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Topology Optimization in Mechanical Design: Methods and Recent Research

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ABSTRACT

Topology optimization has emerged as a transformative computational design method, enabling engineers to optimize material distribution within a designated design space while adhering to performance objectives and constraints. This systematic approach surpasses traditional design methods by facilitating innovative structures that enhance functionality, reduce weight, and improve structural efficiency. This paper reviews key methods in topology optimization, including density-based methods like the Solid Isotropic Material with Penalization (SIMP), which, despite its popularity, faces challenges such as computational burdens and discrete representation issues. Alternatives such as level-set methods and Moving Morphable Component (MMC) methods are explored for their advantages in achieving clear boundaries and improved computational efficiency. Furthermore, evolutionary and genetic algorithms are examined for their capability to address complex optimization problems by mimicking biological evolution. The integration of topology optimization with advanced manufacturing technologies, particularly additive manufacturing, has significantly broadened its applicability, enabling the creation of complex structures previously deemed unfeasible. While advancements have been substantial, ongoing challenges such as computational efficiency and real-world application constraints persist. Future research is directed towards enhancing algorithms, integrating manufacturing processes, and incorporating advanced materials to further revolutionize mechanical design. As computational and manufacturing capabilities evolve, topology optimization is set to play a crucial role in the development of next-generation mechanical systems, fostering the creation of lighter, stronger, and more efficient designs.

Keyword: Optimization, topology MMC, SIMP etc.

1. Introduction and Overview

Topology optimization has emerged as a powerful computational design method that enables engineers to determine the optimal material distribution within a given design space, subject to specific constraints and performance objectives. Unlike traditional design methods that rely on intuition and experience, topology optimization offers a systematic approach to discover novel structures with enhanced functionality and performance. In recent years, topology optimization has gained significant traction in mechanical design due to its ability to generate innovative solutions that often surpass conventional designs in terms of weight reduction, structural efficiency, and multifunctionality.

The fundamental principle of topology optimization is to identify the optimal distribution of material within a design domain that maximizes or minimizes an objective function while satisfying constraints such as stiffness, weight, or stress limitations. Topology optimization methods have been widely used in various industries, particularly due to their potential for providing promising design candidates for mechanical devices [1]. The increased interest in topology optimization is largely driven by advancements in manufacturing technologies, particularly additive manufacturing, which has removed many of the constraints of traditional manufacturing processes. Topology optimization is an advanced technique for structural optimization that aims to achieve an optimally efficient structure by redistribution of materials while ensuring fulfilment of load-carrying, performance, and initial boundary conditions [2].

Recent research has moved toward optimization strategies based on genetic algorithms and topology optimization methods for energy-absorbing structures with desired stress-strain curves [3]. This evolution represents a shift from forward design methods that focus on controlling geometric parameters and material types to inverse design methods that optimize structures based on target performance characteristics. This review article explains the ideas of design optimization, topology optimization, and how they may be applied to various machine or automobile components [4], highlighting the versatility and broad applicability of these methods across different domains.

2. Fundamental Methods in Topology Optimization

2.1 Density-Based Methods

Density-based methods, particularly the Solid Isotropic Material with Penalization (SIMP) approach, represent one of the most established frameworks in topology optimization. Among the topology optimization methods, the SIMP method is often chosen due to its simplicity and convenience [5]. The SIMP method works by assigning a density value to each element in the design space, with these densities typically varying continuously between 0 (void) and 1 (solid). A penalization factor is then applied to intermediate densities to encourage the solution to converge toward a discrete 0-1 design.

However, the SIMP method has certain limitations. SIMP method is typically integrated with conventional finite element analysis (FEA) which has limitations in computational accuracy. Achieving high accuracy with FEA needs a substantial number of elements, leading to computational burdens [5]. Additionally, the discrete representation of the material distribution may result in rough boundaries and checkerboard structures [5], which can be problematic for manufacturing.

Recent advancements have sought to address these limitations. Particularly, density-based and discrete-based approaches to topology optimization have been compared for their effectiveness in biomechanical applications [6]. Research findings demonstrate that with the discrete-based approach, a mass reduction of around 45% was achieved, almost double of the density-based approach, offering physical properties which provide comprehensive advantages for biomechanical applications [6]. This indicates that while density-based methods are widely used, alternative approaches may offer superior performance in specific applications.

