Review | Received 24 August 2025; Revised 13 March 2026; Accepted 16 March 2026; Published 18 March 2026
https://doi.org/10.55092/sc20260005

Research development in intelligent generative design methods for steel modular structures

Yang Liu[1,2], Kaiyue Zhou[1], Zhihua Chen[1,2], Jiadi Liu[1,2],*and Hongbo Liu[1,2,3,4]

[1] School of Civil Engineering, Tianjin University, Tianjin 300072, China
[2] State Key Laboratory of Hydraulic Engineering Intelligent Construction and Operation, Tianjin 300354, China
[3] School of Civil Engineering, Hebei University of Engineering, Handan 056038, China
[4] Hebei Provincial Key Laboratory of Low-carbon Construction and Resilience Improvement of Construction Engineering, Handan 056038, China

* Correspondence author; E-mail: jdliu@tju.edu.cn.

Highlights:

- A systematic review of AI-driven generative design for modular construction is conducted.
- The evolution from single-objective tools to integrated, sustainable design solutions is identified.
- Future research integrating data-driven methods with domain knowledge for practical engineering is outlined.

Abstract: In recent decades; the field of artificial intelligence is undergoing rapid advancement; diverse technologies increasingly supporting the intelligent transformation of the construction industry. A key research challenge in modular construction is to generate structurally feasible designs that ensure both quality and efficiency. Although the concept of generative design has drawn great attention in this field; reviews of relevant research findings remains lacking. The analysis is structured around two technical scopes—classic artificial intelligence and modern artificial intelligence—and examines the application of various AI techniques across several core aspects of structural design: intelligent generation of structural schemes; single and multi-objective optimization; and modular spatial layout and construction drawing generation. Statistical findings reveal that AI technologies have progressively evolved from localized; single objective applications toward integrated; market-oriented; and sustainability-aware solutions for modular construction projects. Finally; this paper puts forward several future research directions; focusing on data-driven and knowledge-integrated approaches; validation in practical engineering contexts; and multi-objective sustainable optimization. These trends aim to enhance the overall capability of intelligent generative design for modular structures. What's more; this paper encompasses modular systems of various materials; with the emphasis placed on their shared generative design methodologies.

Keywords: generative design; modular construction; artificial intelligence; structural design

1. Introduction

1.1. Background

In 1990s, the concept of "structural rationalism" was proposed by Viollet le Duc. It has emphasized that architectural forms should genuinely reflect the logic of structural forces. Driven by this theory, the development of modern architectural structural design is reflected in advances across multiple stages, including design theory, methodology, technology, and normative standards [1]. Nowadays, the structural design methodology comprises several main stages, including structural scheme design, scheme optimization, and construction drawing design. Among these, design decisions made by engineers during structural scheme design stage, especially early design stage, significantly influences the subsequent structural performance.

Modular construction is a kind of building in which modular units are prefabricated in factories, transported to the construction site, then lifted and assembled into complete buildings. The common module unit is the containerized unit [2–5]. In this review, the term "modular construction" specifically refers to "steel box modular building", which are defined as follows: A box module is a kind of prefabricated 3D units in buildings, based on standard shipping containers or similar box-shaped structures. It is manufactured in factories through industrialized production lines, with the main structure, enclosure systems, internal pipelines, and finishing works completed during production, thereby endowing it with full building functionality. These units feature uniform interfaces and dimensional specifications, enabling rapid hoisting and assembly on construction sites to form various architectural configurations.

This scope also includes generative design studies focusing on individual components including precast beams, slabs, columns and braces in conventional prefabricated buildings. Furthermore, the reviewed literature encompasses modular systems of various materials, with the emphasis placed on their shared generative design methodologies rather than specific material details.

1.2. Motivation

A thorough investigation of existing modular construction practices reveals several prevalent challenges in their structural design:

(1) Low efficiency and repetitive tasks: The standard structural design process in engineering involves producing construction drawings, creating 3D models, and performing structural safety calculations and verifications. However, architectural design institutes and other units exhibit a relatively low reuse rate of completed drawings, leading to a high proportion of repetitive tasks throughout the design process [6,7].

(2) High reliance on manual expertise and inconsistent quality: Contemporary design patterns demonstrate a significant dependence on decisions made during the early design phase. This often results in a disconnect between the design scheme and construction requirements, low efficiency in drawing production, and insufficient transparency in the design process [8–10].

(3) Difficulty in handling multi-objective constraints: Common design schemes struggle to simultaneously satisfy all requirements within diversified objectives. These schemes rely heavily on engineers' knowledge and experience. Consequently, the prevalent "human centered" design model finds it challenging to incorporate all explicit and implicit rules and constraints systematically [1,11,12].

(4) Inherent complexities in dynamic performance: Unlike conventional monolithic structures, modular buildings assembled from discrete units exhibit distinct dynamic behaviors due to discontinuities at inter modular connections. The mechanical performance, especially the lateral stiffness and overall vibrational characteristics, is highly sensitive to the stiffness and integrity of these connections [13]. This adds a layer of complexity to the generative design process, as AI-generated structural schemes must not only satisfy static strength requirements but also ensure dynamic performance under wind load and seismic load.

Consequently, Modular construction is widely used for temporary buildings and rapid construction projects [1,14]. Therefore, adopting a faster and more intelligent design paradigm is imperative to bridge the gap between the pressing need for rapid drawing production in design units and the currently underdeveloped design efficiency and scheme quality.

1.3. Research gap

In such cases, adopting automated and intelligent design patterns has become a significant industry demand [14]. Recent advancements in Artificial Intelligence (AI) have introduced numerous transformations in architectural planning, design, construction, and maintenance [1,15,16]. Intelligent design methodologies underpinned by AI have emerged as a pivotal catalyst for advancing structural design [17–19], providing a comprehensive technical framework for optimizing modular structural design patterns.

While the concept of intelligent generative design has gained attention in this field, a systematic synthesis of highly relevant research findings remains lacking. Although comprehensive reviews exist on the broader application of machine learning in structural design and optimization, such as Sun’s publication, they understandably cover a wide spectrum of structural types and tasks. A focused analysis dedicated specifically to intelligent generative design methods for modular building structures—tracing the evolution from classic to modern AI paradigms and their application across the core design stages—is still absent from the literature. This targeted gap creates difficulties for practitioners and researchers specifically interested in the automated and intelligent design of modular systems.

Generative AI design employs algorithms like deep learning, enabling computers to learn from existing architectural drawings and simulate engineers’ design experience. This process generates new design data from given inputs, such as text, images, video, audio, or code [20–22]. By producing a substantial number of design alternatives and iteratively evaluating them, an optimal solution is identified. This application frequently exhibits characteristics of automated and intelligent structural design [17,18,23,24]. This approach effectively produces structural solutions that are more efficient, rationally designed, and exhibit superior performance.

The concept of generative design was proposed by Frazer in 1994 [25]. Its essence involves creating iterative algorithms by simulating natural evolutionary processes using computers. Subsequently, intelligent design methodologies based on knowledge-based system algorithms [26] and biologically inspired methods emerged for application in architectural structural design. However, the functionality of these early algorithms was constrained by parameter sensitivity and data complexity. The coding process is known to be relatively complex [10,27], which has been shown to result in reduced design efficiency and inconvenient expression of requirements as well as hindered the wide application of early algorithms. The majority of AI Most AI technologies emerging before 2012 are classified as Classic AI methods [28].

Significant progress in AI, particularly in deep learning, was achieved after 2012, leading to its extensive application in engineering domains [29]. AI technologies from this stage are referred to as modern AI methods [28]. Research indicates that AI technology has demonstrated notable efficacy in modular structural design. For instance, Bhosekar and Ierapetritou [30] proposed a new method for analyzing the flexibility of modular structures, utilizing a machine learning-based classifier model and establishing a multi-objective design optimization framework. Liu *et al*. [31] proposed a novel framework system based on the Graph Constrained Generative Adversarial Network (GC-GAN) paradigm to facilitate the rapid generation of floor plans for high-rise residential buildings.

Currently, the application of generative AI shows promising potential for further development. Integrating Large Language Models (LLMs) with architectural design is a key focus of several development initiatives, such as OpenAI's DALL·E and ChatGPT, DeepMind's AlphaFold, and China's independently developed DeepSeek. Zhang *et al*. [32] developed a general workflow based on LLM planning, which takes architectural descriptions as input and ultimately generates error-free EnergyPlus building energy models. Nevertheless, targeted generative AI technologies specifically applied to the modular design paradigm require further exploration. It is foreseeable that generative design will substantially transform the design paradigm for modular structures. This study reveals that exploration into technology development, practical application, and algorithm model construction remains inadequate. The absence of a comprehensive and systematic theoretical framework and clear research directions in this field [14] creates difficulties for practitioners when selecting structural generation methods. Concurrently, fully capitalizing on the significant benefits offered by automated and intelligent structural design methodologies remains challenging. These issues have become obstacles to the development and application of generative design technology, necessitating collaborative efforts from numerous scholars and engineers within the industry to address this situation.

1.4. Objectives

Based on the mentioned research background and identified gaps, this paper aims to provide a systematic review of the research developments in intelligent generative design methods for modular building structures. The objectives and organizational structure of this article are outlined as follows:

Chapter 1: Introduction. This chapter elaborates on the challenges in modular structural design, the opportunities presented by Artificial Intelligence, and defines the research motivation, gaps, and objectives of this study.

Chapter 2: Overview of generative design. It reviews the fundamental concepts, historical development, and application frameworks of generative design in architectural and structural engineering, establishing a theoretical basis for subsequent analysis.

Chapter 3: Literature review methods and preliminary analysis. This chapter explains the systematic literature retrieval strategy and screening process employed. It also provides a quantitative analysis of the included literature, covering temporal distribution, research themes, and technology types, to reveal developmental trends in the field.

