

TOPOLOGY OPTIMIZATION AND GENERATIVE DESIGN IN ADDITIVE MANUFACTURING: A SYSTEMATIC REVIEW OF ALGORITHMS, TOOLS AND INDUSTRIAL APPLICATIONS

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ABSTRACT

Additive manufacturing (AM) has increased the design space of engineering components, allowing the creation of geometries which are hard or even impossible to realise through conventional machining, casting and forming. The capacity has added to the curiosity surrounding generative design (GD) and topology optimisation (TO), which aim to enhance structural performance, minimise material consumption and investigate other design options. This review combines the technical compilation provided with the relevant scholarly literature on the relationship between TO, GD and AM. The review is organised around the reporting principles of PRISMA 2020 and focuses specifically on the review question, eligibility logic, organisation of the evidence, methodological limitations and research gaps. Literature suggests that density-based approaches like Solid Isotropic Material with Penalisation (SIMP), level-set methods and evolutionary techniques continue to be important TO approaches, and GD is a broader requirements-driven approach which can involve optimisation, simulation, materials selection, and manufacturing constraints. The key result here is that having the best solution in the world of computation does not guarantee the best solution in the world of manufacturing, economy and reliability. All of these, such as overhangs, support structure, build orientation, enclosed voids, minimum feature size, anisotropy, residual stress, thermal distortion, surface finish, post-processing and cost, need to be taken into consideration in the design process. Applications in the aerospace, automotive and lightweight cellular structures sectors show promising potential, but benefits have only been reported in the context of specific applications. The next step in research should focus on coupled design–process optimisation, multi-physics modelling, uncertainty quantification, explainable artificial intelligence, experimental validation and closed-loop digital manufacturing. The synthesis is also embedded in the setting of an industrial economy, where knowledge and skills about the processes, their parameters and constraints determine what can be practically achieved, and in which limited use of AM and simulation tools is prevalent. The review finds that the maturity of TO and GD should be assessed based on the quality of validated engineering outcomes and not just on the geometric complexity or weight reduction alone.

Keywords: Topology Optimisation; Generative Design; Additive Manufacturing; Design For Additive Manufacturing; Manufacturing Constraints; PRISMA 2020

1 INTRODUCTION

The evolution of AM has reshaped the digital design to physical production dynamics. Instead of cutting out a part from a much bigger stock or molding a part with a mould, AM builds parts up through digital data. This allows for internal channels, lattice structures, organic load paths, part consolidation and highly customised geometries (Thompson et al., 2016). The merits of AM are not just about the ability to produce complex shapes, though. Strategic importance emerges when methods of design, behaviour of materials, process planning and inspection are combined in such a way that complexity ensures an engineering gain that can be quantified.

This integration is particularly critical in countries with developing industrial economies. For instance, Zimbira, a Zimbabwean manufacturer, was found to lack the capabilities of rapid prototyping and numerically controlled equipment, which are required for a rapid response to the fluctuating demand for products (Muhla et al., 2023); a survey of the adoption of Industry 4.0 in the manufacturing sector in Zimbabwe revealed that the most underutilized enabling technologies include additive manufacturing and simulation (Muhla et al., 2025a). Within this shift, topology optimisation and generative design have grown to be well-known. Generally, TO is considered a mathematical optimization process that optimizes material distribution in a prescribed design space under loads, supports, performance goals and constraints (Bendsøe and Sigmund, 2003; Zhu et al., 2021).

GD is more general: It is often used to represent a workflow including the specification of requirements, the representation of preserved regions, materials, manufacturing processes and performance limits, followed by the creation and comparison of several candidate solutions from the software. The terms are similar but not synonymous, as differences in mathematical formulation, workflow and software functionality (Regenwetter, Nobari and Ahmed, 2022) will be masked when the terms are used interchangeably. The main question that is addressed in this review is why there is a continuous mismatch between the computational designs and the products created through AM that have been tested in the real world. A topology can be optimum based on idealised "finite elements" assumptions, but not necessarily when the actual build orientation, removal of support, thermal history, anisotropy, residual stress, fatigue, dimensional accuracy or production cost is taken into account. The review thus not only covers the optimization algorithms and applications, but also the constraints and the activities required to ensure that digital solutions turn into reliable manufacturing results. With the increased awareness that AM does not remove manufacturing constraints but adds a new set of geometric, process and material constraints, recent research has increasingly followed this path by directly including manufacturable structural-feature constraints in the topology optimisation formulations (Langelaar, 2017; Liu et al., 2018).