2.2 Level-Set Methods

Level-set methods have emerged as a powerful alternative to density-based approaches for topology optimization. This approach presents a velocity field level set method for topology optimization, which can precisely track the layout (topology/shape) of structures with clear/smooth boundaries. Compared with density-based methods, the level set method can avoid the difficulties in the definition of material distributions and material properties for intermediate densities, which also leads to more accurate results [7].

Using the velocity field level set method can map the original variational boundary shape optimization problem into the finite dimensional space and solve the optimization problem efficiently by general optimizers [7]. Additionally, the self-adjoint scheme can be used in the sensitivity analysis, which avoids solving additional adjoint problems [7], thus improving computational efficiency.

Recent research has introduced variations of the level-set method for specific applications. An effective periodic evolutionary level set method (P-EA-LSM) has been developed for the optimization of periodic structures. P-EA-LSM uses a low-dimensional level-set representation based on moving morphable components to parametrize a single unit cell, which is replicated in the design domain according to a predefined pattern [8]. This approach is particularly valuable for designs that require periodic structures, such as lattice materials.

2.3 Moving Morphable Component (MMC) Methods

The Moving Morphable Component (MMC) method represents a relatively newer approach to topology optimization that offers several advantages over traditional methods. Explicit topology optimization methods have received increasing interest in recent years, with the Moving Morphable Component (MMC) method being implemented for three-dimensional topology optimization through efficient and easy-to-extend Matlab code [9]. By virtue of the function aggregation technique, accurate sensitivity analysis, which is also easy to extend to other problems, is achieved in the MMC method [9]. Additionally, based on an efficient identification algorithm for load transmission path, the degrees of freedoms (DOFs) not belonging to the load transmission path are removed in finite element analysis (FEA), which significantly accelerates the optimization process [9].

Comparisons with other methods have demonstrated the advantages of the MMC approach. Compared to corresponding 2D code, the performance of the optimization results, the computational efficiency of FEA, and the convergence rate and the robustness of optimization process are greatly improved with the 3D MMC method [9]. These improvements make the MMC method particularly valuable for complex three-dimensional optimization problems.

2.4 Evolutionary and Genetic Algorithms

Evolutionary and genetic algorithms offer a different approach to topology optimization, drawing inspiration from biological evolution. Recent research has proposed optimization strategies based on genetic algorithms for mechanical metamaterials, along with the development of structural mutation algorithms and design-domain-independent mesh generation methods to improve the efficiency of finite element analysis and optimization iteration [3].

These algorithms operate by evolving a population of potential solutions through processes of selection, crossover, and mutation. In some approaches, the unit cell is optimized using an evolutionary algorithm and the structural responses are calculated for the entire system [8]. This evolutionary approach can be particularly effective for complex optimization problems where traditional gradient-based methods may struggle.

Research has also developed a Bézier-based biased random-key genetic algorithm to address printability constraints in the topology optimization of concrete structures [10], demonstrating the flexibility of evolutionary approaches in handling manufacturing constraints. This integration of evolutionary algorithms with practical manufacturing considerations represents an important direction in making topology optimization more applicable to real-world engineering problems.

3. Recent Advancements in Computational Methods

3.1 Machine Learning and AI Integration

The integration of artificial intelligence and machine learning into topology optimization represents one of the most significant recent developments in the field. Generative adversarial networks (GANs) have emerged as a popular alternative to traditional iterative topology optimization methods, although they can be challenging to train, have limited generalizability, and often neglect important performance objectives such as mechanical compliance and manufacturability [11].

To address these limitations, researchers have proposed new architectures such as TopoDiff that use conditional diffusion models to perform performance-aware and manufacturability-aware topology optimization. This method introduces a surrogate model-based guidance strategy that actively favors structures with low compliance and good manufacturability. Compared to state-of-the-art conditional GANs, this approach reduces the average error on physical performance by a factor of eight and produces eleven times fewer infeasible samples [11].

The technical route of replacing the topology optimization process with artificial neural network (ANN) models has gained popularity. These ANN models, once trained, can rapidly produce an optimized design solution for a given design specification [12]. However, the complex mapping relationship between design specifications and corresponding optimized structures presents challenges in the construction of neural networks with good generalizability [12].

To address these challenges, a new design framework has been proposed that uses deep learning techniques to accelerate the topology optimization process. Specifically, an efficient topology optimization (ETO) framework has been developed in which structure update at each iteration is conducted on a coarse scale and a structure mapping neural network (SMapNN) is constructed to map the updated coarse structure to its corresponding fine structure. As such, fine-scale numerical simulations are replaced by coarse-scale simulations, thereby greatly reducing the computational cost [12].

