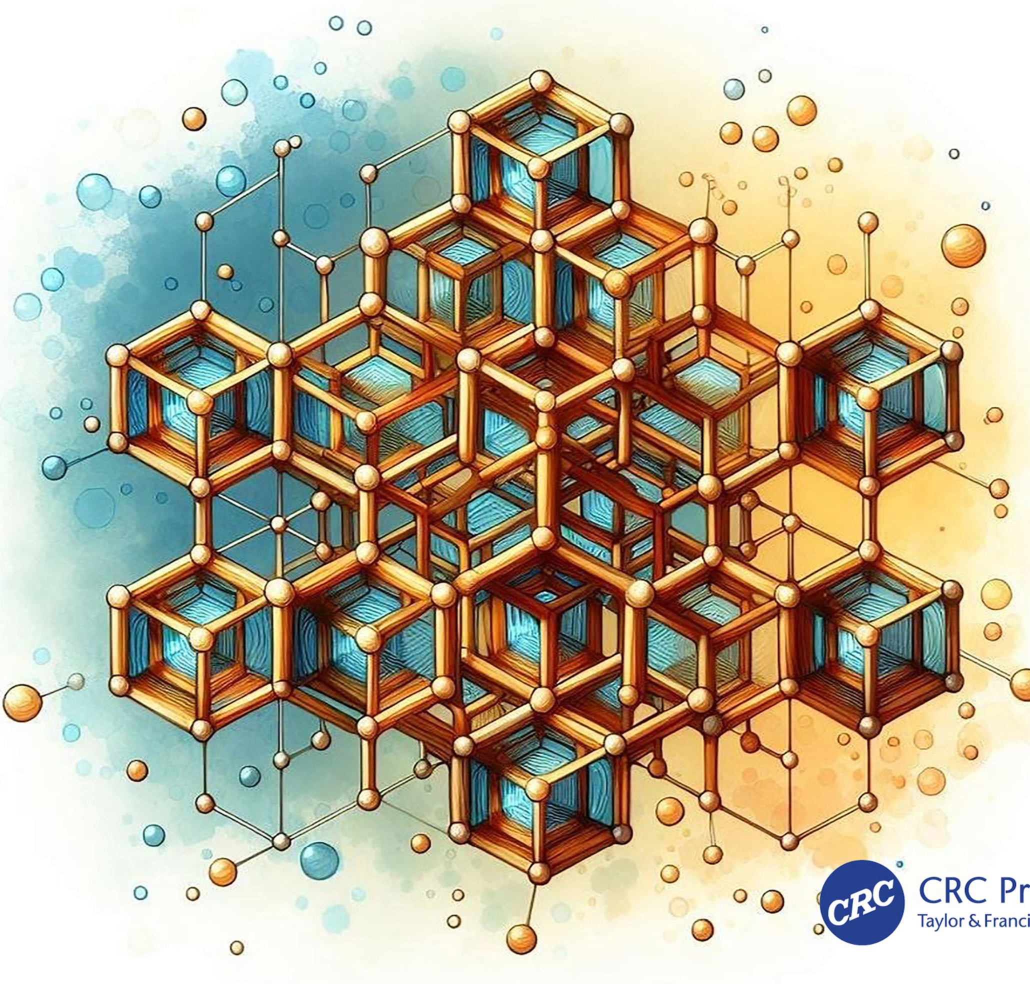
Artificial Intelligence Assisted Structural Optimization

Adithya Challapalli and Guoqiang Li



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Artificial Intelligence Assisted Structural Optimization

Artificial Intelligence Assisted Structural Optimization explores the use of machine learning and correlation analysis within the forward design and inverse design frameworks to design and optimize lightweight load-bearing structures as well as mechanical metamaterials.

Discussing both machine learning and design analysis in detail, this book enables readers to optimize their designs using a data-driven approach. This book discusses the basics of the materials utilized, for example, shape memory polymers, and the manufacturing approach employed, such as 3D or 4D printing. Additionally, the book discusses the use of forward design and inverse design frameworks to discover novel lattice unit cells and thin-walled cellular unit cells with enhanced mechanical and functional properties such as increased mechanical strength, heightened natural frequency, strengthened impact tolerance, and improved recovery stress. Inverse design methodologies using generative adversarial networks are proposed to further investigate and improve these structures. Detailed discussions on fingerprinting approaches, machine learning models, structure screening techniques, and typical Python codes are provided in the book.

The book provides detailed guidance for both students and industry engineers to optimize their structural designs using machine learning.

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Preface

In the dynamic field of structural engineering, the quest for materials that offer superior strength-to-weight ratios is relentless. The advent of machine learning has revolutionized this pursuit, enabling us to explore and optimize lightweight structures with unprecedented precision and creativity.

This textbook, *Artificial Intelligence Assisted Structural Optimization*, is designed to bridge the gap between traditional structural engineering principles and the cutting-edge techniques of artificial intelligence. It is crafted for students, researchers, and professionals who are eager to harness the power of machine learning to innovate in the design and analysis of lightweight structures.