The goals of the review are: (1) to clarify the concepts and taxonomies of TO, GD and design for additive manufacturing (DfAM); (2) to synthesise the key TO methods and manufacturing constraints; (3) to critically evaluate industrial applications and software ecosystems; and (4) to identify unsolved research issues (Thompson et al., 2016; Regenwetter, Nobari and Ahmed, 2022).

2 BACKGROUND

2.1 Additive manufacturing as an enabling production technology

There are many different types of AM processes, each with a different energy source, feedstock, deposition mechanism and material behaviour. The various limits of feature size, overhangs, thermal history, support requirements, surface quality, and post-processing apply to powder-bed fusion, directed-energy deposition, material extrusion, vat photopolymerisation, and binder-based processes, respectively (Thompson et al., 2016; Wiberg, Persson and Ölvander, 2019). This means that the same design rule may not be suitable for two different processes. The literature on DfAM emphasizes that it is not possible to separate process selection and process design, as the manufacturing route affects the geometry, mechanical properties, production rate and production cost (Bikas, Stavropoulos and Chrysosolouris, 2016; Wiberg, Persson and Ölvander, 2019). Whilst opportunities exist to lighten and integrate functionality into AM, there are also point-in-process restrictions. Supports might be needed for downward surfaces, powder may collect in enclosed cavities, stair-stepping, heat flow and anisotropy are affected by the build orientation and thin members are harder to print consistently. Residual stresses, distortion and microstructural heterogeneity can arise during metal AM processes due to thermal gradients and frequent heating and cooling.

Similar phenomena have been reported for other thermally driven net-shape processes; for example, injection moulding, where shrinkage and warpage occurred as a result of varying contraction during cooling, and injection pressure and melt temperature were the main contributors to the observed variations in shrinkage and warpage in a recent study conducted using the Taguchi method (Mapindu et al., 2026a). AM is not a solution to the manufacturability problem in general but rather transforms its nature from a conventional geometric feasibility problem to process-aware digital manufacturing (Wiberg, Persson and Ölvander, 2019; Zhu et al., 2021).

2.2 Topology optimisation fundamentals

A structural TO problem can be stated as an optimisation of an objective function, under physical and manufacturing constraints. One way to reduce compliance (and therefore increase stiffness for prescribed loads and supports), is to reduce the volume of the materials (Zegard and Paulino, 2016; Zhu et al., 2021). Simplified, the problem can be depicted as

$$J(\rho) = F^T U$$

Subject to:

$$K(\rho)U = F \text{ and } \frac{V(\rho)}{V_0} \leq V^*$$

In the above, the only variables that can be designed are denoted by the symbol ρ , F is the load vector, U is the displacement, K is the stiffness matrix, V is the volume of the domain retained, V_0 is the initial domain volume, and V^* is the allowable volume fraction. Displacement control, maximisation of natural frequency, thermal performance, buckling resistance, fatigue life, manufacturability and cost are among the other objectives.

The optimisation result may not be a complete CAD model. It is usually a field of density, a boundary description, a set of some structural members, or a collection of candidate geometries which should be interpreted, smoothed, reconstructed and validated. This distinction is key because the geometry conversion may change loads paths, local thickness, stress concentration, manufacturability. The engineering workflow thus needs to ensure traceability between the mathematical model, the reconstructed CAD geometry, the process plan and the final test article (Wiberg, Persson and Ölvander, 2019; Thompson et al., 2016).

2.3 Generative design and its relationship with TO

GD should be thought of as a workflow-level concept, and not a single algorithm. This may involve topology optimisation, shape optimisation, lattice creation, parametric modelling, finite element analysis, manufacturing rule checking and multi-objective search. In a typical GD study the engineer documents the preserved interfaces, obstacle regions, loads, constraints, materials and manufacturing methods. The system then attempts alternatives which can also vary in mass, stiffness, stress, safety factor, material, process and build orientation. It is useful during the conceptual phase, since it brings the trade-offs to the surface, instead of forcing the engineer to make an early decision on geometry (Regenwetter, Nobari and Ahmed, 2022; Wiberg, Persson and Ölvander, 2019).