3.2 Neural Network Approaches

Neural network approaches for topology optimization have evolved rapidly, with novel methodologies emerging to address specific challenges. Neural Implicit Topology Optimization (NITO) represents a novel approach to accelerate topology optimization problems using deep learning. NITO stands out as one of the first frameworks to offer a resolution-free and domain-agnostic solution in deep learning-based topology optimization [13].

The performance advantages of neural network approaches can be substantial. NITO synthesizes structures with up to seven times better structural efficiency compared to state-of-the-art diffusion models and does so in a tenth of the time [13]. These efficiency gains make neural network approaches particularly valuable for time-sensitive design applications.

One of the key innovations in neural network approaches is the development of new methods to represent boundary conditions. In the NITO framework, a novel method, the Boundary Point Order-Invariant MLP (BPOM), has been introduced to represent boundary conditions in a sparse and domain-agnostic manner, moving away from expensive simulation-based approaches [13]. This approach has significant advantages in terms of generalizability and efficiency.

NITO circumvents the domain and resolution limitations that restrict Convolutional Neural Network (CNN) models to a structured domain of fixed size—limitations that hinder the widespread adoption of CNNs in engineering applications. This generalizability allows a single NITO model to train and generate solutions in countless domains, eliminating the need for numerous domain-specific CNNs and their extensive datasets [13]. Despite its generalizability, NITO outperforms state-of-the-art models even in specialized tasks, is an order of magnitude smaller, and is practically trainable at high resolutions that would be restrictive for CNNs [13].

3.3 Isogeometric Analysis for Topology Optimization

Isogeometric analysis represents a significant advancement in the numerical methods used for topology optimization. An isogeometric analysis (IGA) based SIMP method has been proposed for optimizing the topology of shell structures based on Reissner-Mindlin theory. This approach uses NURBS to represent both the shell structure and the material distribution function with the same basis functions, allowing for higher accuracy and smoother boundaries [5].

The optimization model in isogeometric analysis typically takes compliance as the objective function with a volume fraction constraint and the coefficients of the density function as design variables [5]. The Method of

Moving Asymptotes is employed to solve the optimization problem, resulting in an optimized shell structure defined by the material distribution function [5].

One of the key advantages of isogeometric analysis is the quality of the resulting boundaries. To obtain fairing boundaries in the optimized shell structure, further processing is conducted by fitting the boundaries with fair B-spline curves automatically [5]. Additionally, the IGA-SIMP framework can be applied to generate porous shell structures by imposing different local volume fraction constraints [5].

Comparative studies have demonstrated the advantages of isogeometric analysis over traditional finite element approaches. Numerical examples have shown that the IGA-SIMP method outperforms the FEA-SIMP method and produces smoother boundaries [5]. These benefits make isogeometric analysis particularly valuable for applications where boundary quality and accuracy are critical considerations.

4. Applications in Advanced Manufacturing

4.1 Integration with Additive Manufacturing

The synergy between topology optimization and additive manufacturing has been a catalyst for innovation in structural design. The advent of Additive Manufacturing (AM) is uncovering the limits of the current CAD systems and, at the same time, is highlighting the potentials of Topology Optimization (TO) and Generative Design (GD) tools that had not been fully exploited until now [14]. This convergence of advanced design and manufacturing technologies enables the realization of complex, optimized structures that would be impossible to fabricate using traditional manufacturing methods.

Differently from the traditional design approach in which designers occupy a predominant role in each stage of the design process, the introduction of TO and GD tools in the product development process pushes toward simulation-driven design approaches which imply a significant change in the role of the designer [14]. This shift transforms the designer's role from manual creation to guiding and interpreting the results of computational design processes.

The integration of topology optimization with additive manufacturing offers substantial benefits for practical applications. A methodology that integrates advanced principles of topology optimization and additive manufacturing techniques has been proposed to optimize frame structures for improved performance. Experimental evaluations of thrust and moment of motors are performed to assess the performance of enhanced structures, with a focus on advancing the design through computer-aided simulations of static structural analysis and impact tests [15].

Additive Manufacturing (AM), also known as 3D printing technology, is a method of manufacturing machine parts through joining layers of material. AM opens up the possibility of fabricating complex structures, especially for structures that have been subjected to topology optimization techniques [2]. This manufacturing flexibility is particularly valuable for realizing the complex geometries that often result from topology optimization.