Within these pages, you will find a comprehensive exploration of the fundamentals of machine learning, as well as its application to the design of lightweight structures. From the basics of data analysis to the complexities of neural networks and deep learning, this book provides a step-by-step guide to the tools and techniques that are transforming the field.

Through a blend of theoretical knowledge and practical case studies, readers will gain the skills necessary to develop their own machine-learning models for structural optimization. The book also discusses the ethical considerations and future implications of using machine learning in structural engineering, ensuring that readers are fully prepared for the challenges and opportunities that lie ahead.

Authors

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1 Introduction to Structures with Complex Geometrical Configurations

1.1 INTRODUCTION

The word "structure" in this book refers to rod, beam, plate, and shell and a combination of them by arranging them together according to a certain order. "Structural optimization" suggests a process to design structures with the maximum load-carrying capacity and the least weight penalty. The focus of this book will be on design and optimization from a structural point of view without much emphasis on the base materials. However, when needed, we will also introduce some fundamentals on materials used to construct the structures, particularly for new materials such as smart materials. This chapter provides background on several lightweight structures, their applications, existing optimization techniques, and the importance and advantages of implementing data-driven optimization techniques for these structures.

There are several lightweight structures such as open- and closed-cell foams, lattice structures, thin-walled cellular structures, auxetic structures, hybrid plate-lattice structures, etc. Extensive research has been focused on these structures due to their multiple advantages in structural, acoustic, optimal, electromagnetic, and thermal properties. Numerous theoretical models to predict and analyze the structural behavior of the structures have been developed. With the advancement in manufacturing techniques such as additive manufacturing or 3D/4D printing and complex design and simulation tools, the process of design and optimization for these structures has become simpler.

The realization of lightweight structures requires advanced manufacturing techniques that can accurately translate complex digital designs into physical structures. Several manufacturing methods have emerged as key enablers in bringing irregular lattice structures from the digital realm to the tangible world. Digital fabrication techniques, including computer numerical control (CNC) machining and laser cutting, are commonly employed to manufacture irregular lattice structures. These techniques allow for precision and repeatability in creating intricate lattice patterns from a variety of materials, including metals, polymers, and composites. The rise of additive manufacturing, or 3D printing, has revolutionized the production of lightweight structures or mechanical metamaterials. This technique

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builds structures layer by layer directly from digital models, offering unparalleled design freedom. 3D printing enables the creation of overly complex and customized lightweight structures that would be challenging or impossible to produce using traditional methods.

In terms of designing lightweight structures with superior structural capacities but without much weight penalty, computer-added design has played an important role. Recently, generative design software has played a pivotal role in shaping irregular-shaped structures. By leveraging algorithms and artificial intelligence, generative design tools explore numerous design possibilities based on specified parameters such as material properties, load conditions, and manufacturing constraints. This iterative process results in optimized lightweight structures that meet or exceed performance requirements. The versatility of lightweight structures finds expression across a spectrum of industries, each benefiting from the unique advantages offered by these innovative designs.

In many engineering applications, lightweight is highly desired, for example, aerospace structures, offshore oil platforms, wind turbine blades, autos, and ships, where weight reduction is paramount and lightweight structures offer a compelling solution. The ability to optimize structural performance and distribute loads efficiently aligns with the demands of these engineering applications. Components such as lightweight panels, brackets, body of cars, and even entire airframe structures can benefit from the weight-saving potential of irregular-shaped structural designs.

The field of biomedical engineering embraces lightweight porous structures for applications ranging from orthopedic implants to tissue scaffolds. Implants with porous structures can mimic the mechanical properties of bone while promoting osseointegration. In tissue engineering, porous structures serve as frameworks for the growth of new tissues, providing support and guidance for regenerative processes.

Architects and structural engineers incorporate porous structures such as lattice structures into building designs to achieve both aesthetic and functional objectives. From facades and partitions to entire structural elements, porous patterns redefine the possibilities of architectural expression. The adaptability of these structures to different load conditions makes them valuable in creating resilient and visually captivating buildings.

In the automotive industry, the pursuit of lightweight yet robust components is a driving force behind the adoption of porous structures. Engine components, chassis elements, and even interior components benefit from the weight reduction achieved through optimized pattern designs. This not only enhances fuel efficiency but also contributes to overall vehicle performance and safety.

While lightweight porous structures offer a plethora of advantages, they are not without challenges, and ongoing research aims to address these complexities.

Computational Complexity: The design and analysis of porous structures can be computationally demanding, especially when utilizing generative design and simulation tools. Handling large datasets and optimizing complex structures require advanced computational resources. Researchers are actively exploring ways to enhance the efficiency of these processes to make porous structures more accessible.

Material Considerations: The choice of materials for porous structures is critical to their performance. Different applications demand materials with specific mechanical properties, thermal conductivity, or biocompatibility. Advancements in material science, including the development of new alloys, new polymers, new ceramics, and their composite materials, contribute to expanding the potential applications of porous structures.