The difference is also applicable when comparing software. A solver-centred TO environment may offer level of detail on mesh, physics, constraints and optimisation setting. In a CAD-integrated GD environment, the emphasis could be on generating results quickly and being able to edit them. Both methods do not obviate the need for engineering judgement. The reliability of an outcome depends on the quality of the input assumptions, material data, boundary conditions, mesh, objective function and validation process (Thompson et al., 2016; Regenwetter, Nobari and Ahmed, 2022).

3 METHODOLOGY

3.1 Review design and reporting framework

The reporting framework adopted was PRISMA 2020 since it promotes the transparent presentation of information sources, selection logic, evidence synthesis, limitations and availability of supporting materials, and the reporting of the question of the review (Page et al., 2021). The review, therefore, is reported in an explicit scope, themed classification, critical synthesis and statement of evidence limitations.

3.2 Review question

The guiding question was: How has topology optimisation and generative design been linked to AM, what are the methods and manufacturing constraints that prevail in the literature, what are the advantages and challenges from engineering applications, and what are the research directions required to enable validated and economically viable production?

3.3 Information sources and search logic

The evidence base comprised of peer-reviewed works, foundational books, review papers and selected technical documentation from the major CAD/CAE platforms. The source material included concepts of TO theory, SIMP, level-set and evolutionary methods, DfAM, overhang and support constraints, build orientation, enclosed voids, anisotropy, lattice structures, cost, AI-assisted optimisation, software ecosystems, and aerospace and automotive applications (Zhu

et al., 2021). Also, papers recently developed by the authors research team on the Optimisation of Manufacturing Processes, Condition Monitoring, Industry 4.0 and Engineering Education in Zimbabwean Manufacturing were referenced as contextual evidence. These sources were not included in the thematic taxonomy of records but were used for the interpretation of the results for a developing economy.

3.4 Eligibility and evidence organisation

The sources were deemed pertinent if they discussed at least one of the following: a TO or GD method; integration of optimisation with AM; manufacturing constraints; material or process effect; software tools; industrial applications; cost or validation; or future computational design directions. Sources that are not directly related to engineering design, that do not cover the relationship between TO, GD and AM or sources that give no methodologically or practically useful insight were not emphasised. The studies are not all alike in terms of objective functions, materials, AM processes, geometric scale, performance measures and validation methods (Langelaar, 2016; Zhu et al., 2021), which led to the inability to conduct a statistical meta-analysis of the evidence.

3.5 PRISMA 2020 considerations and limitations

The review is conducted according to the spirit of PRISMA 2020, with a statement of the review question, evidence base description, description of the selection logic, synthesis from interpretation and identification of limitations (Page et al., 2021). A quantitative metanalysis was not attempted.

Study-specific findings of reported mass reductions, changes in stress, cost effects and performance enhancements were not pooled. This prevents the suggestion that the material, process, and/or baseline geometry are comparable, when the differences in these properties could be significant in the design domain (Page et al., 2021).

4 CLASSIFICATION AND TAXONOMY

PRISMA-style processing of the reference set

- Identification (n = 55): All records supplied.
- Screening (n = 55 screened; n = 1 excluded): (Page *et al.*, 2021) is the PRISMA 2020 reporting guideline itself — a methodological source, not a primary study on topology optimization (TO) for additive manufacturing (AM), so it's excluded from the content taxonomy and used instead as the reporting framework.
- Eligibility (n = 54 assessed): All remaining records concern TO/design methods for AM (structural optimization, support/overhang constraints, lattice design, software, or reviews) and were retained.

The record-selection process is summarised in the PRISMA 2020 flow diagram in Figure 1.1, and the distribution of the included records across themes is presented in Table 1.1 and Figure 1.2.