The practical benefits of this integration can be substantial. Models produced through topology optimization and additive manufacturing have demonstrated reduced weights of 43%, 59%, 70%, 73%, and 77%, while maintaining the ability to support their required loads. The results show that combining structural optimization and additive manufacturing can take advantage of both approaches and show significant potential for modern manufacturing [2].

4.2 Design for Additive Manufacturing Constraints

While additive manufacturing offers unprecedented freedom in fabricating complex geometries, it still imposes certain constraints that must be considered during the topology optimization process. One of the obstacles in the process of optimizing structures for mechanical parts is that these optimized structures sometimes encounter difficulties during the manufacturing process [2]. Addressing these manufacturability challenges is crucial for translating optimized designs into functional physical components.

The integration of topology optimization into additive manufacturing provides unmatched possibilities for the sustainable manufacturing of lightweight, intricate, custom parts with less material at a lower production time and cost. Recent studies have aimed to apply and benchmark topology optimization methods, in conjunction with additive manufacturing, to enhance the design of functional components used in aerospace applications, while simultaneously providing an experimental verification and comparative analysis of such optimization techniques [16].

Specific methods have been developed to address additive manufacturing constraints in topology optimization. A density-based technique and a level-set method have been used to perform analysis and optimization for aerospace brackets, with fabrication performed using fused deposition modelling [16]. The results of these optimizations are promising, with optimized designs achieving a 20% weight reduction while maintaining the compression displacement of the initial components at the given load. These results demonstrate that topologically optimized components can significantly enhance the design of real-life components, such as those used in weight-sensitive industrial applications [16].

Frequency optimization plays a vital role in designing machines and structures to avoid destructive responses caused by external excitation. With the development of additive manufacturing, increasingly more organic structures produced by topology optimization can be physically fabricated. Therefore, the combination of topology optimization and additive manufacturing is promising and widely investigated. Recent research has proposed a concurrent topology optimization method for maximizing the natural frequency of Fused Deposition Modelling (FDM) parts printed by a Hybrid Deposition Path (HDP) pattern [17]. This approach demonstrates how topology optimization can be tailored to the specific characteristics and constraints of particular additive manufacturing processes.

5. Specialized Applications of Topology Optimization

5.1 Medical Implants and Devices

Topology optimization has found significant applications in medical device design, particularly for implants where customization, weight reduction, and biomechanical compatibility are critical. Prosthetic implants, particularly hip endoprostheses, often lead to stress shielding because of a mismatch in compliance between the bone and the implant material, adversely affecting the implant's longevity and effectiveness. Recent work has aimed to demonstrate a computationally efficient method for density-based topology optimization of homogenized lattice structures in a patient-specific hip endoprosthesis [18].

The benefits of topology optimization in medical applications can be substantial. Through topology optimization, the root means square error (RMSE) of the stress deviations between the physiological femur model and the optimized total hip arthroplasty (THA) model compared to an unoptimized-THA model could be reduced by 81% and 66% in specific anatomical zones [18]. This significant improvement in stress distribution can reduce the risk of implant failure and improve patient outcomes.

Recent developments in additive manufacturing have led to significant opportunities in the design and fabrication of implantable medical devices due to the advantages that AM offers compared to conventional manufacturing, such as high customizability, the ability to fabricate highly complex shapes, good dimensional accuracy, a clean build environment, and reduced material usage. The study of structural design optimization (SDO) involves techniques such as Topology Optimization (TO), Shape Optimization (SHO), and Size Optimization (SO) that determine specific parameters to achieve the best measurable performance in a defined design space under a given set of loads and constraints. Integration of SDO techniques with AM leads to utmost benefits in designing and fabricating optimized implantable medical devices with enhanced functional performance [19].

Additive manufacturing methods enable the rapid fabrication of fully functional customized objects with complex geometry and lift the limitations of traditional manufacturing techniques, such as machining. Therefore, the structural optimization of parts has concentrated increased scientific interest, especially for topology optimization processes. Recent research has analyzed the working principles and approaches of TO procedures along with an investigation and comparative study of novel applications like TO process of a tibial implant designed for additive manufacturing (DfAM)[6].

