solutions can be generated. Additionally, the ability for the proposed method to generate sets of high-performing solutions satisfies requirements for GD to be used for mass customisation outcomes.

This research represents a *near-net* GD method; however, these techniques can be expanded upon in future work to approach *net* design. This could include the automation of CAD solution generation from shape optimised solutions through scripting of commonly used engineering CAD platforms. Pre-processing tools for additive manufacture, such as slicing, toolpath, and support structure generation, can be incorporated into the generative design workflow. Further work could also consist of the incorporation of higher order and resolution modelling into the workflow once high-performing solutions have been identified. In this way, we can leverage the computationally inexpensive nature of the proposed methodology to search many solutions quickly, and then spend available computational resources evaluating and refining only the best solutions identified from this search. These techniques should continue to be expanded upon, as they show promise in the further industrialisation of additive manufacturing technologies.

Appendix


Topology 1
Top View
Iso View
Front View
Side View
Topology 2
Top View
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Topology 3
Top View
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Topology 4
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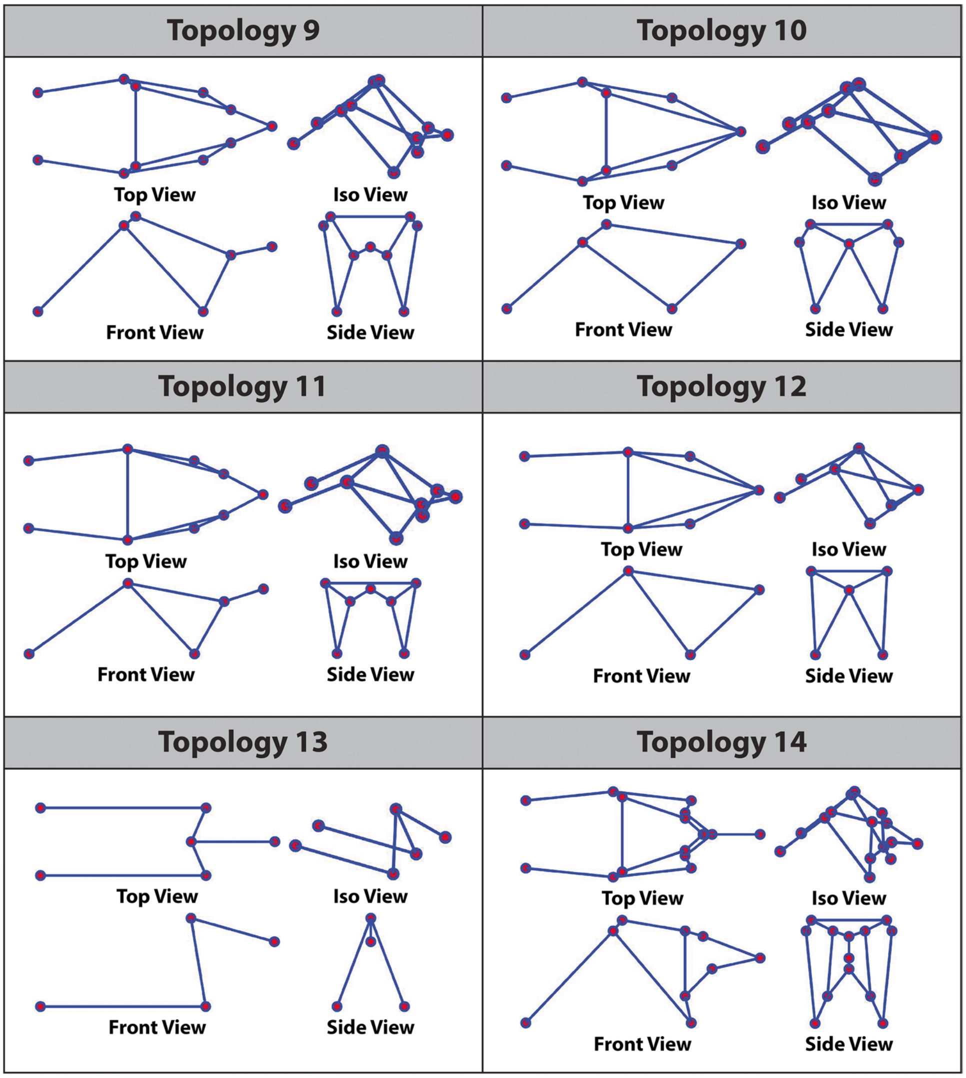

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Author contribution • Marcus Watson: generation of method, formal analysis, visualisation, compilation, investigation of data, writing, editing.

• Martin Leary: conceptualisation, critical analysis, writing, editing, revision, project administration, supervision, funding acquisition.

• David Downing: revision, critical analysis, project administration, supervision.

• Milan Brandt: project administration, funding acquisition.

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Code availability Not applicable.

Declarations

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Consent to participate Not applicable.

Consent for publication Not applicable.

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