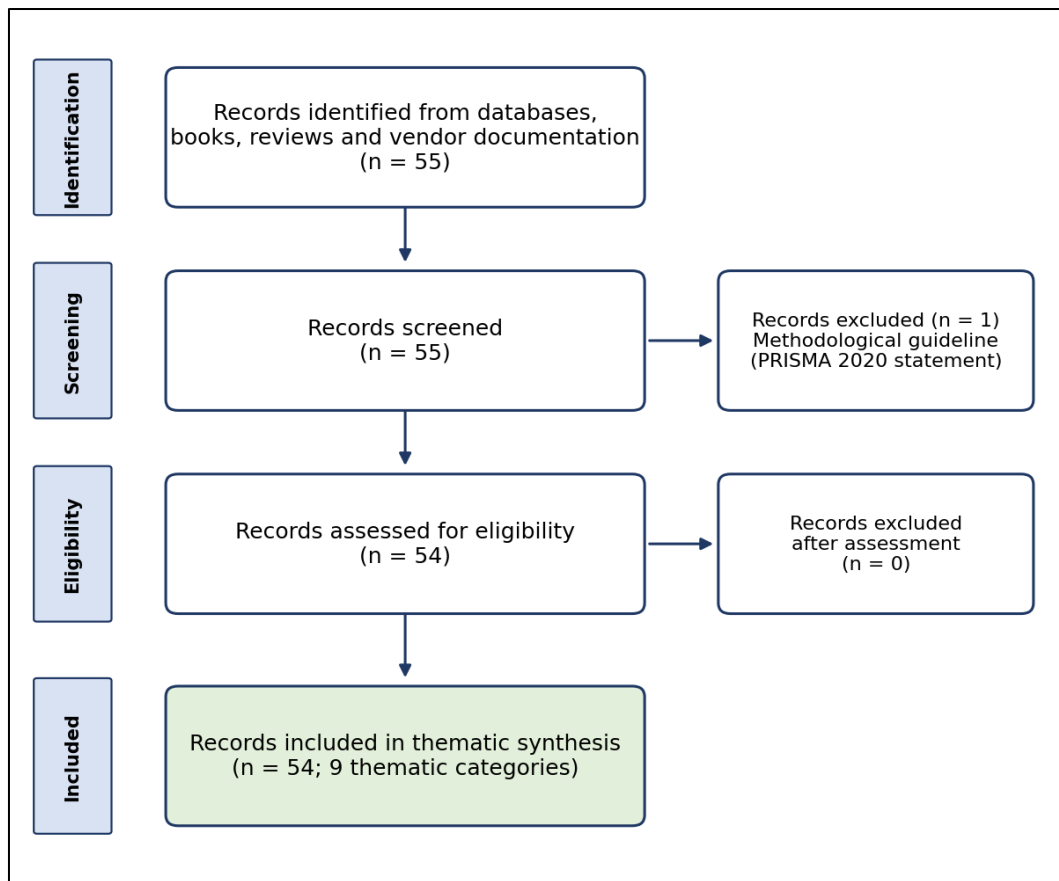


Figure 1: PRISMA 2020 flow diagram of record identification, screening, eligibility and inclusion (adapted from Page et al., 2021)

Table 1: Thematic taxonomy (9 categories)

Category	n	Scope
Overhang / Self-Supporting Constraints	11	TO formulations embedding overhang-angle or self-supporting filters e.g (Liu <i>et al.</i> , 2018; Guo <i>et al.</i> , 2017; Langelaar, 2017)
Reviews & Surveys (TO/DfAM)	10	Broad state-of-the-art or critical reviews of TO for AM and design-for-AM
Software, CAD Tools & Industry Documentation	8	Vendor references and CAD/generative-design tool comparisons (Altair, Ansys, Autodesk, etc.)
Manufacturing Integration & Applications	6	Case studies linking TO output to manufacturability, cost, or part consolidation
Support Structure Design & Optimization	5	Dedicated optimization of sacrificial/auxiliary support structures
Lattice, Cellular & Graded Structures	5	Periodic/graded lattice and cellular design for AM
Generative Design & AI/ML-Based Methods	4	GAN/deep-learning and generative-design approaches
Foundational TO Theory & General Methods	3	Core TO theory not AM-specific (e.g. Bendsøe and Sigmund, 2003; connectivity constraints)
Thermal / Residual Stress-Aware TO	2	TO formulations accounting for build-induced thermal/residual stress