Chapter 4: Application of generative design methods based on classic AI technologies. It focuses on reviewing representative studies, technical characteristics, and application limitations of classic AI methods in the generative design, optimization, and layout of modular structures.

Chapter 5: Application of generative design methods based on modern AI technologies. This chapter provides an analysis of how modern AI technologies, such as deep learning, generative adversarial networks, reinforcement learning and large language models. All of their applications are driving advances in the automation, intelligence, and performance optimization of generative design.

Chapter 6: Future development trends and conclusion. It offers a forward-looking discussion on potential development paths and challenges for intelligent generative design, focusing on hybrid intelligence, integration in engineering practice, and multi-objective sustainable optimization. This chapter also summarizes the conclusion of the review and provides suggestions for future research directions.

Through this structure, this study seeks to systematically present the research landscape of intelligent generative design methods in the field of modular structures, providing a comprehensive reference for researchers and engineers.

2. Overview of generative design

2.1. Generative design

The development of generative design is inextricably linked to the iterative progress of computer technology. Driven by rapid advancements in both software [33,34] and hardware [35,36] capabilities, the architectural structural design field has witnessed the emergence and evolution of various design paradigms, such as computer-aided design (CAD) and parametric design. This progression follows an overarching trend from "digitalization" to "automation" and finally to "intelligence" [1]. The core distinction lies in the different forms through which computer technology exerts its effectiveness in structural design:

(1) "Digital Design" refers to the process of representing buildings using software platforms like Building Information Modeling (BIM) and CAD. Its essence is CAD.

(2) "Automated Design" denotes the process of generating structural models and performing analytical calculations automatically through specific algorithmic iteration mechanisms.

(3) "Intelligent Design" places significant emphasis on autonomous learning and the continuous refinement and enhancement based on existing knowledge, aiming to produce complex solutions that go beyond Boolean calculations [1].

Generative design methods represent a recent development in the field of intelligent design, integrating new elements of "digitalization", "automation", and "intelligence" [37].

The evolution of generative design is further marked as a collaborative partner in the engineering process. It is underpinned by a spectrum of computational strategies that leverage artificial intelligence and algorithms to autonomously generate a multitude of structurally feasible solutions. These strategies are distinguished by their capacity to concurrently process multifaceted design criteria and constraints, such as material properties, manufacturing methodologies, and key performance objectives, like stiffness maximization or mass minimization [38]. This integrative approach enables the exploration of diverse structural configurations and material combinations in a single study, systematically generating a range of optimal or near-optimal alternatives that satisfy complex architectural and engineering requirements in distinct ways. The methodology proves particularly potent for modular structures, where it can efficiently balance global system performance with the specificities of prefabricated unit assembly [1,38].

The scope of application has consequently undergone gradual expansion. Early efforts focused on generating single-functional planar topological relationships. Today, the field encompasses parametric modeling of complex architectural forms, intelligent selection of multi-scale structural systems, and multi-objective collaborative optimization informed by environmental performance simulations. The current generative design process for building structures, with relevant engineering applications [6,39,40], exhibits distinct “intelligent” characteristics, which primarily involve three steps:

(1) Feature learning and data construction: AI technology extracts features from a substantial number of historical structural design drawings. Through machine learning, it assimilates insights from engineers’ design experiences and theories, ultimately forming a comprehensive dataset.

(2) Constructing intelligent models, such as deep neural networks, is imperative for understanding the mapping relationship from architectural schemes to structural designs and for acquiring generation capabilities.

(3) Scheme generation and output: A well-trained intelligent system, based on the input architectural design scheme, simulates engineers’ design thinking to generate structural design schemes (buildable construction deliverables). The outcomes are typically innovative, economically viable, and align with specified requirements.

2.2. Intelligent design process of modular buildings

The intelligent design process for modular buildings builds upon the general principles of building structural design while developing its own distinct characteristics. This process typically begins with the quantification of design constraints, where structural engineers translate performance indices, environmental factors, and cost objectives into specific parametric constraints.

Subsequently, AI iterative mechanisms, such as genetic algorithms [23,41], machine learning [23], and deep learning [23,31,42] are employed to automatically generate a multitude of design alternatives. These alternatives encompass various modular unit combinations, overall structural floor plans [27], and structural visualisation models [17], thereby providing a rich basis for making decisions.

Previous academic explorations in intelligent design and analysis offer valuable references for modular structures. Several review studies have systematically organized this field [29,43]. Specific applications include: Adeli and Hawkins[44] utilizing biologically inspired methods for optimizing modular high-rise buildings, Taiwo *et al.* [19] constructing a generative AI framework for construction enterprises via the Delphi method and Ko *et al.* [45] pioneering machine learning-based spatial layout planning and outlining several future development pathways.

However, research specifically focused on generative design for modular structures, as a distinct typology, remains fragmented and lacks systematic consolidation. Earlier reviews,such as the one by Jeong and Jo [46]laid a foundational understanding. However, the field has since witnessed an explosive growth, particularly driven by modern AI technologies after 2020, which have fundamentally reshaped the capabilities and applications of generative design. This gap in the current research landscape, especially concerning the AI-driven paradigm shift after 2020, makes it challenging to gain a comprehensive understanding of the field’s latest development and technological pathways.

Therefore, a dedicated and up-to-date systematic review is particularly critical and necessary, which constitutes the core objective this review aims to fulfill.

3. Literature review methods

This section details the methodology employed in this systematic literature review to ensure transparency, reproducibility, and rigor. The review aims to systematically synthesize the latest advancements in "AI technology-based generative design methods for modular structures", with a specific focus on the application of AI models during the structural design phase.

3.1. Literature database and retrieval strategy

A systematic literature search strategy was formulated and executed, comprising the following four key components:

(1) Database selection: The search was performed across multiple major academic databases, including Web of Science Core Collection (WOS), Scopus, China National Knowledge Infrastructure (CNKI). This approach aimed to comprehensively cover high-impact research literature published internationally and in Chinese.

(2) Primary and supplementary sources: Given its authority and broad recognition, the Web of Science Core Collection was designated as the primary literature source for this study [28]. Scopus served as a supplementary source to enhance the coverage of international literature, while CNKI, Wanfang, and VIP were utilized to exhaustively retrieve core Chinese journal articles covering indexes such as SCI, EI, Peking University Core, CSSCI, CSCD, and AMI.

(3) Search query and timeframe: To ensure precision and reproducibility, a structured search query based on keyword combinations was developed, as detailed in Table 1. The publication date range was set from January 1990 to June 2025 to capture the technology's complete evolution from its inception to the present state.

(4) Screening and synthesis: The literature initially identified through the above strategy will be screened according to predefined inclusion and exclusion criteria, followed by systematic synthesis to ensure comprehensiveness and representativeness.

3.2. Literature search and data screening

To ensure a systematic, transparent, and reproducible literature screening process, this study adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [47]. The complete screening process is illustrated in Figure 1 (the PRISMA flow diagram).

Initially, searches were conducted across three databases—Web of Science Core Collection, Scopus, and CNKI—using the search formulas detailed in Table 1, with the publication type limited to journal articles. This preliminary search identified a total of 521 potentially relevant records (WOS: 334, Scopus: 183, CNKI: 4).

Table 1. Systematic search queries used for literature retrieval.

Domain	Boolean Search Formula
(a) Generative Design (GD)	(“generative design” OR “form finding”) AND (“architect*” OR “building” OR “structural engineering” OR “structural form”) AND (“modul*” OR “prefabricat*” OR “component”) [a,b,c,d]
(b) Classic AI-based Methods	(“generative design” OR “form finding”) AND (“architect*” OR “building” OR “structural engineering” OR “structural form”) AND (“modul*” OR “prefabricat*” OR “component”) [a,b,c,d]
(c) Modern AI-based Methods	(“building” OR “architect*” OR “structural form”) AND (“modul*” OR “prefabricat*” OR “component”) AND (“structural design” OR “form generation”) AND (“intelligen*” OR “automat*” OR “artificial intelligence” OR “AI” OR “design intelligence” OR “generative” OR “optimiz*”) AND (“expert system*” OR “fuzzy logic” OR “genetic algorithm” OR “generative grammar” OR “evolution*” OR “the force density method” OR “thrust network analysis” OR “combinatorial equilibrium modeling” OR “3D graphic statics”) [a,b,c,d,e,f,g]

[a] The asterisk serves as a wildcard character to capture variations of a word. Searches were typically conducted within the fields of Title, Abstract, and Keywords; [b] “architect*” refers to architecture, architectural, architect; [c] “modul*” refers to module, modular, modularity, modularization; [d] “prefabricat*” refers to prefabrication, prefabricated, prefabricate; [e] “intelligen*” refers to intelligence, intelligent, intelligently; [f] “automat*” refers to automation, automated, automatic, automate; [g] “optimiz*” refers to optimization, optimize, optimizing, optimizer.

Subsequently, a multi-stage screening process was implemented based on predefined inclusion and exclusion criteria:

(1) Duplication removal: Duplicates were removed automatically using reference management software and manually verified for cross-database overlaps, resulting in a set of unique records.

(2) Initial screening (Title, Abstract): Two reviewers independently screened the titles and abstracts of these unique records, excluding studies that were clearly irrelevant.

(3) Full text assessment: The full texts of the remaining articles were retrieved and thoroughly reviewed. Articles that did not meet the thematic focus, lacked clear methodological descriptions, or provided insufficient data were excluded.