Endoprostheses are exposed to the risk of aseptic loosening, making the design of the prosthesis shaft to achieve physiological force application of great importance. Additive manufacturing offers the potential to fabricate highly variable topologies but challenges the designer with a large number of design variables. Recent work has developed a method to determine an optimized density topology that approximates a given mechanical stress state in the bone after implantation, performing topology optimization of the density distribution of the implant [20].

5.2 Aerospace and Automotive Applications

Aerospace and automotive industries have been at the forefront of adopting topology optimization due to the critical importance of weight reduction and structural efficiency in these sectors. The performance of quadcopter frames, particularly in terms of weight and crash resistance, is significantly influenced by their structural design and manufacturing process. Recent research has proposed a methodology that integrates advanced principles of topology optimization and additive manufacturing techniques to optimize the frame structure for improved performance [15].

In the specific case of quadcopter design, the TO technique is employed to determine the optimal distribution of material within the frame, governed by constraints such as weight reduction and mechanical strength. Results demonstrate that the overall performance of a quadcopter frame is significantly improved by this methodology, showcasing advancements in stability, weight reduction, and crashworthiness [15].

With the increase in wind turbine power, the size of the blades is significantly increasing to over 100 meters, making it increasingly important to optimize the design for the internal layout of large-scale offshore composite wind turbine blades to meet structural safety requirements while improving blade power generation efficiency and achieving light weight. Recent work has elaborately designed the full-scale internal layout of an NREL 5 MW offshore composite wind turbine blade via the topology optimization method [21].

In wind turbine applications, the aerodynamic wind loads of the blades are first simulated based on computational fluid dynamics. Afterwards, the variable density topology optimization method is adopted to perform the internal structure design of the blade. Then, the first- and second-generation multi-web internal layouts of the blade are reversely designed and evaluated in accordance with the stress level, maximum displacement of blade tip and fatigue life. In contrast with the reference blade, the overall weight of the optimized blade was reduced by 9.88% with the requirements of stress and fatigue life, indicating a better power efficiency [21].

Studies have aimed to apply and benchmark topology optimization methods, in conjunction with additive manufacturing, to enhance the design of functional components used in aerospace applications, such as industrial brackets, which were optimized with the aim of weight reduction without sacrificing original mechanical stiffness [16]. The optimized designs achieved a 20% weight reduction while maintaining the compression displacement of the initial components at the given load. The achieved results demonstrate that topologically optimized components can significantly enhance the design of real-life components, such as those used in weight-sensitive industrial applications [16].

5.3 Energy-Absorbing Structures

Energy-absorbing structures represent a specialized application of topology optimization where the goal is to design components that can effectively dissipate energy during impact or loading events. Compared with the forward design method through the control of geometric parameters and material types, the inverse design method based on the target stress-strain curve is helpful for the discovery of new structures. Recent research has proposed an optimization strategy for mechanical metamaterials based on a genetic algorithm and established a topology optimization method for energy-absorbing structures with the desired stress-strain curves [3].

The performance of optimized energy-absorbing structures can be impressive. The algorithm realizes the design of ideal energy-absorbing structures, which are verified by additive manufacturing and experimental characterization. The error between the stress-strain curve of the designed structure and the target curve is less than 5%, and the densification strain reaches 0.6[3]. This high level of accuracy in matching the target stress-strain behaviour demonstrates the effectiveness of topology optimization for energy-absorbing applications.

Special attention has been paid to passive pedestrian protection and occupant protection, with reasonable solutions given through the design of a multiplatform energy-absorbing structure. The proposed topology optimization framework provides a new solution path for the elastic-plastic large deformation problem that is unable to be resolved by using classical gradient algorithms or genetic algorithms and simplifies the design process of energy-absorbing mechanical metamaterials [3].

Assembly complexity and manufacturing costs of engineering structures can be significantly reduced by using periodic mechanical components, which are defined by combining multiple identical unit cells into a global topology. Additionally, the superior energy-absorbing properties of lattice-based periodic structures can potentially enhance the overall performance in crash-related applications [8]. This demonstrates the value of periodic structures in energy absorption applications, highlighting the versatility of topology optimization in addressing various design challenges.

6. Advanced Optimization Methods

6.1 Multi-Material Topology Optimization

Multi-material topology optimization (MMTO) extends traditional single-material approaches by allowing the simultaneous optimization of material distribution and selection. Numerical tools such as topology optimization have seen large development in both academic and industrial settings, enabling the optimization of structural objectives and/or attributes, subject to a wide range of constraints, pertinent to the engineering and design problems of automotive and aerospace industries. Classical TO methods assume the use of a single material (SMTO), however, a recent and important advancement in this field is multi-material topology optimization, capable of simultaneous material existence and selection optimization [22].