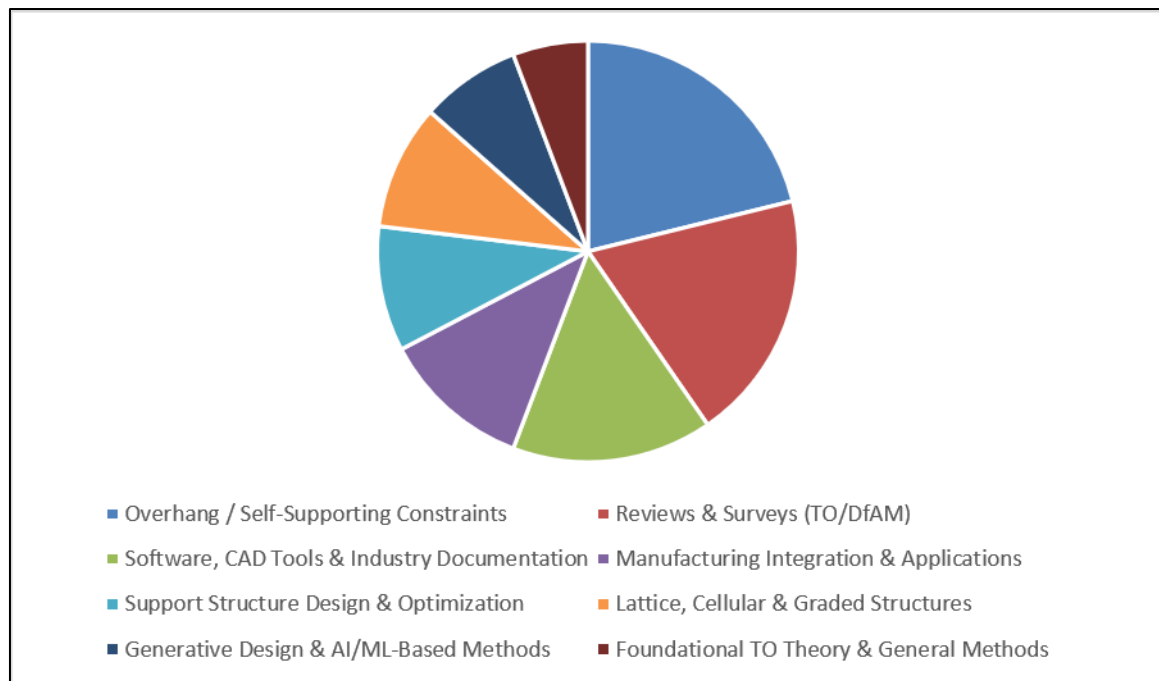


Figure 2: Distribution of the included records across the nine thematic categories (source: authors' classification)

5 CRITICAL ANALYSIS AND SYNTHESIS

5.1 From weight reduction to performance-driven design

One of the significant features of TO and GD is that it moves away from the material approach of design towards the geometry approach of performance. The removal of material may be done in areas of low stress, while it remains in key load paths. In AM, this can help to save mass, allow part consolidation, and produce internal structures that are challenging to make through traditional manufacturing methods. Particularly in the aerospace sector, mass is important as that of components influences the payload, fuel usage and system efficiency. In the automotive industry, the goal of optimised brackets, mounts, and structural elements is also to achieve weight reduction, stiffness, and streamlined assembly (Plocher and Panesar, 2019; Zhu et al., 2021). However, a mere weight loss is not enough to prove success. A lighter part could need more support material, a longer build time, use of expensive powder, extensive post-processing or further inspection. A topology which has less weight but higher fatigue sensitivity or dimensional variability or failure probability may not be appropriate. This performance parameter is therefore multidimensional: structural function, process reliability, material efficiency, production time, lifecycle cost, maintainability and qualification requirements must be considered in an integrated manner.

Post-processing is an optimisation problem in its own right! In CNC milling of mild steel, surface roughness was controlled by feed rate (82.81% contribution), the spindle speed controlled flank tool wear (63.40%), and Grey Relational Analysis (GRA) was required to solve the conflicting optima (Mapindu et al., 2026b, Mapindu et al., 2026d). Thin wall AM parts created after topology optimisation, or allowances and finishing routes, introduce additional constraints to these trade-offs, therefore it is better to take these into account during the topology optimisation process.

5.2 Manufacturability is a design variable, not a final inspection

There is a strong group of arguments in the literature that manufacturing constraints should be considered in optimisation. The true effects of overhangs and support requirements and minimum feature size are process dependent and are often assumed to be geometric proxies. The critical angle depends on the material, machine setting, feature length, and layer thickness and energy input. Externally, opening size can also be a factor and the path tortuosity, gravity and powder flow also influence whether a cavity can be cleared (Jiang, Xu and Stringer, 2018; Wiberg, Persson and Ölvander, 2019; Zhu et al., 2021).