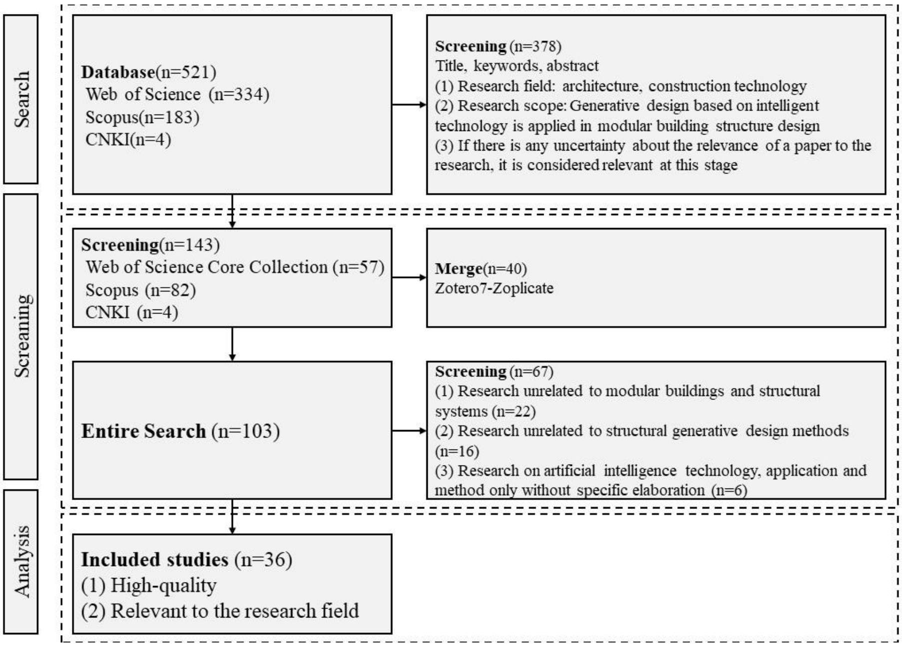

Figure 1. PRISMA retrieval flowchart.

Any disagreements between the reviewers were resolved through consensus or by consulting a third researcher. The final set of articles included for analysis in this review was thereby determined. Detailed screening results and reasons for exclusion at each stage are documented in the PRISMA flow diagram.

To ensure a systematic, transparent, and reproducible literature screening process, this study strictly followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The complete flow of the search and screening process, along with the results at each stage, is detailed in Figure 1 and involved the following three phases:

In phase “searching”, a systematic search across the Web of Science Core Collection, Scopus, and CNKI databases initially identified 521 potentially relevant records (see Table 2).

Table 2. Literature database search results.

Database [a]	(a) Generative Design	(b) Classic AI Methods	(c) Modern AI Methods	Total
Web of Science Core Collection	241	43	50	334
Scopus	107	39	37	183
CNKI	2	1	1	4
Grand total	350	83	88	521

[a] Results are based on the search queries detailed in Table 1 and represent the initial number of records identified before screening.

In phase “screaming”, the titles, abstracts, and keywords of the 521 records were screened against predefined inclusion criteria:

(1) Research field: Focus on architecture and construction technology.

(2) Core content: Involvement of intelligent generative design for modular building structures.

(3) Conservative principle: Records of uncertain relevance were retained for the next stage.

This screening resulted in 143 publications. These were imported into Zotero [48] for management. A combination of automated deduplication (using a plugin, which merged 37 duplicates) and manual checking (removing 3 further duplicates) identified 40 duplicates in total. Consequently, 103 unique records proceeded to full text review.

In phase “analysis”, the full texts of the 103 articles were thoroughly assessed for eligibility based on stricter criteria. The exclusion criteria were:

(1) Not focus on modular building structures: conventional high-rise structures [47,49–52], frame structures [53].

(2) Not focus on generative design approaches: parametric design [54].

(3) Not focus on structural design: urban planning [55] and building-integrated photovoltaics [49–52,56,57].

(4) Not focus on architectural structural forms: bridges [58,59] and pipelines [55,60].

Applying these criteria led to the exclusion of 36 articles. Ultimately, 67 articles were confirmed to align perfectly with the scope of this review and were included for next synthesis and analysis.

3.3. Preliminary literature analysis

An initial analysis of the screened literature reveals an evolutionary path of computer technology in architectural structural design. Digital design technologies, epitomized by CAD and BIM, have enabled the digital representation of the entire building structure lifecycle, laying the groundwork for subsequent automation and intelligence [1]. Building upon this, traditional parametric design methods primarily rely on human-defined rules and logic.

To further enhance design automation, scholars have begun exploring the integration of AI technology with these digital design platforms. The core objective is to automate specific stages within the modular structural design process, aiming to significantly reduce manual effort and time consumption. However, the analysis indicates that existing successful applications are mostly concentrated in relatively mature areas. For more pivotal and complex stages in the structural design process, such as autonomous structural modeling, intelligent scheme generation, and multi-objective collaborative optimization, AI technology's deep integration remains at an early stage, facing challenges like model construction, knowledge representation, and making multi-objective decisions. This finding clarifies the current research frontier and bottlenecks, providing a clear rationale for the subsequent detailed analysis of how Classic and modern AI technologies are applied to, and differ in tackling, these core challenges.

3.4. Annual trends and content analysis

Based on the final set of 67 included articles, this review charts their annual publication trend (Figure 2) and analyzes the distribution of research topics to reveal the field's emerging priorities.

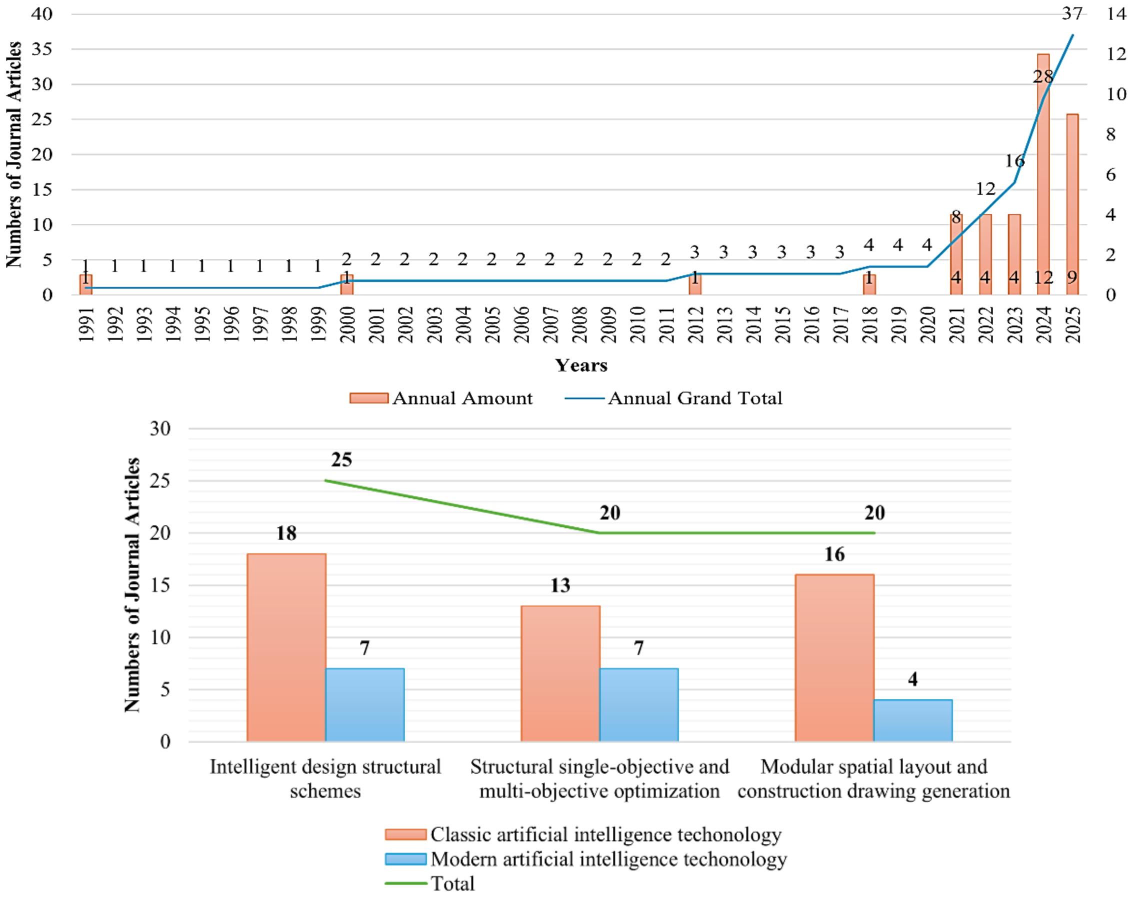

Figure 2. The trend chart of the number of journal published papers retrieved.

3.4.1. Publication trend analysis

The annual distribution of the final 67 included publications (Figure 2) clearly delineates the field's evolution from obscurity to emergence. During the nascent stage (1991–2010), only four relevant publications appeared over nearly two decades, indicating that intelligent generative design for modular structures was still conceptual, receiving minimal attention from academia and industry, with practice relying on traditional methods. The field entered a slow development stage (2011–2020), characterized by fluctuating but gradual growth in publication numbers. This phase was primarily facilitated by preliminary advancements in technologies like BIM, the Internet of Things, and early AI technologies, which provided the necessary technical foundation. Nevertheless, its development pace lagged behind the broader digital transformation trend within the prefabricated construction sector [61].

A rapid growth stage (2021–2025) commenced, marked by an explosive increase to 59 publications, accounting for 88.1% of the total. This surge is driven by national strategies promoting intelligent construction and the maturation of modern AI technologies, particularly deep learning. Most notably, the number of articles retrievable for the first half of 2025 alone has already surpassed the total for the entire year of 2024, strongly signaling that this field is rapidly accelerating as a key emerging academic frontier and research focus.

3.4.2. Research topic distribution

In relation to the substance of the text, a selection of two review articles has been made [62,63]. A systematic analysis of the research themes is conducted across the 67 articles. This analysis reveals the focal points of intelligent generative design within the modular structural design process. The distribution of core research topics is summarized in Table 3.

Table 3. Distribution of research topics in the reviewed literature (Total: 67 articles).