MMTO is of heightened importance in industries where many costly engineering materials can be used, but their selection is delegated to engineer experience. Consideration of modal characteristics (i.e., natural frequencies) in MMTO efforts have seen marginal development in recent years yet is vital to industries whose products are subject to uncontrolled environments and vibratory motion [22].

One of the computational challenges in MMTO is the integration with commercial finite element analysis (FEA) software. Where frequency has been considered in MMTO, mathematical frameworks require the usage of model attributes that are not extractable from commercial FEA solvers, leading to reduced computational efficiency. Recent research has presented an advancement of the frequency-constrained MMTO sensitivities previously utilized in SMTO, enabling the use of commercial solvers, thus inheriting computational improvements [22].

Lattice structures are becoming an increasingly attractive design approach for diverse engineering applications due to their high specific strength and stiffness, considerable heat dissipation, and relatively light weight. Recent work has focused on a two-scale concurrent optimization of lattice structures, which involves simultaneously optimizing the topology at both the macro- and micro-scales to achieve an optimal topology [23].

6.2 Multi-Objective Optimization

Multi-objective optimization in topology optimization involves the simultaneous consideration of multiple, often competing, performance criteria. The design and manufacturing of high value industrial components is experiencing a change of paradigm with 3D printing. In this change, metamaterials have an important role because when a component is 3D-printed, it is performed from the micro level, where custom structures may be designed to endow the material and the component with special or customized mechanical properties. Topology optimization techniques facilitate the design of both the microstructures and the overall component topology, and today the component topology may be designed assuming a continuous spectrum of mechanical properties facilitated by different locally designed microstructures [24].

Traditional approaches to topology optimization often use intermediate density variables and impose limits on these variables. However, current topology optimization techniques do not operate directly with the mechanical properties of the material, but through density intermediates, using density-based limits like a minimum or maximum density, assuming a homogeneous base material. Novel topology optimization algorithms have been proposed which operate directly on the mechanical properties and energies, without employing density intermediates. The proposed approach reduces the algorithmic complexity since the optimization is performed by the direct iterative update of the mechanical properties, through information taken from its finite element analysis [24].

The advantages of direct mechanical property optimization can be substantial. This methodology can reach similar results as current techniques based on a gradient descent optimization, eliminating the need for external parameters and, hence, increasing ease of use and robustness. The proposed technique is especially suitable for two-level concurrent material-component design using functionally graded metamaterials [24].

6.3 Uncertainty and Reliability-Based Optimization

Incorporating uncertainty and reliability considerations into topology optimization is crucial for designing structures that perform robustly under real-world conditions. The material redistribution abilities of traditional deterministic topology optimization are effective in addressing stress-related design issues in thermal elastic structures. However, uncertainties are inevitable in the real world. The structural strength of a design, achieved through deterministic topology optimization, is highly susceptible to these uncertainties, which may result in failure [25].

To address these challenges, novel methods for topology optimization in stress-constrained thermoelastic structures have been introduced, taking into account the uncertainties associated with heat sources and loads. The Kieisselmeier–Steinhauser function is employed to aggregate the stress constraint when constructing the performance function [25].

In order to improve optimization efficiency, the sequential optimization and reliability assessment method is used to decouple the double-layer loop reliability-based topology optimization. Initially, the derivative of stress-based performance functions with respect to heat source and load uncertainty variables is derived, thereby facilitating the use of modified chaos control for assessing structural reliability and imposing constraints [25].

The adjoint method and chain rule are utilized to obtain the derivative information of the performance function with respect to density variables, guiding the topology updates. Multiple design examples have demonstrated the effectiveness of the presented method. Monte Carlo simulations for the optimized results have been performed to show that the presented method can obtain a structure that meets reliability requirements [25]. This validation using Monte Carlo simulations provides confidence in the robustness of the optimized designs under uncertainty.

7. Computational Efficiency and Implementation

7.1 Parallel Computing Approaches

The computational demands of topology optimization, particularly for large-scale problems, have driven the development of parallel computing approaches to accelerate the optimization process. A moderately large-scale topology optimization problem with 3.56×10^6 degrees of freedom can be solved in parallel on a standard multi-process platform [26].