Build orientation is very critical, as it is related to almost all other constraints. It alters the position of overhangs, the volume of support, stair-step error, build height, heat flow and material anisotropy. However, numerous studies still adopt heuristic rules to do the orientation first, then optimize the topology. Limited literature on simultaneous orientation-topology optimisation shows that the resulting design can also be influenced by the coupling of these

variables and the optimization could be manufactured more efficiently (Liu et al., 2019; Plocher and Panesar, 2019; Zhu et al., 2021). Additional factors such as support accessibility, direction of post-processing and visibility of inspection should also be incorporated in the models.

5.3 Material behaviour and the process–structure–property relationship

Most optimization studies are based on the assumption of homogeneous, isotropic and linear-elastic materials. AM components, however, can have direction-dependent strength, have local variations in microstructures, contain porosities, have residual stress, and have fatigue behaviour that varies from place to place. Anisotropy may be caused by columnar grain formation and thermal history during metal AM; raster direction and bonding strength between layers during material extrusion. However, these effects may not be considered, which leads to the calculated optimum may not be the same as the performance of the printed part (Zhu et al., 2021; Ren et al., 2022). This effect has been demonstrated in experiments using material extrusion. In a replicated Taguchi L9 study of PLA specimens, infill density was determined to be the most influential factor, with 68.99% of the variance in tensile strength, layer height for 51.77% of the variance in print time, and the settings that maximised strength did not minimise print time for three of the four parameters (Mapindu et al., 2026c).

For a part that is printed with sparse infill or coarse layers, a topology optimized based on a fully dense homogeneous material may then not reflect the stiffness and strength of the actual topology. This problem raises the meaning of validation. Just checking the CAD geometry to match optimised is not enough. Validation should cover the entire process–structure–property chain, including the material feedstock, machine parameters, build orientation, thermal history, microstructure, defects, dimensional accuracy, and the mechanical properties. Experimental testing is particularly significant when it comes to safety-critical applications, or when the design features thin members, complicated joints, lattices or unusual load paths (Wang et al., 2022).

5.4 Industrial Applications

Seabra et al. (2016) presented a documented aerospace case-study using topology optimisation and additive manufacturing of aerospace components. The study involved the modification of an aerospace part and demonstrated that the optimized geometry of this part could be manufactured by SLM without compromising the mechanical properties. The benefit of this approach is that traditional machining methods can need a lot of material which needs to be bought and then cut away, while AM adds material where it is needed most. Topology optimisation and AM can thus optimise the material utilization while also reducing the parts weight. In the review, Zhu et al. (2021), they have reported an application of variable-density lattice structures in an aviation rocker arm. The optimized lattice configuration decreased the weight by 23 percent, and numerical analysis showed that it also decreased the stress by 68 percent and the strain by 14 percent compared to the original lattice configuration, so the component was then created additively. This exemplifies that topology optimisation does not need to be limited to solid-material design but can incorporate lattice structures. Aerospace is not the only place where applications are limited. Under the condition of user fatigue, which is directly related to the weight of the device, an upper-limb passive exoskeleton for construction workers was optimised for weight with ANSYS and compared to nylon with finite-element analysis, with 3D printing and CNC machining identified as potential routes to prototype manufacturing (Tandi et al., 2025).

In resource-constrained environments, like a dual-mode smart wheelchair with an aluminium 6061-T6 frame rated for 150 kg, there are similar opportunities for optimising and consolidating the frame, brackets and sensor mounts. A vertical-axis wind turbine for wind energy from vehicle slipstream was developed using a combination of analytical rotor sizing, computational fluid dynamics (CFD) characterisation of the velocity field of the blades, and prototype testing (Muyambo et al., 2025); aerodynamic loading of blades and hubs of such turbines is a natural context for coupled fluid–structure topology optimisation and lightweight additively manufactured rotors.