Research Topic	Number of Articles	Primary Focus
Intelligent Generation of Structural Schemes	25	Automated or semi-automated creation of preliminary structural solutions and models.
Single and Multi-Objective Structural Optimization	20	Finding optimal solutions for performance, cost, and other objectives under constraints.
Modular Spatial Layout and Construction Drawing Generation	20	Rational planning of spaces and automated production of construction documents.
Review and Systematic Analysis	2	Summarizing the field's development, challenges, and future trends.

As shown, publications are predominantly concentrated on three core aspects: the intelligent generation of structural schemes, structural optimization, and spatial layout & drawing generation. This distribution underscores that AI is deeply penetrating and reshaping these critical phases of modular structural design.

From a macro perspective, over 75% (more than 50 articles) of the literature involves the application of AI technology in one or multiple core stages of structural design. This overwhelmingly demonstrates that AI is no longer a peripheral tool but is deeply penetrating and reshaping various phases of modular structural design, signaling an inevitable trend towards the intelligent transformation of the design paradigm.

3.4.3. Evolution of research frontiers

A keyword hotspot analysis of 32 articles published between 2020 and 2025 (Figure 3) visually captures the dynamic evolution of the field's research frontiers. In the early phase (2020–2022), research hotspots were relatively concentrated, primarily around specific component performance and direct technical metrics such as "Consumption", "Walls", and "Energy Efficiency". From 2023 to 2025, the keyword map demonstrates a significant trend towards diversification and deepening. On one hand, "Generative Design" and "BIM/Building Information Modeling" emerged as core concerns at the tool level, indicating a shift from solving isolated problems towards establishing integrated intelligent design workflows. On the other hand, the increased prominence of keywords related to architectural forms like "Modular Buildings" and "Housing", coupled with the first appearance of terms such as "Algorithm", "Industry", and "Sustainable Buildings". It collectively reveals a fundamental transition: the research focus is expanding from localized, isolated efficiency gains towards a more comprehensive and systematic engineering integration.

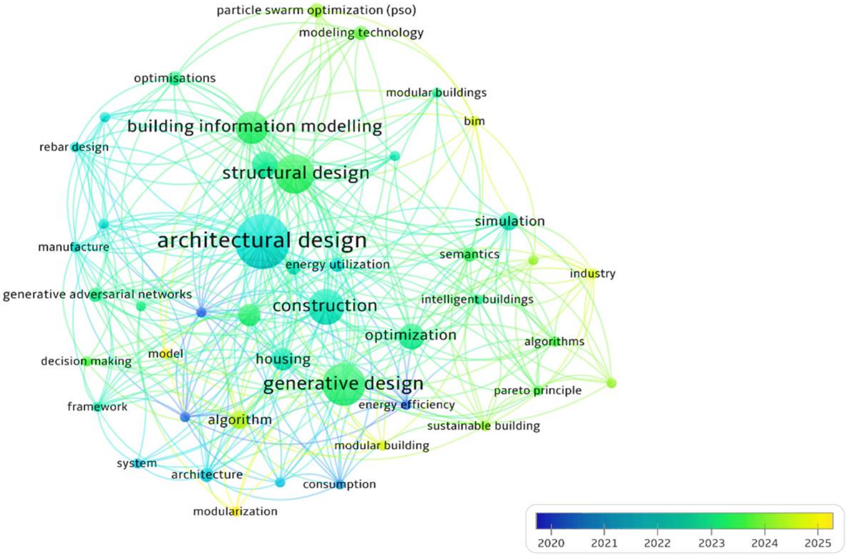

Figure 3. The heat map of the keywords of the journal published papers retrieved.

This integration aims to achieve the combined value of modular buildings in terms of marketability, refined construction, and full-lifecycle sustainability. This evolution signifies that the field is actively constructing a complete research system that integrates design theory, intelligent algorithms, and engineering practice.

4. Application of generative design methods based on classic AI technologies

This chapter reviews the application of classic AI technologies in the generative design of modular structures. While some of the cited methods were initially developed for general structural systems, their principles, limitations, and evolutionary paths are highly relevant and have been directly applied or are readily adaptable to the specific challenges of modular construction, such as component assembly, layout optimization, and rule-based configuration.

In the evolution of intelligent generative design, classic AI technologies laid the preliminary groundwork for automation and optimization. As indicated by the trends in Figure 2, during the nascent and slow development stages prior to approximately 2012, relevant research primarily relied on two categories of classic AI methods: knowledge-based systems and biologically inspired methods. Knowledge-based systems, such as expert systems, fuzzy logic, make decisions by encoding the explicit design rules and logic of human experts. In contrast, biologically inspired methods, such as Genetic Algorithm (GA) [64], Particle Swarm Optimization (PSO) [65], search for optimal or near-optimal solutions within a vast solution space by simulating natural evolutionary processes or collective swarm behaviors.

The common core of these classic methods lies in their reliance on manually predefined, explicit rules. The entire generative process operates within a computational framework of digital constraints established by engineers beforehand, typically encompassing module dimensions, material specifications, weights for optimization objectives, and geometric rules. The system performs iterative computation and reasoning based on these rules, ultimately outputting topological relationships and structural schemes that satisfy all predefined conditions.

Consequently, classic AI methods are particularly suited for scenarios involving relatively simple structural forms, where design objectives and constraint principles are straightforward and readily quantifiable. They significantly enhanced the solving efficiency for such problems and integrated structured knowledge into the design process. Representative papers in this domain are listed in Table 4, and their specific applications will be detailed in the following subsections.

Table 4. Some representative papers with classic AI technologies.

Author	Research Method	Research Objective
Zheng *et al.* [41]	Genetic Algorithm (GA)	To optimize building layout and cost for sales-oriented design in mass customization.
Chang *et al.* [62]	GA	To study intelligent generative design methods for modular steel building layout plans, forming a multi-objective problem.
Lin *et al.* [63]	GA	Aimed specifically at the modularization problem of segmenting floor plans into modular units (ModulePacking).
Dzwierzynska and Lechwar [66]	GA	To design effective structures that are characterized by the lowest possible steel consumption for steel canopies.
Zhou and Xue [67]	Non-dominated Sorting Genetic Algorithm II (NSGA-II)	To formulate parametric MiC envelopes and detailed layout, with the two objective functions being energy efficiency and interior daylight performance.
Xu *et al.* [68]	Particle Swarm Optimization (PSO)	To automatically complete the splitting design of PCSs (prefabricated composite slabs) and minimize composite costs.
Xu *et al.* [69]	Particle Swarm Optimization (PSO)	Aiming at the complex steel bar layout problem in prefabricated building.
Xing *et al.* [70]	Improved Float Encoding Genetic Algorithm (IFGA)	Aiming at the problems of large steel mass and low refinement degree in the design process of temporary broadcast tower structures.
Li *et al.* [71]	Hybrid Genetic Algorithm	For rebar design optimization incorporating DfMA principles to balance material and installation cost.

4.1. Design of structural schemes

The application of classic AI technologies in the intelligent design of structural schemes demonstrates an evolution in paradigm from rule-driven local automation towards system integration and performance-driven approaches.

4.1.1. Rule-driven automated templates

Early research focused on achieving design automation by encoding explicit rules. A representative work is the “Intelligent Parametric Template” (IPT) proposed by Sacks *et al.* [72] in 1991. This research utilized the “knowledge module” within the object-oriented BPDM software to embed design rules into the system, enabling the automated generation of both overall and detailed structural designs for rectangular plan buildings. This marked the potential of classic AI methods in replacing repetitive manual rule application and laid a foundation for subsequent research, albeit with limited capability for handling complex forms and global objectives.

4.1.2. Integration of BIM and optimization algorithms

With the proliferation of BIM technology, the research focus shifted towards intelligent layout and multi-objective optimization at the component level. The core characteristic of this stage was the integration of BIM as a data infrastructure with classic optimization algorithms.

Liu *et al.* [58] developed a BIM-based wall panel generation framework that enabled synergistic control of structural, production, and logistics constraints through algorithms. However, the modular grouping rules still required manual predefinition, highlighting the dependency of such methods on explicit rules. Besides, Li *et al.* [59] further integrated the DFMA principle with a hybrid metaheuristic algorithm to optimize prefabricated steel rebar design, demonstrating the approach’s capability for design solution generation and balancing multiple objectives. A key limitation was the omission of dynamic construction conflict detection.

4.1.3. Expert systems and performance-driven design

As the research scale expanded from components to the overall structure, greater system synthesis and evaluation capabilities were required. Expert systems demonstrated advantages here by integrating domain knowledge for complex reasoning.

The work by Rodrigues *et al.* [73] is exemplary of performance-driven generation. By generating a large number of light steel frame residential models with random geometric parameters and using EnergyPlus for energy consumption simulation, they systematically identified key geometric variables affecting energy performance. This approach moved beyond merely satisfying predefined rules to guiding scheme generation through simulation feedback, providing support for data-informed design decisions and signaling the advancement of classic AI methods towards tackling more complex, higher-dimensional design problems.

4.2. Single-objective and multi-objective optimization of structural design

Structural optimization is a key process for enhancing the performance and economic efficiency of modular buildings. Engineering practice demands designs that simultaneously address multiple objectives like safety, cost, and energy consumption, spurring research into single-objective and multi-objective optimization for such problems.

However, academic progress in this domain remains largely concentrated on addressing relatively singular optimization objectives, yet to fully tackle the prevalent challenge of multi-objective synergy in practical engineering. Before the widespread adoption of biologically inspired methods, structural optimization primarily relied on mathematical programming techniques. A significant and innovative approach within this domain is the neural dynamics model proposed by Adeli and Park [74,75]. This method conceptualizes the optimization process as a dynamic system, where the design variables evolve over time according to a set of differential equations until they reach a stable state, which corresponds to the optimal solution. Theoretically, this model offers a robust mathematical framework for solving complex, non-convex optimization problems by guaranteeing convergence to a local optimum. While their seminal work demonstrated efficacy in optimizing traditional structures like trusses and frames, its core principle—transforming discrete optimization into a solvable dynamic system—represents a foundational methodology that predates and complements many later intelligent optimization techniques. Introducing this model addresses a key gap in the historical narrative of AI in structural design.