Integration of Multiple Materials: Incorporating multiple materials within a porous structure introduces additional challenges but also opens new possibilities. The ability to integrate materials with distinct properties enables the creation of multifunctional structures. Researchers are exploring techniques such as multi-material 3D printing to achieve seamless integration and optimize performance.

Standardization and Certification: As porous structures become more prevalent in critical applications such as aerospace and healthcare, the need for standardization and certification processes becomes paramount. Establishing guidelines and standards for the design, manufacturing, and testing of irregular-shaped porous structures ensures their safety, reliability, and adherence to industry regulations.

Porous structures represent a change in thinking in structural design, challenging traditional notions of symmetry and uniformity. From optimized load distribution to aesthetic innovation, these structures highlight the power of embracing complexity in engineering and architecture.

As technology continues to advance, and researchers delve deeper into the intricacies of porous structures, the possibilities are boundless. The marriage of computational design, advanced manufacturing techniques, and material science heralds a new era where structures are not just functional but are also expressions of creativity and efficiency.

The journey of porous structures is a testament to human ingenuity, pushing the boundaries of what is possible in the quest for structures that are not only strong and efficient but also visually captivating. As industries across the spectrum adopt and adapt these designs, we find ourselves at the cusp of a transformative era where irregularity becomes the norm, and complexity becomes the cornerstone of innovation.

In the following sections, we will introduce the background of several lightweight porous structures.

1.1.1 Foams

A typical porous structure is foam. It is formed by incorporating distributed pores within a matrix. Depending on whether the pores are interconnected or discrete, foams can be widely divided into open- and closed-cell foam. Open-cell foams with irregular cellular structures are formed by packing a complex network of interconnected ligaments. Closed-cell irregular foams are formed by closing the pores with thin walls (Figure 1.1). Due to the excellent stiffness-to-weight ratios

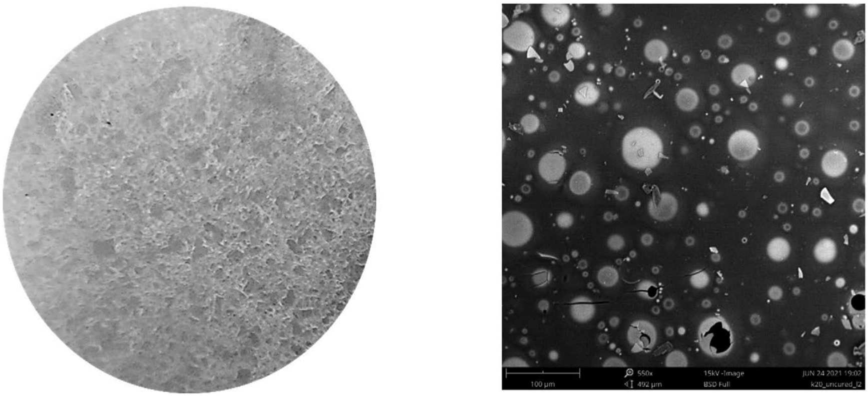

FIGURE 1.1 (a) Open-cell foam prepared by salt leaching method [44] (copyright 2022, ACS, with permission) (b) closed-cell foam [28] (Copyright, 2022, Elsevier, with permission). The image shows a porous structure with irregular string-like connections joining to form cavities depicting an open-cell foam. It also shows a structure with irregular thin walls with closed-cells in the interior depicting a closed-cell foam.

of these structures, they have several applications as a lightweight sandwich core, energy absorber, sound barrier, vibration damping, and tunable thermal conductivity [1].

Several approaches have been used to introduce air bubbles to a matrix, such as polymer matrix [2–6]. These methods include gas foaming, particulate leaching, electrospinning, phase separation, emulsion templating, and solid-state foaming. Recently, 3D/4D printing has also been used for fabricating open-cell foams [7]. While all of these methods are useful for particular applications, gas foaming using a blowing agent such as CO_2 [8] or supercritical CO_2 [9] and particulate leaching using solvable particles such as table salt [10, 11] are considered more common. In both approaches, porosity can be easily controlled by the ratio of the porogen to the polymer. These methods can be considered as physical methods. One more common physical method is to incorporate a hollow microsphere into a matrix. The hollow microspheres include glass microspheres, metal microspheres, carbon microspheres, and polymeric microspheres. The foam produced in this way is closed-cell foam, usually called syntactic foam. In addition to the physical methods, chemical method is also widely used in producing foams. In chemical methods, a foaming agent is involved in a matrix. Upon heating, the foaming agent decomposes and produces a large amount of gas, leading to the foaming of the matrix. Some foaming agents may experience a phase change, from solid to gas, without chemical decomposition. In addition to including a foaming agent in the matrix, another way is to encapsulate the foaming agent first by a soft polymer shell, and upon heating, the foaming agent expands, leading to closed-cell foam.