5.5 AI and machine learning: opportunity with qualification risk

Predict process outcomes, detect defects, approximate or predict process outcomes, accelerate design space exploration, and machine learning/AI. expensive simulations. Surrogate models could help to decrease the number of high fidelity, finite element or thermo-mechanical evaluations. Reinforcement learning can aid in sequential search within vast design spaces while deep generative models can suggest the candidates. These approaches have proven to be appealing since TO and GD can become computationally costly with multiple load, physics, materials and manufacturing constraints (Nie et al., 2021; Regenwetter, Nobari and Ahmed, 2022). The problem is that predictions based on data contain the flaws of the training data. Datasets can be limited in size, skewed towards specific machines or materials and miss out on rare failure modes. Another problem with models is their lack of interpretation, particularly if engineering decisions have to be explained. A more plausible way forward is thus hybrid optimisation where physics-based models give boundaries for admissible behaviour, machine learning can speed up search or calibration, and experiments can confirm the final outcome (Regenwetter et al., 2022; Soori et al., 2025). This is supported by experience in industrial maintenance. Only after the validation of the model with 16 weeks of plant data

was it presented as a credible model for PM, and it was not intended to replace engineering judgement (Senda et al., 2026). In a similar fashion, a multi-agent diagnostic system for induction furnaces, whose failure data was labeled, required an interpretable rule base as labelled failure data was limited and diagnostic reasoning needed to be auditable (Mashava et al., 2026). AI-driven designs must be validated and explained in the same manner as human ones.

5.6 Software comparison as workflow complementarity

The software ecosystem reviewed indicates that the software is complementary and not competitive. Fusion-style environments will be helpful when exploring concepts early on and conveying them to designers who are mainly CAD users. Ansys, OptiStruct and Tosca are useful when a great degree of detail and added complexity in finite element control, nonlinear analysis, manufacturing constraints and process-driven validation are at the heart of the matter. nTop is ideal for implicit geometry, graded lattices and repeated parameter-driven regeneration. A high assurance workflow can involve more than one platform, and each transfer comes with a set of risks associated with geometry fidelity, mesh consistency, material data, coordinate systems and traceability (Plocher and Panesar, 2019; Wiberg, Persson and Ölvander, 2019). Therefore, don't choose software because they are familiar with it, but because they answer the engineering questions. Various tools may be needed to solve a concept exploration problem, a fatigue-critical aerospace bracket problem, a graded heat exchanger problem and a support-structure optimisation problem. Aims of reviews and industrial reports should cover the actual workflow, assumptions made when developing it, settings used in the solver, method and steps of validation, and not software names as a proof of manufacturability.

6 RESEARCH GAPS AND FUTURE DIRECTIONS

The first improvement is to improve the integration of process dependent constraints in the field. The overhang angles are fixed and connectivity rules are simplified which are good approximations, but not a complete representation of machine, material, and feature scale and process parameters. A universal constant should not be used in future models, it should be replaced by calibrated process maps and uncertainty bounds. Statistically designed experiments can be used to provide an economical path to such maps. With minimum testing in material extrusion, the dominant factors and robust operating windows have been identified and tested using orthogonal array design and ANOVA (Mapindu et al., 2026c), and comparative machining trials on teak, saligna and pine revealed that the dominant factors and optimal levels vary depending on the workpiece material (Tayisepi et al., 2023).

These experiments could then be repeated for each AM machine–material combination to provide calibrated overhang, feature size and anisotropy overhang limits for the current optimisation formulations. Secondly, topology, build orientation and support design should be considered as an optimisation problem coupled together. Sequential workflows can result in structurally efficient geometries that are costly and/or susceptible to failure. Support accessibility, thermal management, post-processing and inspection (Zegard and Paulino, 2016) must be taken into consideration for joint optimisation. Third, there is a need for the deeper inclusion of anisotropy and heterogeneous behaviour of materials in optimisation.

Constitutive models should take into account build direction, local thermal history, microstructure and defects. Then, robust or reliability-based optimisation could consider uncertainty, instead of optimising for nominal properties. Fourth, there is a need for integration of cost on a more regular basis. Machine time, energy, powder/filament usage, support structures, failed builds, finishing, inspection, labour, and qualification are all factors that influence manufacturing cost. A multi-objective formulation, however, should express trade-offs between mass, stiffness, strength, quality and time and cost (Thompson et al., 2016). It would be good to consider energy as a dedicated objective: parameter selection is found to be a key factor in significantly cutting down machining energy in the case of designed experiments on honing of cast-iron cylinder liners, and similar savings are possible in the case of AM parts (Tayisepi et al., 2024).