4.2.1. Single-objective optimization

Optimizing for a defined single performance indicator is a strength of classic AI algorithms. The work by Xing *et al*. [70] is a typical example. They employed an improved Genetic Algorithm to optimize a modular temporary broadcasting tower. By introducing differentiated and adaptive strategies, they significantly enhanced search efficiency, ultimately achieving a notable economic benefit of 33.2% reduction in steel mass. This study clearly demonstrates the powerful capability of classic AI algorithms in solving complex single-objective optimization problems for specific structural forms. However, their optimization model is highly specific to the mechanical behavior of tower structures, and the algorithmic strategies used are quite particular. This raises questions about the applicability of their methodology when generalized to more common structural types like containerized modular residences, exposing the limitations in the universality of such early research.

4.2.2. Variant generation and performance screening

Another research strand utilizes the search capability of algorithms to systematically generate a large number of design variants and screen for high-performance solutions. The study by Dzwierzynska and Lechwar [66] on hyperbolic paraboloid modular steel canopies follows this path. The core of this research lies in establishing a workflow that integrates parametric generation with GA screening: first defining the parametric space (module shape, number, layout), then algorithmically generating 25 structural variants, and finally performing optimization screening using the mass coefficient per unit area as the single efficiency index. This approach not only identifies the optimal solution (the 12-element hexagonal variant, saving 23% steel) but also reveals deeper relationships between design parameters and performance, such as the nonlinear negative correlation between the number of modules and structural efficiency. This exemplifies how generative design serves not only to find answers but also to explore design possibilities and understand their inherent rules. Admittedly, this study also focuses on a single objective of material efficiency, neglecting other practical factors like construction cost and complexity.

4.3. Modular spatial layout and construction drawing generation

The core challenge in applying classic AI technologies to spatial layout generation lies in quantifying complex design requirements and mapping them into computable constraint rules. Research in this area shows an evolution from single-objective mathematical optimization towards integrated, performance-driven design.

4.3.1. Mathematical programming and layout optimization

Early research focused on abstracting layout problems into mathematical programming models and solving them with optimization algorithms. The work by Zheng *et al.* [32] and Chang *et al.* [50] exemplifies this paradigm. They formalized modular floor plan layout as integer programming problems and employed Genetic Algorithms (GA) for solution, typically aiming to minimize the number of modules or total cost. These methods are mathematically rigorous and provide preliminary solutions for automated layout, demonstrating the effectiveness of classic AI in solving such structured problems. However, their optimization objectives are singular, and their models are relatively simplified, leading to a disconnect from practical engineering involving multiple requirements.

4.3.2. Geometric rules and design mathematization

To handle more complex geometries, researchers introduced tools like formal grammars. The ModulePacking method proposed by Lin *et al.* [63] is a milestone. Using two-stages “partitioning-merging” strategy and Geometric Constraint Grouping Genetic Algorithm (GGA), it systematically mathematized the overall geometric essence of modular design for the first time, capable of efficiently generating large scale floor plans comparable or superior to those by human designers. Its limitations include a lack of multi-objective optimization capability and room for improvement in rule flexibility. Wang *et al.* [76] attempted to integrate shape grammar with BIM, aiming to establish rule-based mappings from geometric dimensions to functional attributes. This work demonstrates the potential of encoding design knowledge into rules, but the construction of its rule base remains highly dependent on manual expertise, lacking generality and scalability, revealing the bottlenecks knowledge-based systems face in acquiring and representing complex design knowledge.

4.3.3. Performance-driven integrated workflows

The latest progress is reflected in constructing integrated, performance-driven design workflows. The research by Shen and Ye [77] is exemplary. Their PDAD workflow integrates a Genetic Algorithm, performance simulation (EnergyPlus, Radiance), and clustering algorithms, forming a complete “generation, simulation, optimization, decision” closed loop. The breakthrough of this method lies in moving beyond singular objectives like geometry or cost to directly optimizing for environmental performance (daylighting, energy consumption, thermal comfort), and aiding decision-making through visual clustering, significantly enhancing the scientific basis and sustainability of design. This marks a shift from solving mere “layout problems” to supporting complex “design processes”. Naturally, this integrated approach demands high computational resources, and its applicability awaits validation across more building types.

4.4. Structural form-finding and topology optimization

Structural form-finding, which seeks to identify efficient and expressive structural forms based on mechanical principles and constraints, represents a foundational application of generative design. Classic

AI, particularly biologically inspired methods, has been extensively applied to this domain, often framed as a topology optimization problem.

The pioneering work by Hajela *et al*. [64] demonstrated the application of GA to structural topology optimization, laying the groundwork for using evolutionary computation to explore non-intuitive, high-performance structural layouts. This paradigm shift moved beyond simple sizing optimization of predefined members to the generative exploration of the structural layout itself.

While the neural dynamics model proposed by Adeli and Park [74,75] offered a robust mathematical framework for optimization, its application was often in conjunction with or as an alternative to these population-based methods for finding optimal material distribution within a design domain. The core strength of these classic methods lies in their ability to handle discrete design variables and non-convex search spaces, making them suitable for generating novel structural forms for modular assemblies where the connectivity and arrangement of modules are paramount. However, their computational cost for high-resolution form-finding and their reliance on manually defined objective functions remain significant limitations.

As Papallo *et al*. [38] highlight, generative strategies are particularly suited for navigating complex design spaces to discover non-intuitive, high-performance solutions that meet tailored mechanical objectives. This core capability is exploited in both classic and modern AI approaches for modular structures, from using evolutionary algorithms to explore module arrangements to employing deep generative models for synthesizing novel structural layouts that satisfy predefined performance criteria. This evolution towards integrated, performance-driven form-generation is further elaborated in Section 5.2.

The review of classic AI applications reveals a clear evolutionary trajectory from rigid, rule-based automation towards more flexible, performance-driven generation. Knowledge-based systems excelled at codifying explicit engineering rules for defined problems, such as generating standard floor layouts, but struggled with complexity and novelty. Biologically inspired methods introduced a powerful capability for exploration and optimization within large solution spaces, enabling breakthroughs in layout planning and single-objective performance gains.

A key strength of these methods is their interpretability and direct control by engineers, as the rules and objectives are explicitly defined. This makes them suited for scenarios where compliance with specific codes and standards is paramount. However, their fundamental limitation lies in their dependency on this manual rule definition. They cannot autonomously learn implicit design patterns or performance tradeoffs from data. Consequently, they often fail to generalize beyond their predefined problem scope and can be computationally expensive for high-dimensional, multi-objective problems. The transition towards integrating simulation feedback marked a significant step forward, yet the “intelligence” remained largely in the predefined algorithmic loop rather than within the model itself.

5. Generative design applications based on modern AI technology

This chapter delves into how modern AI technologies are driving advances in the generative design of modular structures. The data-driven nature of these methods is particularly suited to handling the complexity and prefabrication constraints inherent in modular systems. The applications discussed herein, from scheme generation to multi-objective optimization, are analyzed for their potential and demonstrated efficacy in addressing the core design tasks of modular buildings.

Following the breakthrough advancements in deep learning in 2012, modern AI technologies, characterized by their data-driven core, have begun to profoundly influence the generative design of modular structures. Modern AI primarily encompasses Deep Learning and Reinforcement Learning, with typical architectures including Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), and Recurrent Neural Networks (RNNs/LSTMs), among others [6]. These technologies enable a higher degree of design automation and intelligence by automatically learning complex feature representations and mapping relationships from vast datasets, offering a new paradigm.

The fundamental advantage of modern AI methods, compared to classic AI technologies that primarily rely on manually predefined rules, lies in their data-driven, end-to-end learning capability. They can learn underlying design specifications, structural mechanics principles, and aesthetic preferences directly from historical design data, thereby automatically generating novel structural schemes that meet multifaceted requirements. This ability to discover and model complex rules from data allows them to demonstrate stronger generalization and adaptability when dealing with high-dimensional, nonlinear design problems. Furthermore, the models can be continuously refined with the introduction of new data, possessing significant iterative evolution potential.

Leveraging these characteristics, modern AI technologies provide revolutionary tools for modular structural design. The subsequent sections will delve into the specific applications, progress, and challenges of these technologies in core stages such as structural scheme generation, optimization, and drawing production. Representative papers in this domain are listed in Table 5.

Table 5. Some representative papers with modern AI technologies.

Author	Research Method	Research Objective
Gao *et al*. [22]	Large Language Models (LLMs)	To create a comprehensive framework for parametric generative design in industrialized construction that integrates multiple design disciplines and optimization criteria.
Ghannad and Lee [42]	Coupled Generative Adversarial Network (CoGAN)	To ameliorate these knowledge and practice gaps of the expensive, time consuming process and lack of a systematic approach in modular housing design.
Liu *et al*. [58]	Generative Adversarial Network (GAN) Deep Reinforcement Learning (DRL)	To overcome this limitation of existing studies not being able to automatically generate clash-free rebar arrangements for real world precast concrete elements (PCEs).
Li *et al*. [71]	Artificial Neural Network (ANN) NSGA-III	To fill this gap of computational demand and lack of generalizability in performance-driven generative design for sustainable buildings.
Tusnin *et al*. [79]	Machine Learning Ensemble Models (Decision Trees)	To analyze and design modular buildings made of blocks and to overcome the limitations of time consuming numerical analysis (FEM).
Xia *et al*. [80]	Graph Model (GBIM)	Proposing a systematic framework to organize information and developing a unified model for representing steel modular buildings and multiple tasks.