Many studies have reported substantial theoretical, numerical, and experimental results to understand and predict the mechanical behavior of these porous structures [12]. Clearly, the mechanical properties of foams highly depend on the porosity. It has been widely accepted that the relative strength and stiffness are coupled with relative density for foams with scholastic pores [13–15]:

$$E/E_s \propto (\rho/\rho_s)^n; \quad \sigma_e/E_s \propto (\rho/\rho_s)^n; \quad \sigma_p/\sigma_y \propto (\rho/\rho_s)^n; \tag{1.1}$$

where E is Young's modulus of the foam, E_s is Young's modulus of the cell wall material (solid), ρ is the density of the foam, ρ_s is the density of the cell wall material (solid), σ_e is the elastic collapse stress of the foam (cell wall buckles), σ_p is the plastic collapse stress of the foam (cell wall yields), and n is the scaling factor. Based on the literature, $n = 2 \sim 3$, depending on if the cell is closed or open [13–15]. It is clear from Equation (1.1) that, for ultralow density foam, the mechanical properties of the foam degrade significantly. For example, if the relative density is 10% and $n = 3$, Young's modulus and collapse stress become 0.1% of their original values. Therefore, the grand challenge in foam is how to achieve high strength and stiffness with minimal weight penalty.

Compared to conventional open- and closed-cell foams, which are formed by directly including air bubbles or pores in the matrix, syntactic foams, which include hollow particles in the matrix, usually have higher mechanical properties than directly incorporating air bubbles in the matrix. Many theoretical, numerical, and experimental studies have been conducted on polymeric syntactic foams, including shape-memory polymer-based syntactic foams. Readers can find more details in the representative publications [16–33].

Several studies suggest that the strength and stiffness of the open-cell and closed-cell foams depend on the ligament or thin wall bending. While the irregular open-cell foams primarily fail due to bending or buckling of the walls, the irregular closed-cell foams fail due to cell wall buckling or rapture at extremely low loads [34–37]. Open-cell foams, which are less dense compared to closed-cell foams, are flexible and soft with several industrial applications such as medical packaging, sponges, furniture, seat cushioning, electronic and power equipment, sound insulation, shock absorption, scaffold, etc. Closed-cell foams trap air within the cell walls as they have solid walls blocking the pores and are more rigid compared to open-cell foams. As discussed earlier, one type of closed-cell foam is syntactic foam, which is formed by dispersing hollow spheres into a polymer matrix. They provide better insulation compared to open-cell foams due to the trapped air in their closed cells and also absorb less moisture. Due to their higher strength, closed-cell foams have applications in protective gear such as knee and arm sleeves, electronic device cases, shoe and footwear, heating, ventilation, air conditioning (HVAC) systems, aircraft, and automobile parts. While the open-cell foams have lower strengths, closed-cell foams have lower shock absorption and less breathability due to their closed-cells.

A recent development is to use smart polymers such as polymers with shape memory, self-healing, and self-sensing capabilities as the matrix and hybrid hollow particles as the inclusions. For example, Li and John prepared a smart syntactic foam by dispersing hollow glass microspheres into a shape memory polymer (SMP) matrix, which showed that the impact-induced cracks could be closed due to the shape memory effect, leading to tolerance to multiple impact events [38]. By further incorporating thermal plastic particles as a healing agent, 3D woven-fabric-reinforced SMP-based syntactic foam composites [39] and grid-stiffened SMP-based syntactic foam composites [40] exhibited self-healing capabilities per the biomimetic close-then-heal (CTH) strategy for damage self-healing [41, 42]. In recent years, two-way shape memory polymers (2W-SMPs) [43, 44] have also been used to prepare syntactic foams, which demonstrated reversible actuation, i.e., expansion upon cooling and contraction upon heating. Most recently, shape memory vitrimers (SMVs) have been used to prepare multifunctional syntactic foams by incorporating silver- and nickel-plated hollow glass microspheres [45, 46], which exhibited electrical conductivity and Jouel heating, electromagnetic interference shielding, damage self-healing, and end-of-life recycling capabilities, in addition to lightweight and good mechanical properties.

In summary, foams as porous structures have many potential applications in various sectors. In addition to the classical applications, foams can also be used to seal cracks and joints in structures such as joints and cracks in pavement and bridge decks [47–49]. In this book, however, we will focus on other mechanical metamaterials such as lattice structures, thin-walled structures, and plate-lattice structures.