Numerical implementations using FreeFEM for finite element analysis, PETSc for distributed linear algebra, and Mmg for mesh adaptation have been developed [26] to leverage parallel computing capabilities efficiently.

These tools allow for the distribution of computational tasks across multiple processors, significantly reducing the time required to solve large optimization problems.

A subdomain-based parallel strategy for structural topology optimization has been developed [10], which further enhances the efficiency of solving large-scale problems. This approach divides the design domain into multiple subdomains, each of which can be processed in parallel, reducing the overall computation time.

7.2 Software Implementations and Tools

The practical application of topology optimization is facilitated by the development of software tools and implementations that make these methods accessible to engineers and designers. An efficient and easy-to-extend Matlab code for the Moving Morphable Component (MMC) method for three-dimensional topology optimization has been released, implementing new numerical techniques [9]. This accessibility is crucial for the broader adoption of topology optimization in engineering practice.

Topology optimization has been a popular design method among CAD designers in recent decades. This method optimizes the given design domain by minimizing/maximizing one or more objective functions, such as the structure's stiffness, while respecting given constraints like volume or weight reduction. Companies providing commercial CAD/FEM platforms have taken this design trend into account and have included TO in their products over the last years [27].

To help designers navigate the landscape of available tools, comparative studies among the most applied topology optimization software have been conducted. Online databases of identified TO software have been developed in the form of tables, allowing interested CAD designers to access and edit content, contributing to the creation of an updated library of available TO software [27].

Deeper comparisons among commercial software platforms—SolidWorks, ANSYS Mechanical, and ABAQUS—have been implemented using common case studies such as a bell crank lever, a pillow bracket, and a small bridge. These models were designed, optimized, and validated numerically, as well as compared for their strength. Software evaluations considered optimization time, optimized designs, and TO possibilities and features[27]. These comparisons provide valuable guidance for practitioners in selecting the most appropriate tools for their specific design challenges.

7.3 Efficiency Improvements

Improving the computational efficiency of topology optimization algorithms is a continual focus of research, with various approaches being developed to reduce computation time and resource requirements. It is well known that the computational cost of classic topology optimization methods increases rapidly with the size of the design problem because of the high-dimensional numerical simulation required at each iteration. A new design framework has been proposed that uses deep learning techniques to accelerate the TO process. Specifically, an efficient topology optimization (ETO) framework has been presented in which structure update at each iteration is conducted on a coarse scale and a structure mapping neural network (SMapNN) is constructed to map the updated coarse structure to its corresponding fine structure[12].

The benefits of this approach are substantial. As such, fine-scale numerical simulations are replaced by coarse-scale simulations, thereby greatly reducing the computational cost. In addition, fragmentation and padding strategies are used to improve the trainability and adaptability of SMapNN, leading to better generalizability. The efficiency and accuracy of the proposed ETO framework are verified using both benchmark and complex design tasks. It has been shown that with the SMapNN, TO designs of millions of elements can be completed within a few minutes on a personal computer [12]. This dramatic reduction in computation time makes topology optimization more accessible and practical for everyday engineering applications.

Passive heat sinks cooled by natural convection are reliable, compact, and low-noise, being widely used in various applications. Recent advancements in fluid topology optimization (TO) have enabled the study of two- and three-dimensional optimum design and thermal modelling for natural convection problems using a reaction–diffusion equation (RDE)–based level-set method. The main findings reveal that using the body-fitted mesh adaptation, the proposed methodology can capture the explicit fluid–solid boundary and avoid the continuation approach to penalize the design variable to the binary structure [26]. This approach not only improves the quality of the optimized designs but also enhances computational efficiency.

8. Future Directions and Challenges

8.1 Current Limitations and Research Gaps

Despite significant advancements in topology optimization methods, several limitations and research gaps remain to be addressed. Generative adversarial networks (GANs) can be challenging to train, have limited generalizability, and often neglect important performance objectives such as mechanical compliance and manufacturability [11]. These limitations highlight the need for more robust and comprehensive optimization approaches.

The complex mapping relationship between design specifications and corresponding optimized structures presents challenges in the construction of neural networks with good generalizability [12]. This complexity makes it difficult to develop machine learning models that can effectively generalize across different design problems and constraints.

Most of the methods rely on gradient information in the optimization process, which poses difficulties for crash problems where analytical sensitivities are usually not directly applicable [8]. This limitation restricts the application of topology optimization to certain types of mechanical problems, particularly those involving dynamic or nonlinear behaviour.