5.1. Design of structural schemes

Modern AI technologies, particularly deep learning, offer new pathways for structural scheme generation that transcend traditional rule-driven paradigms. Their core advantage lies in the ability to learn design logic and performance mappings directly from complex data, enabling highly efficient automated intelligent design. Notably, as the latest paradigm in generative AI, diffusion models have demonstrated immense potential in image generation and quality, and are beginning to be explored for seamless integration in architectural and structural design. For instance, Leng *et al*. [81] proposed a novel diffusion model named ArchiDiffusion, which can automatically generate rational architectural floor plans from simple sketches and further proceed to shear wall design. This work exemplifies the prospective application of modern AI technologies in bridging cross-disciplinary design processes and achieving end-to-end intelligent generation.

5.1.1. Structural state prediction using discriminative models

One approach employs modern AI as a powerful surrogate model to drastically accelerate structural analysis and optimization processes. For instance, research has utilized ensemble decision tree models to predict the stress and strain state of a structure. This method involves feature engineering on design parameters to establish a fast mapping from these parameters to structural responses. This effectively circumvents the substantial computational burden associated with repeated Finite Element Analysis in traditional optimization, solving the problem of excessive time consumption and enabling rapid scheme iteration.

5.1.2. Automated scheme synthesis using generative models

Another more revolutionary approach focuses on directly generating code-compliant layout design of the primary structural system itself.

The work by Fu *et al*. [82–84] is a benchmark in this direction. They proposed a Dual Generative Adversarial Network (Dual GAN) framework for the layout design of conventional steel frame brace structures. The core of their model lies in decoupling the complex bracing layout task: one GAN is dedicated to generating the type of bracing, while another GAN concurrently determines their optimal spatial distribution. This approach can directly output diverse, holistic structural schemes that comply with fundamental engineering principles, which have been validated through structural analysis. Adapting this automated design paradigm for lateral force-resisting systems to the specific constraints of modular structures represents a key challenge. Addressing this challenge is essential for enabling rapid generation of feasible structural schemes from architectural layouts.

5.2. Form-finding and topology optimization

Modern AI has profoundly transformed structural form-finding by introducing data-driven surrogate modeling and end-to-end generative capabilities, moving beyond the iterative optimization loops of classic methods.

A significant trend involves using Deep Neural Networks (DNNs) as surrogate models to accelerate physics simulation. The work by Gaynutdinova *et al*. [27] is exemplary, where a symmetric positive definite convolutional network was developed to predict the reduced-order stiffness matrix of modular structures. This approach bypasses computationally expensive Finite Element Analysis (FEA) during optimization, enabling rapid evaluation of countless structural forms and their mechanical responses. This method facilitates the efficient optimization of module types and configurations for global performance.

Beyond surrogate modeling, deep generative models are being explored for direct form generation. Fu *et al*. [82,83] pioneered the use of Generative Adversarial Networks (GANs) and physics informed models for the automated layout design of steel frame brace structures. Their models learn to generate structurally rational bracing layouts directly from data, capturing implicit design rules that are difficult to codify explicitly. This represents a shift from optimizing a structure to generating a structural concept.

Furthermore, Reinforcement Learning (RL) and Monte Carlo Tree Search (MCTS) offer shifting approaches. The AlphaTruss framework by Luo *et al*. [85] demonstrates how MCTS can efficiently navigate the vast combinatorial space of truss layout design, finding optimal configurations through strategic search without requiring gradient information. Similarly, Fu *et al*. [82–84] developed physics-informed deep RL frameworks for autonomous steel frame design, where an agent learns to sequentially place and size members to satisfy performance criteria, effectively performing intelligent form-finding.

The emergence of diffusion models marks the latest frontier. While Leng *et al*. [81] and Li *et al*. [86] have focused on architectural layout and shear wall bracing design, their methodology underscores the potential of these models for generating diverse and complete structural forms conditioned on various inputs, such as sketches or performance constraints. This points towards a future where AI can collaboratively generate both the architectural massing and its underlying, efficient structural skeleton in an integrated manner.

In summary, modern AI has profoundly transformed structural form-finding. From surrogate modeling with DNNs to strategic search with MCTS and RL, and now to the direct synthesis of structural forms using generative models like GANs and Diffusion models, the field is rapidly evolving. The recent work on FrameDiffusion by Li *et al*. [86] epitomizes this evolution. By leveraging the powerful generative prior of diffusion models, it enables the exploration of a vast and diverse space of structurally coherent bracing topologies, effectively performing data-driven form-finding. This approach complements and extends the capabilities of traditional form-finding methods, offering a powerful new tool for the generative design of modular structures, where discovering novel, efficient, and buildable global configurations is a primary goal.

5.3. Single-objective and multi-objective optimization of structural design

Modern AI technologies have revitalized structural optimization, with applications evolving from pure neural network approaches to hybrid intelligent models, significantly enhancing the capability to handle complex, nonlinear optimization problems.

5.3.1. Foundation and development of neural networks in structural optimization

Pioneering work on introducing neurodynamics concepts into structural optimization was conducted by Adeli and Park [74,75], who proposed dedicated neural network architectures for discrete optimization problems. This idea laid the groundwork for subsequent research. Modern developments based on this foundation involve more complex network architectures and multi-objective integration. For instance, Li *et al*. [59] proposed a multi-objective generative design framework integrating multi-task learning (using ANNs) and code compliance checks. This framework simultaneously optimizes building energy consumption, life cycle cost, and daylighting performance through shared representations, demonstrating the potential of deep learning in handling multi-objective tradeoffs. However, the framework primarily focuses on environmental and economic performance, lacking sufficient integration of core objectives like structural safety and durability, reflecting the comprehensiveness limitations of early performance-driven design.

5.3.2. Hybrid intelligent models: fusion of classic and modern AI

To overcome the limitations of single approaches, hybrid models that fuse classic and modern AI demonstrate significant advantages. These models typically leverage the strong search capabilities of classic algorithms while utilizing the learning capacity of neural networks to build accurate surrogate models or handle complex mappings. The work by Ding *et al*. [78] is a prime example. They constructed a hybrid PSO-RBF neural network model and integrated it with computer vision and BIM technologies. In this model, the Particle Swarm Optimization (PSO) algorithm is responsible for optimization search, while the Radial Basis Function (RBF) network serves as an efficient surrogate model, predicting the thermal expansion deformation of prefabricated components under real conditions with high accuracy (error of only 0.02mm) via a temperature compensation mechanism. This hybrid strategy combines precise modeling of physical processes with the global search ability of intelligent algorithms, enabling accurate control and optimization of complex effects (like thermal deformation) that are challenging for traditional methods to monitor, marking a significant advance from idealized models towards complex real scenarios. The evolution of hybrid models continues towards greater complexity and autonomy. Beyond combining classic optimizers with surrogate models, the integration of multiple AI paradigms is emerging. A seminal example is the work by Fu *et al*. [87], which fuses Multi-Agent Systems (MAS) with Physics-Informed Neural Networks (PINNs) and Deep Reinforcement Learning (DRL). This sophisticated hybrid architecture leverages the decentralized decision-making of MAS, the physical accuracy of PINNs, and the strategic learning capability of DRL to create a system that can autonomously navigate the complex design space of steel structures. This underscores a future direction where hybrid intelligence moves beyond simple coupling to deep, synergistic integration, offering a powerful toolkit for tackling the multi-objective optimization challenges inherent in modular structural design.

5.4. Modular spatial layout and construction drawing generation

In the domain of spatial layout and drawing generation, modern AI technologies, particularly generative models, are driving design automation to a higher level. Their application has evolved from generating preliminary schemes to integrating design rules and domain knowledge to achieve buildable designs aligned with engineering practice.

5.4.1. Scheme generation and rule embedding with Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) offer a new paradigm for automatically generating architectural scheme drawings that comply with specifications. The work by Ghannad and Lee [42] is an early exploration, employing Coupled Generative Adversarial Networks (CoGAN) to automatically generate feasible, buildable, and cost-effective modular residential layout schemes. The core value of this framework lies in demonstrating the potential of GANs to learn and replicate complex design patterns, filling a model gap in generative design for modular residences. However, its limitations are apparent: a lack of case validation, unquantified benefits, and unknown adaptability to complex terrains.

To enhance the professionalism of generated outcomes, subsequent research has focused on embedding explicit domain knowledge into the GAN's generation process. The FrameGAN-sym method proposed by Xu *et al*. [69] is representative of this direction, integrating structural design rules like symmetry. Advancing this concept further, Fu *et al*. [83] developed a Physical Rule-Guided Generative Adversarial Network. Their model goes beyond geometric rules by incorporating fundamental principles of structural mechanics directly into the learning process. This approach ensures that the generated steel frame brace layouts are not only visually plausible but also adhere to core physical laws, significantly improving their structural rationality and reliability. This represents a significant stride towards building trust in AI-generated designs for critical applications like modular structures, where structural integrity is paramount.

Moving beyond explicit geometric rules, some studies have integrated higher level of structural performance metrics directly into the GAN's learning objective. For instance, the work by Liao *et al*. [88] not only generated shear wall layouts but also incorporated structural performance feedback to guide the model towards producing designs that are not only geometrically valid but also mechanically sound. This approach of "physics-informed" or "performance guided" generation represents a significant advancement over purely data-driven models, ensuring that the output aligns with fundamental engineering principles—a consideration paramount for the safety of modular structures.

5.4.2. Deep integration of Graph Neural Networks (GNNs) and BIM

For modular buildings, which inherently possess topological connections, Graph Neural Networks (GNNs) demonstrate unique advantages. They can directly map components and their relationships in a BIM model into a graph structure for processing. Gan [9] pioneered a BIM-based graph data model. By defining a model view conforming to the IFC standard and developing graph theory transformation algorithms, they achieved efficient data extraction from BIM to graph models, laying the data foundation for GNN-based generative design. Their study verified the feasibility of the technical route but did not delve into multi-disciplinary collaboration scenarios.

The work by Xia *et al*. [80] goes a step further. Their proposed Graph-based BIM generation method (GBIM) constructs a unified semantic framework. This method integrates multi-domain knowledge through progressive ontology development, eliminates semantic conflicts, and transforms the ontology into an operable graph model. This enables dynamic flow and synchronization of design information between design and management, truly achieving management collaboration. This framework is highly systematic and significantly enhances the level of integration, representing a significant step towards engineering practice, although its actual efficacy requires quantitative validation through specific engineering data.