1.1.2 Lattice Structures

Regular porous structures such as periodic lattice structures are formed by connecting several thin rods in different orientations; see Figure 1.2 for examples. Depending on the number of rods and their connectivity, they exhibit either a stretching-dominated or a bending dominated behavior. Unlike the irregular open-cell foams that predominantly fail due to bending, the lattice structures fail due to stretching or bending of the rods. It is shown that the stretching-dominated lattice structures provide about ten times stiffer and three times stronger mechanical properties under the same relative densities than the bending-dominated structures. Extensive research has been conducted into design, fabrication, and evaluation of these lattice structures. Several lattice unit cells were proposed with superior performance and various advantages in structural, thermal, impact, vibrational, and acoustic domains [50]. The octet lattice structure is one of the best stretching-dominated structures with orthotropic structural behavior [51]. Gyroid and double gyroid structures were proposed with excellent impact absorption capabilities [52]. Hollow rods were also used to design lattice structures to enhance their energy absorption capabilities [53]. Pyramid lattice structures were used to manufacture hybrid sandwich panels to have higher damping performance [54]. The effective properties of lattice structure were initially studied by Deshpande and Fleck, proposing and using an octet unit cell as a base model [52]. Continuum mechanics models were proposed to study the linear and nonlinear effective properties of

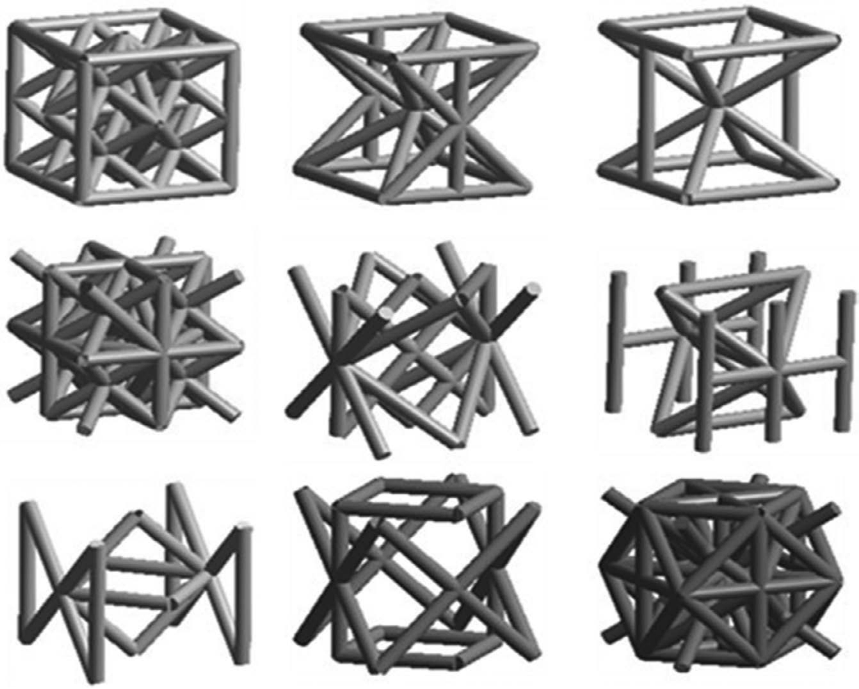

FIGURE 1.2 Several lattice structures formed by combining various cylindrical rods in different orientations. The image shows several unit cells formed by connecting slender rods in different orientations. They can be imagined as structures formed by leaning several pillars together with common joints.

lattice structure [55–61]. Also, several fabrication techniques and structural performance of these lattice structures were explored by different groups. Advanced additive manufacturing techniques made the manufacturing of these complex lattice structures rapid and in different scales from micro to macro. Due to their lightweight and effective stiffness properties, the lattice structures were extensively designed by topology optimization to reduce the mass and material consumption. They have been used to design lightweight biomedical implants, wind turbine blades, UAV wings, automobile and bike chassis, helmets, etc.

1.1.3 Thin-Walled Cellular Structures

Thin-walled structures were initially formed through mimicking honeycombs, bamboo stems, bone cross sections, muscles, beetle wings, etc. [62–65]. Figure 1.3 shows several examples. As the name suggests, these structures were formed by connecting several thin walls in different orientations. While the dominating mode of failure for these structures is the thin wall bending or buckling, they have excellent applications in lightweight packaging, energy absorption,

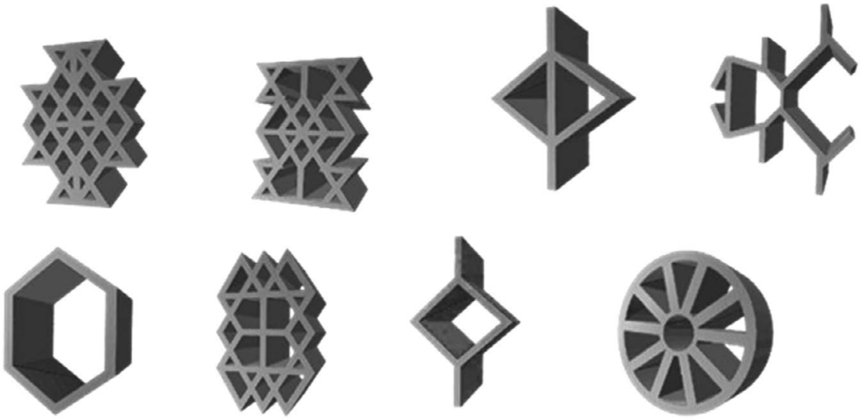

FIGURE 1.3 Several thin-walled cellular unit cells. The thin-walled structures can be imagined as unit cells formed by connecting several walls in different orientations, but only in two dimensions.