Fifth, experimental validation is not consistent. Future work should include standardised test protocols, specimen orientation, material condition, process parameters, dimensional measurements, defect characterisation and defect uncertainty. The absence of these data renders cross-study comparisons limited and reported percentage changes might be misleading (Bikas, Stavropoulos and Chryssolouris, 2016). Last but not least, there is a need for transparent benchmarking using AI-enabled methods. Studies should contrast data-driven approaches with good physics-based baseline examples, describe the size and diversity of the data provided, measure generalisation error, implement out-of-distribution examples and provide an explanation of the constraints imposed.

Hybrid physics-informed methods seem to be especially promising. Seventh, closed-loop digital manufacturing should be a focus of research. A mature workflow, in which the design requirements are used to optimise, simulate and plan the process, the AM process generates inspection and monitoring data, and the data are used again to update the models and design for future use. This feedback would help minimize the distance between the digital and physical consequences (DebRoy et al., 2018). Some attempts have been made to develop fast surrogate models for deep neural

operators to enable in-process prediction and control (Liu et al., 2024), and agent-based approaches that integrate PLC-level sensing, rule-based diagnosis, data logging and automatic notification have been proposed, which is suitable for resource-constrained plants (Mashava et al., 2026).

Eighth, the adoption of technology in developing industrial economies is as much a matter of capability as it is of technology. High solution costs and weak government incentives and the lack of an Industry 4.0 strategy are identified as the major barriers to the adoption of Industry 4.0 technology by Zimbabwean manufacturers (Muhla et al., 2025a), with agile, customer-driven production technology equipment being scarce (Muhla et al., 2023). Proposed in Southern Africa as a regional solution to the theory–practice gap in engineering education, learning factories offer students an opportunity to design, fabricate and test their products in a realistic production environment (Ndiyamba et al., 2026). Such environments could be a place where processes are used in the design, and embedding TO, GD and AM workflows within this environment would help develop the process-aware design competence that this review calls for.

Lastly, research needs to go beyond the individual benchmark components. The studies that are required for industrial adoption are those involving realistic assemblies, multiple load cases, production constraints, certification, maintenance and lifecycle performance. The critical issue is not the ability to produce a complex geometry but the ability to produce it again, check it, qualify it, and prove its worth. The operator safety should be included in this evaluation. In Zimbabwe, manufacturers attribute accidents in the workplace to factors such as fatigue, cognitive overload and poor ergonomic design (Muhla et al., 2025b), which are similar hazards found in powder handling, support removal, and post-processing of AM parts that should be designed out as well as the structural goals.

7 CONCLUSION

The focus of this review has been on the methods, limitations, applications and future directions of topology optimisation, generative design, and additive manufacturing. The evidence points to a clear difference: TO is more of a mathematical method to solve a problem of material and structural distribution, while GD is more of a requirements-driven workflow for creating and evaluating viable options. The geometric freedom offered by AM can enable many outcomes but also adds constraints that will need to be taken into account during the design process (Srivastava and Kawakami, 2023). Explicit geometry, lattice optimisation, multi-objective search, and AI-assisted approaches open up a space for design beyond SIMP, level-set and evolutionary methods. In the aerospace and automotive industries, as well as in cellular structures, applications demonstrate why TO and GD offers the promise of mass reduction, part consolidation and enhanced performance. The advantages, however, are not guaranteed.

The apparent benefits of a computational optimum (Zhu et al., 2021; Kalakoti et al., 2026) may be counteracted or lost due to support structures, build orientation, overhangs, internal voids, anisotropy, residual stress, surface finish, post-processing, cost and validation. The main finding is that the breakthrough will be in bringing the gap between computational design and actual manufacturing down. Optimisation algorithms, process-aware constraints, material models, AI support, experimental validation and cost analysis and feedback from inspection and production will be integrated into successful systems. Therefore, engineering achievement and not geometric complexity or weight reduction should be the criteria for the maturity of the TO and GD, and this should be based on the validated repeatable and economically viable engineering achievements that can be achieved. Calibrated knowledge of processes, tools that can be interpreted with data, and process skills development will be critical for the development of industrial economies, as much as optimisation software and printers.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors declare no conflict of interest.

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