The application of GNNs extends beyond generative design into structural optimization. For instance, Hayashi and Ohsaki [89] demonstrated that by representing a steel frame as a graph, a reinforcement learning agent could effectively perform discrete cross-section optimization. This underscores the dual utility of graph representations in the AEC industry: they can facilitate both the generative synthesis of new designs (as in GBIM) and the performance optimization of existing or generated structural topologies. For modular buildings, this implies that a unified graph model could potentially support the entire design process, from initial layout generation through to the detailed optimization of module specifications and connection designs.

5.4.3. Layout exploration strategy based on Monte Carlo Tree Search

Beyond data-driven paradigms based on deep learning, AI methods centered on advanced search strategies also demonstrate unique value in layout generation. The AlphaTruss framework proposed by Luo *et al.* [85] innovatively applies Monte Carlo Tree Search (MCTS) to the layout optimization of truss structures. Through an iterative mechanism of "selection, expansion, simulation, backpropagation", MCTS performs strategic search within vast combinatorial design spaces, with its core advantage being the ability to handle high-dimensional discrete optimization problems without requiring gradient information.

Although this method targets mass minimization of idealized trusses, differing from the holistic layout requirements of container-based modular buildings, its methodological approach holds significant transfer potential. The search logic of MCTS can be naturally adapted to modular layout scenarios: formulating the modular assembly process as a sequential decision-making problem, where each "action" corresponds to the placement, rotation, or type selection of a modular unit, and the "reward" function can be designed as a multi-objective metric comprehensively reflecting structural performance, spatial efficiency, construction cost, and buildability.

Compared to deep generative models that require large training datasets, MCTS, as a model-free search method, exhibits significant advantages in data-scarce scenarios. Future research could explore combining MCTS with machine learning, using neural networks to predict the long term returns of layouts to accelerate search, forming a hybrid intelligence framework similar to AlphaGo, thereby providing a new technical pathway for modular building layout generation.

5.5. Applications of Large Language Models

Large Language Models (LLMs), representing the current frontier of AI technology, have achieved a fundamental breakthrough in universal alignment between natural language and machine instructions. This characteristic holds revolutionary potential for modular structural design: it dramatically lowers the barrier of human to computer interaction, allowing designers to describe their intents in natural language to drive complex generative and optimization processes. Although the application of LLMs in architectural design is still in its infancy, their potential as an intelligent interactive hub for integrating existing professional tools and knowledge is beginning to emerge.

The research by Gao *et al.* [22] is an early exploration in this direction. They proposed a parametric generative design framework integrating Knowledge Graphs (KG) and multi-objective optimization. Within this framework, the Large Language Model (LLM) plays the crucial role of a demand parser and interaction interface: it processes the user's design requirements via natural language processing and utilizes Knowledge Graph Question Answering (KGQA) to retrieve relevant design codes and constraints from a structured domain knowledge base. This parsed and enriched information is then translated into explicit input parameters to drive the backend multi-objective optimization algorithm for scheme generation and tradeoffs analysis.

The unique value of this method lies in constructing an automated pipeline of "natural language requirement", "structured knowledge", "optimization algorithms". This method preliminarily validates the feasibility of using an LLM as an “intelligent front-end” for the design workflow and offering a new approach to enhancing overall design efficiency. However, the study also exhibits clear initial limitations: Firstly, its application scenario is narrowed to the single objective of energy efficiency optimization, not yet demonstrating the LLM’ s generalizability in handling more complex, multi-dimensional design objectives. Secondly, the LLM’ s function within this framework is relatively basic. Its potential issues like “hallucination” and its deeper capabilities in logical reasoning and creative generation have not been fully explored or validated. Future research urgently needs to expand LLM applications to broader design goals and investigate their potential as a core reasoning engine, beyond merely an interaction interface.

Beyond GANs and GNNs, diffusion models have emerged as a powerful class of deep generative models, demonstrating remarkable capabilities in generating complete and diverse images. Their application is now extending to architectural and structural layout generation. A notable example is the work by Leng *et al*. [81], who proposed “ArchiDiffusion”, a novel framework that leverages diffusion models to automate the design process from architectural sketches to structural shear wall layout generation. This approach effectively connects the conceptual architectural design phase with the detailed structural design phase, showcasing the potential of modern AI in creating a more continuous and intelligent design workflow. While their study focuses on shear wall structures, which differs from the steel frame brace systems typical of container-based modular buildings, it exemplifies the trend of using advanced generative AI to bridge disciplinary gaps within the AEC industry.

Modern AI technologies have fundamentally shifted the generative design paradigm from a rule-based to a data-driven approach. Their primary advantage is the ability to learn complex, often implicit, mappings from architectural intent to structural solutions directly from historical data, enabling a level of automation and adaptability previously unattainable.

Discriminative models have proven highly effective as fast and accurate surrogate models, drastically accelerating exploration and optimization processes. Generative models, particularly GANs and GNNs, have demonstrated remarkable potential in automating the synthesis of code-compliant structural layouts and drawings, learning the “language” of structural design. The emergence of LLMs and diffusion models points towards a future of natural, intuitive human to AI collaboration and cross-disciplinary integration.

However, this power comes with new challenges. The performance and generalization of these models are critically dependent on large, high-quality datasets, which are often scarce in the modular construction domain. The “black box” nature of deep learning models can erode engineer trust and make it difficult to debug or enforce specific constraints. Furthermore, while excellent at interpolation within their training data, they can produce unrealistic or unbuildable outputs when faced with truly novel design scenarios. The hybrid approaches, combining the learning power of modern AI with the search and rule-based rigor of classic AI, appear to be a promising path forward, aiming to capture the benefits of both paradigms while mitigating their respective weaknesses.

6. Future development trends and conclusion

6.1. Deficiencies or challenges of the current research

Although generative design methods have achieved significant progress in the field of modular building structures, several critical challenges remain on the path towards large-scale engineering application.

6.1.1. Data requirements and model generalization capability

The performance of modern AI methods, particularly deep learning models, is highly dependent on large-scale, high-quality training datasets. However, in the modular construction domain, data resources such as text, images, and drawings with specific research focus are significantly scarce. This data scarcity directly constrains the development of high-performance generative models. As noted by Wang and Lu [90], generative adversarial networks require a large amount of design drawing data with specific research focuses for training, which is often difficult to obtain.

Furthermore, even with data, the generalization capability of models poses a major challenge. Models often perform well on specific dataset but their applicability drops sharply when deployed for projects with different functional requirements, structural forms, or regulatory standards. The research by Gao *et al*. [22] also confirms that while their framework effectively improves energy efficiency and cost effectiveness, the model's generalization ability for modular structural forms under various functional uses is insufficient, making it difficult to meet the diverse needs of actual engineering projects.

6.1.2. Adaptability in practical applications

Most current research is concentrated on theoretical and laboratory settings, lacking tight integration with real-world engineering scenarios. Many methods prove effective under ideal conditions but fail to fully account for the complexity, uncertainty, and economic constraints of construction sites.

For instance, the study by Xu *et al*. [69] theoretically achieved clash-free rebar arrangement at beam-column joints in prefabricated buildings. However, the performance of this rebar design across different practical scenarios still requires further validation through engineering application. On the other hand, many studies based on parametric design impose significant constraints regarding the dimensions and quantities of standardized prefabricated components. In contrast, more projects often need to accommodate non-standard site conditions and flexible design changes, demanding generative models with greater flexibility and adaptability, rather than rigidly adhering to predefined rules.

6.1.3. The complexity of multi-objective optimization

Modular structural design is inherently a process of multi-objective tradeoffs, requiring simultaneous consideration of structural safety, architectural function, economic cost, and environmental impact, among others. Existing research still faces severe challenges in handling multi-objective optimization.

Firstly, the optimization process is prone to converging to local optima. For example, the study by Li *et al*. [71] effectively reduced energy consumption and cost through multi-task learning. However, when dealing with more complex building shapes and multi-objective problems, their optimization strategy tended to over-focus on local improvements based on predefined rules, potentially deviating from the original intention of autonomous learning and automatic generation [78].

Secondly, the current system of optimization objectives is incomplete. Zhou and Xue [67] pointed out that although existing methods can optimize certain passive design strategies, for modular building design, the optimization objectives need further expansion and deepening. It is crucial to systematically incorporate more performance indicators, such as wind load and seismic response, vibrational serviceability, thermal comfort, and carbon emissions, and comprehensively consider the coupled effects of various factors like structural forms and material choices on the building’s overall performance [13].

6.2. Future research trends

Addressing the current deficiencies, future work should focus on the following key directions to propel generative design from laboratory research to engineering practice.

6.2.1. Data-driven and knowledge integration

To overcome the challenges of data scarcity and poor model generalization, future research should dedicate efforts to developing a hybrid intelligence paradigm. The impressive results achieved by state-of-the-art generative models, such as the FrameDiffusion model for steel brace layout generation [86], showcase the immense potential of data-driven approaches. However, the performance of such sophisticated models is often contingent upon large, high-quality datasets. Future studies need to more systematically explore how to imbue these powerful data-driven learners with structured domain knowledge to enhance their robustness and reduce their data appetite, making them more practical for the modular construction domain where specific data is limited.

Specifically, while the work by Gao *et al*. [22] preliminarily demonstrated the value of combining knowledge graphs with optimization algorithms, future studies need to more systematically explore deep integration mechanisms between domain knowledge and data-driven models. This entails embedding professional knowledge, such as design codes and structural principles, into neural networks in computable forms, for instance, by using knowledge graphs to constrain the generation process or incorporating physical equations into the loss function, thereby reducing reliance on historical data while enhancing the rationality of outputs.