heat dissipation, and impact tolerance. Especially, the honeycomb-inspired thin-walled cellular structures formed by connecting several hexagonal unit cells have been widely studied and used in both academic research and industrial applications [63]. The hierarchical inner structures of tabular bones and muscles were mimicked to design energy-absorbing and impact-resistant cellular structures with a 176% increase in energy absorption [64]. Trabecular honeycomb structures with high energy absorption properties inspired by beetle Electra are five times better than conventional quadrilateral tubes used in the crash box beams of modern devices and vehicles [65]. Frequency optimization of the thin-walled structures was shown to be an important criterion to avoid destructive response [66]. The thin-walled structures have several industrial applications due to their energy absorption properties. Honeycomb sandwich panels are being extensively used for lightweight and energy-absorbent packaging, spoilers, vehicle bumpers, tubeless tires, floors, kitchen cabinets, etc.

1.1.4 Auxetic Structures

Auxetic structures which can be lattice structures, thin-walled structures, or a combination of both have negative Poisson's ratio, i.e., under compression, contrary to structures that thicken, the auxetic structures get thinner. Figure 1.4 shows several examples. Poisson's ratio is the ratio of lateral strain over longitudinal strain, which is positive for conventional structures. In other words, it tells how much a structure gets thicker in the lateral direction while under compression in the longitudinal direction or thinner in the transverse direction while under tension in the axial direction. However, with auxetic structures, the opposite happens. Under axial compression, the auxetic structures get thinner in the transverse

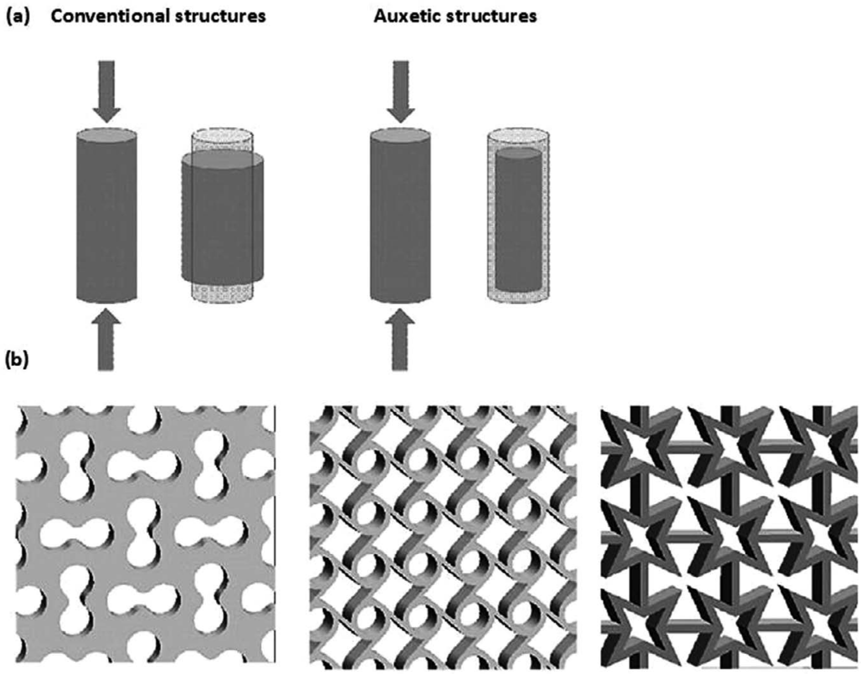

FIGURE 1.4 (a) Deformation of conventional and auxetic structures and (b) auxetic lattice structures. The images in section (a) shows the deformation contour of a conventional thin cylinder compressed. After compression, the cylinder becomes shorter and wider. It also shows an auxetic structure. Under compression it becomes shorter and thinner. In section (b), three different examples of auxetic structures are shown. One has peanut-shaped holes oriented in two directions to form an auxetic behavior, others have circular and star-shaped holes connected to show auxetic behavior.

direction, and under longitudinal tension they get thicker in the lateral direction, resulting in a negative Poisson's ratio. The structural orientation of the inner pores can be accredited for this behavior in auxetic structures. This unique behavior which is a result of their structural orientation has several applications in medical, sport, and automobile devices [67]. Several two- and three-dimensional auxetic structures have been proposed so far with abundant numerical and experimental comparisons [68, 69]. Auxetic structures have been used to design shape adaptable seats, bandages, sensors, deployable tops, and sleeves in the fashion industry, etc.