Unrestricted material unit cell designs are often associated with high computational power and connectivity problems, and highly restricted lattice unit cell designs may not reach the optimal desired properties despite their lower computational cost [23]. This trade-off between design freedom and computational efficiency represents a significant challenge in the optimization of lattice structures.

Previous research on generative design using deep neural networks required tedious iterations between the neural network and design optimization, as well as post-processing to generate functional designs. Additionally, design constraints such as volume fraction could not be enforced [28]. These limitations highlight the need for more integrated and efficient approaches to generative design.

8.2 Emerging Trends and Future Research Directions

Several emerging trends and future research directions are shaping the evolution of topology optimization in mechanical design. The potential of using diffusion models in topology optimization suggests a general framework for solving engineering optimization problems using external performance with constraint-aware guidance [11]. This approach represents a promising direction for integrating advanced machine learning techniques with traditional optimization methods.

The review anticipates the utilization of automated design exploration methods (i.e., topology optimization and data-driven methods) to further enhance the design optimization procedure of lattice-structured materials [29]. This integration of data-driven approaches with topology optimization has the potential to discover novel lattice structures with superior performance characteristics.

A two-stage non-iterative formulation has been proposed to overcome limitations in generative design. In the first stage, a conditional generative adversarial network (cGAN) is utilized to control design parameters. In the second stage, topology optimization (TO) is embedded into cGAN (cGAN+TO) to ensure that desired functionality is achieved [28]. This integrated approach demonstrates the potential for combining generative models with topology optimization to create more efficient and functional designs.

The integration of artificial intelligence (AI) and machine learning (ML) in structural optimization has expanded opportunities to improve device performance, adaptability, and durability [19]. This trend toward AI-enhanced optimization is likely to continue, with increasingly sophisticated models being developed to address complex design challenges.

The combination of versatility, efficiency, and performance underlines the potential of neural implicit field approaches to transform the landscape of engineering design optimization problems [13]. These approaches offer a promising direction for future research, potentially enabling more efficient and effective optimization of complex structures.

8.3 Integration with Other Design Methods

The integration of topology optimization with other design methods represents a promising direction for enhancing its capabilities and applicability. Comparative studies of different design methods for Additive Manufacturing based on the adoption of Topology Optimization and Generative Design tools have been conducted. These comparisons aim to offer a reflection on the evolution of the traditional approach when TO and GD tools are used, and to highlight the potential and limitations of these optimization tools when adopted in an integrated manner with CAD systems. Furthermore, such comparative studies can be a useful and practical source for designers to identify the most appropriate approach to adopt based on their needs and project resources [14].

Size optimization (SIO), shape optimization (SHO), and topology optimization (TPO) methods have been compared and analyzed. Based on these optimization methods, a combined topology-shape optimization (PTPO-NSHO) method has been proposed, and boundary shape modelling methods have been established and used in these approaches. These optimization methods have been employed to optimize specific mechanical components, and their optimization time and results have been compared [30]. This integration of different optimization approaches can leverage the strengths of each method to achieve superior results.

Integrated topology and shape optimization approaches have been applied to improve the natural frequency of structures [10], demonstrating the potential benefits of combining different optimization methodologies. This integrated approach allows for the simultaneous consideration of both the material distribution and the geometric shape of the design, leading to more comprehensive optimization.

Conclusion

Topology optimization has evolved significantly in recent years, with advances in computational methods, integration with additive manufacturing, and applications across various domains. The field has moved from simple density-based methods to sophisticated approaches incorporating machine learning, multi-material considerations, and reliability-based design. The integration with additive manufacturing has been particularly transformative, enabling the realization of complex, optimized structures that were previously impossible to fabricate.

Despite these advancements, challenges remain in computational efficiency, handling multiple objectives and constraints, and addressing uncertainties in real-world applications. Future research directions include the development of more efficient algorithms, better integration with manufacturing processes, and incorporation of advanced materials and multi-physics considerations.

As computational power continues to increase and manufacturing capabilities advance, topology optimization is poised to play an increasingly important role in the design of next-generation mechanical systems, enabling engineers to create structures that are lighter, stronger, and more efficient than ever before. The ongoing integration with artificial intelligence and machine learning techniques holds particular promise for addressing complex design challenges and discovering novel structural configurations beyond what is possible with traditional design approaches.

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