1.1.5 Hybrid-Plate Lattice Structures

Plate lattice structures (PLS) or shell-lattice structures are formed by stanching thin walls in three dimensions. While these structures look like a combination of 3D lattice structures and 2D thin wall structures they were proposed

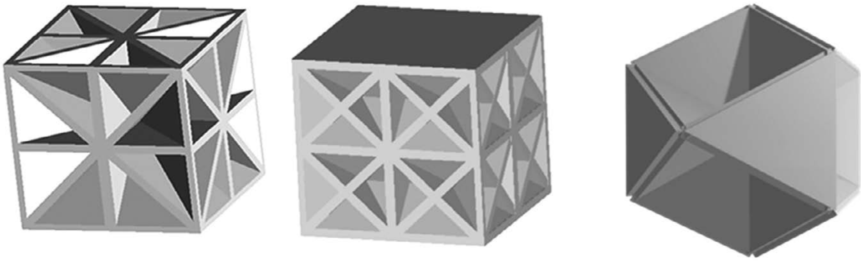

FIGURE 1.5 Plate-lattice unit cells. These cells can be imagined as several thin walls connecting to each other in different orientations in three dimensions.

to provide near-optimal mass-specific stiffness that exhibits a nearly isotropic plastic response. These materials are composed of plates that utilize material constraints in two directions [70]. At low relative densities, the stiffness of these plate-lattice structures is about 200% higher than that of lattice structures formed by thin rods [71].

During investigations into pure stiffness optimization, Sigmund et al. [72] made a noteworthy observation that optimal structures such as truss-like structures tend to be close-walled rather than open-walled. In his study, Sigmund found that a closed box with a microstructure consisting of thin walls displayed a significantly higher stiffness, around 2-3 times greater, compared to an open-cell structure featuring 12 trusses positioned along the edges of a cube with a low volume fraction. Furthermore, Liu et al. [73] used an analytical method to show that the stiffness of a cubic plate is two times higher than the stiffness of a cubic truss of the same mass. In any given loading direction, plate-lattices exhibit superior structural efficiency, meaning they distribute strain energy more evenly among their components and have a greater proportion of members aligned favorably with the loading direction, in contrast to a corresponding beam-lattice [71]. Therefore, the findings suggest that further investigation is warranted for the PLS. Nevertheless, these benefits are offset by a substantial rise in fabrication complexity. The closed-cell structures of three-dimensional plate lattices render traditional fabrication methods, such as assembly techniques unfeasible, leaving additive manufacturing as the sole viable approach. However, extracting raw materials contained within the closed-cells remains a difficult task. Figure 1.5 shows several examples.

1.1.6 Biomimetic and Hierarchical Lightweight Structures

The structures that are inspired or mimicked from nature are called biomimetic structures. These structures carry forward the inherent structural advantages present in the natural structures from which they are inspired. Several lightweight structures such as irregular open-cell foams, honeycombs structures, and auxetic structures were initially inspired through biomimicry. Trabecular bone is the inspiration to design several open-cell irregular foams and thin-walled cellular structures. The widely studied hexagonal honeycomb cellular structures were inspired from honeycomb. Several plant stems were mimicked to design lightweight rods with better buckling resistance.

From 2D and 3D lightweight structures, the authors have proposed several higher order lightweight structures by replacing the rods in 3D lattice unit cells with an array of similar or other mini-unit cells; see Figure 1.6. It is studied that these higher order structures (Second) have a factor of 1.5 improvement in the scaling relationship for strength and a factor of 1.6 improvement for modulus over first-order structures. From the point of view of fractals, these structures show geometrical similarities, and the dimension is a fraction, instead of a whole number. Similarly, studies have been focused on optimizing several other lightweight structures by replacing the local rods or thin walls to design higher order lightweight structures which shall be presented in detail in the coming chapters [74–80].

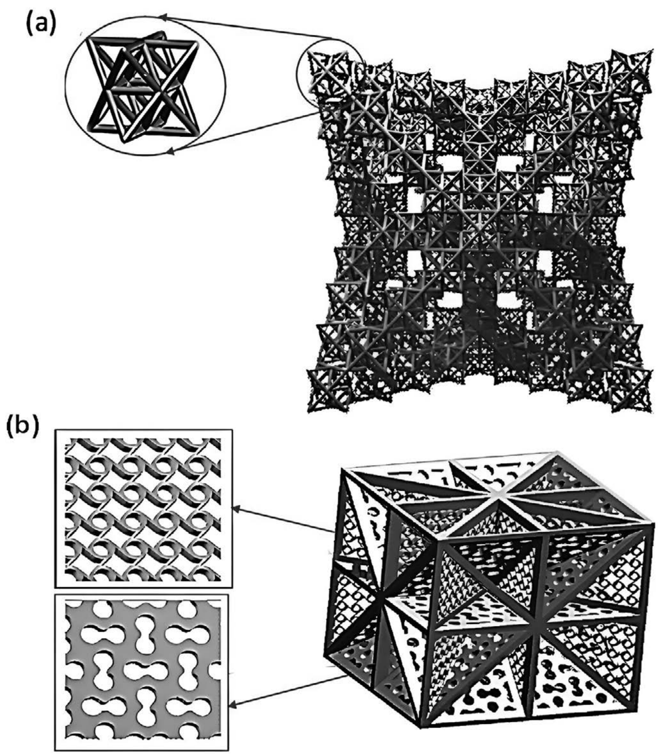

FIGURE 1.6 (a) Second-order octet lattice structures and (b) higher order plate lattice unit cell with auxetic walls. Second-order octet unit cell can be imagined as filling a lattice truss unit cell by replacing the slender rods with smaller unit cells of the same structure.

1.1.7 Summary and Future Perspective

This chapter delves into the realm of lightweight structures, covering a diverse array of configurations such as open- and closed-cell foams, lattice structures, thin-walled cellular structures, auxetic structures, and hybrid plate-lattice cells. These structures offer multifunctional advantages in structural, acoustic, and thermal properties, making them increasingly prominent in both academic research and industrial applications.

The chapter discusses mechanical behaviors, fabrication techniques, and applications of various lightweight structures. For instance, irregular foams, with their intricate cellular architectures, offer exceptional stiffness-to-weight ratios and find applications in lightweight sandwich cores and energy absorption systems. Lattice structures, formed by interconnecting thin rods, exhibit superior stiffness and strength properties, revolutionizing lightweight design across industries. Thin-walled cellular structures, inspired by natural phenomena like honeycombs and trabecular bones, excel in energy absorption and impact resistance applications. Auxetic structures, characterized by a negative Poisson's ratio, exhibit unique mechanical behavior with applications in medical devices, sports equipment, and automotive components. The chapter also introduces hybrid plate-lattice structures, which combine the advantages of lattice and thin-walled structures, offering near-optimal mass-specific stiffness and isotropic plastic responses. Advanced manufacturing techniques, including additive manufacturing, have played a pivotal role in realizing these complex structures, enabling rapid prototyping and customization.

To summarize, there are several lightweight structures, and each of them has its own advantages and disadvantages and fields of applications [70, 80–96]. Based on the mode of deformations, the lightweight structures have applications in different fields. The open-cell and closed-cell foams are being extensively used for a variety of industrial insulation applications. The lattice structures are advantageous for high strength and stiffness applications, while thin-walled structures are good for energy absorption or damping applications. Figure 1.7 shows the comparisons of several lightweight structures [97].

While several studies have been focused on the design, analysis, and manufacturing techniques for these lightweight structures, it is believed that there exists a wide range of unexplored design space. The continuous demand for lightweight, strong, multi-functional, and cost-effective structures calls for novel structure design and optimization techniques. With the advancement in computational science and data-driven techniques, structural design using artificial intelligence has become a current area of research. Methods such as machine learning, statistical analysis tools, data mining, etc., help in reaching closer to the global optimal solutions and much easier surpassing complex numerical analysis. Hierarchical structures and combinations of different lightweight structures and multifunctional materials are a potential area of interest and are yet to be explored. Because in the biological realm, most structures are made of porous lightweight structures, they provide bioinspiration for humans to mimic these biological structures or

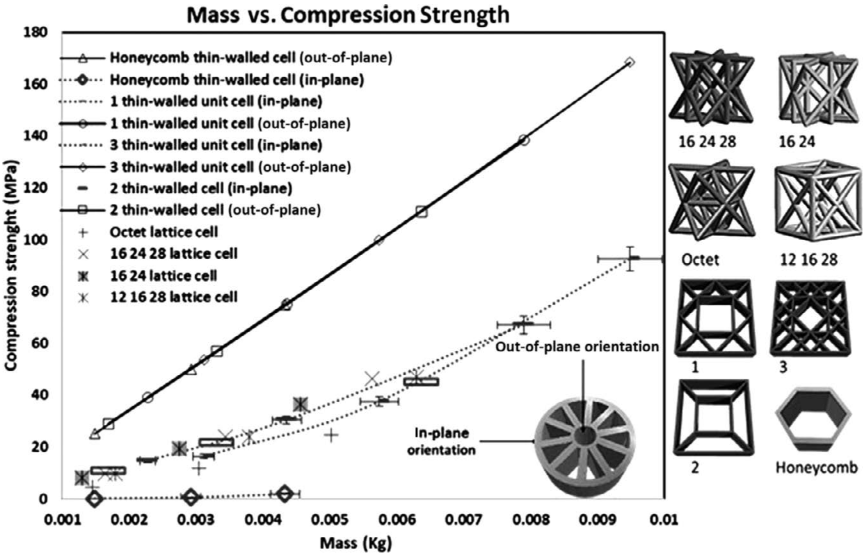

FIGURE 1.7 Mass versus strength comparisons of lattice truss unit cells, and thin-walled unit cells in the in-plane and out-of-plane orientations [97] (Copyright 2023 Elsevier, with permission). It can be seen that the thin-walled unit cells in the out-of-plane orientation have higher compression strengths, while the lattice truss unit cells and the thin-walled unit cells in the in-plane orientation have similar strength properties.

help create a database for training machine learning models. More discussions on several lightweight structures, design, and optimization techniques using data-driven techniques will be presented in the coming chapters.

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