Furthermore, significant effort should be directed towards developing few-shot learning and transfer learning techniques tailored for modular construction, enabling models to learn effectively from limited data and achieve cross-project knowledge transfer, ultimately leading to a new generation of intelligent design systems that combine the reliability of expert knowledge with the adaptability of data-driven approaches.

6.2.2. Closed-loop verification and process integration for engineering practice

To ensure the practical value of generative design methods, it is crucial to strengthen their validation in real environments and their integration into existing workflows.

Since most current research remains theoretical, future work must establish a complete engineering “design, simulation, validation” closed loop. By integrating scheme generation with high-fidelity simulation and feedback from actual projects, models can self-optimize based on real performance data. Although Pibal *et al*. [91] achieved lifecycle integration using BIM, further development is needed to achieve dynamic, real-time optimization tracking capabilities.

Concurrently, the challenge of integrating generative design tools with existing systems must be addressed. By achieving seamless integration with mainstream BIM platforms and project management processes, intelligent generation can become a natural component within designers’ workflows, thereby promoting the widespread adoption and scalable application of this technology in the engineering sector.

6.2.3. Whole-lifecycle and multi-objective collaborative optimization

To address the complexity of multi-objective optimization, future optimization frameworks need to be more systematic and comprehensive.

Firstly, the current system of optimization objectives should be expanded to include not only traditional indicators like energy consumption and cost but also multidimensional metrics such as structural safety, building physics performance, constructability, and whole-lifecycle carbon emissions. This aligns with the direction of multi-factor coupling consideration suggested by Zhou and Xue [67]. The work by Liao *et al*. [92] provides a concrete blueprint for how seismic resilience, a paramount aspect of structural safety, can be seamlessly integrated as a core objective within a generative AI workflow, moving beyond a mere post-hoc verification check.

Building on this foundation, more advanced methods for intelligent trade-off and decision support need to be developed. This involves not only handling high-dimensional, conflicting objectives through optimization algorithms but also clearly presenting the performance trade-off relationships of different schemes using visualization techniques. Ultimately, by constructing human-in-the-loop decision support systems, designers can be assisted in making optimal choices within complex multi-objective spaces, thereby achieving the ultimate goals of sustainable development and comprehensive performance enhancement.

Future research should also explore the synergistic integration of classical mechanics-based form-finding methods with modern AI paradigms. Combining the structural rationality of the former with the constraint-handling capacity of the latter, this hybrid approach holds particular promise for designing complex, larger-span, higher-height or architecturally expressive modular systems, where finding efficient forms that respect local modular assembly constraints remains a significant challenge.

6.2.4. More AI-enhanced form-finding methods

Another fundamental category of generative approaches is grounded in the principles of mechanical equilibrium and geometric constraints. This family encompasses classical techniques such as the Force Density Method (FDM) [93,94], Thrust Network Analysis (TNA) [95], Combinatorial Equilibrium Modeling (CEM) [96], and 3D Graphic Statics (3DGS) [97] and many other methods. These equilibrium-driven strategies have established applications in generating diverse structural typologies, such as shell structures [98], cable net structures [99–101], and tensile membrane systems [102–104]. Recent studies on FDM and CEM have demonstrated their promising structural form-finding capabilities when integrated with AI.

FDM is a numerical technique that determines equilibrium geometry by solving linear equations with predefined force densities. This method was originally proposed by Schek [94] in the early 1970s for cable net analysis. It provides structurally rational solutions for generating modular structures [101]. Recent research seeks to integrate artificial intelligence with FDM to improve computational efficiency [100,105]. Beyond specific AI to FDM integration, the core aim of such enhancement is intelligently generating structurally sound, performance-optimized, and constructible forms. This aim aligns closely with the requirements of volumetric modular units. These AI-augmented methods can contribute to both global form generation and local connection optimization [101]. A prominent example by Tam *et al* [106] is the work integrating Geometric Deep Learning (GDL) with physics-informed modelling to address constrained, ill-conditioned, and nonlinear inverse shell form-finding problems. This neural framework predicts funicular shells—defined by edge forces and vertex positions—that satisfy static equilibrium while closely matching target geometries and patterns provided as meshes. The approach introduces three key innovations: a relaxed, numerically stable physics objective utilizing efficient differentiable graph operators to mitigate ill-conditioning, a stochastic augmentation strategy that enhances generalization to infeasible inputs by training on geometries with varying funicular feasibility and a hierarchical GDL architecture capable of learning directly from irregular n-gon surface meshes modeled as cell complexes. By incorporating vertex, edge, and face features without simplifying graph data structures, this system significantly improves mesh modelling versatility. This work demonstrates how physics-based learning can transform the solution of ill-posed inverse problems, offering a robust method for optimizing mesh-based architectural structures under variable connectivity and complex design constraints.

CEM is a generative form-finding method for 3D structures based on graphic statics and combinatorial topology [96]. It generates forms through the manipulation of topological, form, and force diagrams [96,107]. A key AI enhancement pathway is the use of machine learning surrogate models to predict feasible topologies for CEM, moving towards near-real generative design [107]. The foundational works by Ohlbrock and D'Acunto [96], as well as Wan *et al.* [108], established the core framework and introduced iterative routines for loads like self-weight. This addresses fundamental computational limitations and enables efficient exploration of complex, constrained morphologies, such as branching structures [107]. This capability is crucial for generating mechanically balanced spatial layouts for complex modular configurations [107]. Bleker *et al.* [109] proposed a novel Logic-Informed Graph Neural Network (LIGNN) framework to automate and enhance the CEM workflow for structural form-finding. The core innovation lies in the integration of CEM's discrete, logic-based validity rules directly into the machine learning process through a custom semantic loss function. The methodology involves: firstly, developing a synthetic dataset of valid CEM topology diagrams for bridge-like structures; secondly, introducing a two-stage generative model where a Preprocessing GNN (PP-GNN) predicts origin vertex locations, and a Primary LIGNN (P-LIGNN), empowered by the semantic loss, performs edge classification to generate valid CEM input graphs that satisfy all equilibrium conditions; finally, incorporating a Modification LIGNN (M-LIGNN) to enable human-in-the-loop design by allowing users to request specific topological changes while ensuring the output remains a valid CEM solution.

In summary, recent researches [100,105] have sought to integrate AI with classical form-finding methods to improve computational efficiency and handle multi-objective constraints. There is currently no related research on these methods applied to steel box modular building. Although direct applications to container-based modular structures are not yet predominant, the core aim of these AI-enhanced methods aligns closely with the system's requirements. Therefore, these methods can be probably applied to two critical design stages. In the conceptual form-finding phase, they enable rapid generation and evaluation of mechanically balanced layouts, addressing the challenge of validating structural rationality for complex modular configurations [99,93]. In the joint detailing phase, they support the simultaneous optimization of performance and geometric compatibility of connections, resolving conflicts between standardization and irregular assembly conditions [101]. This integrated, data-driven workflow enhances both structural integrity and construction feasibility for modular buildings.

6.3. Conclusion

In conclusion, it is important to acknowledge the limitations of this review. The findings and trends identified are constrained by the scope of the literature search strategy, including the selected databases (Web of Science, Scopus, CNKI), the predefined keywords, and the publication timeframe (1990–2025). While the PRISMA methodology was rigorously followed to ensure a systematic process, some relevant studies might have been inadvertently excluded. Furthermore, the rapid evolution of AI technologies, particularly in the realm of large language and diffusion models, means that the state-of-the-art is continuously advancing, and the most recent breakthroughs may not be fully captured. Finally, the review primarily focuses on peer-reviewed journal articles, thus may not encompass all relevant innovations reported in conference proceedings or industry white papers. Future updates to this review would benefit from expanding these boundaries.

Generative design methods demonstrate broad application prospects in the field of modular building structural design. This review has systematically examined and substantiated that, while current research has achieved notable results in key areas such as structural scheme generation, multi-objective optimization, and automated drawing production, significant bottlenecks remain concerning core challenges like data dependency, model generalization capability, adaptability to engineering practice, and multi-objective synergistic optimization.

Looking ahead, this study identifies three pivotal directions for fostering high-quality advancement in the field: promoting the deep integration of data-driven methods and domain knowledge, strengthening closed-loop verification and process integration geared towards practical engineering applications, and establishing a whole-lifecycle, multi-objective sustainable optimization framework. Besides, the integration of AI with classical mechanical principles, as discussed, exemplifies a promising path toward such deep integration, potentially bridging conceptual design and practical constraints. This developmental pathway is anticipated not only to systematically enhance the design efficiency and comprehensive performance of modular structures but also to provide solid technical support and an innovative paradigm for the intelligent transformation and sustainable development of the construction industry.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used generative AI tools only to improve language and readability. The authors take full responsibility for the content of the manuscript.

Acknowledgments

This research was sponsored by the Natural Science Foundation of Tianjin, China (52578230) and the Hebei Key Laboratory of Low-Carbon Construction and Resilience Enhancement of Construction Engineering (HKL-LRC-2025-7).

Authors’ contribution

Conceptualization, Liu Yang; methodology, Zhou Kaiyue; validation, Liu Jiadi; formal analysis, Liu Yang; investigation, Zhou Kaiyue and Liu Hongbo; resources, Chen Zhihua; data curation, Chen Zhihua;

writing—original draft preparation, Zhou Kaiyue; writing—review and editing, Liu Yang; visualization, Liu Jiadi; supervision, Liu Yang and Liu Jiadi; project administration, Liu Yang; funding acquisition, Liu Yang and Liu Hongbo. All authors have read and approved the manuscript for publication.

Conflicts of interest

The authors declare no conflict of interest.

References

[1] Lu X, Liao W, Gu D, Xu Z, Zheng Z. Research progress of building structural design methods from simulation-based to artificial intelligence-based. *Eng. Mech.* 2025, 42(3):1–17.

[2] Murray-Parkes J, Bai Y, Styles A. *Handbook for the design of modular structures, modular construction codes board*. Melbourne: Monash University 2017, pp. 1–216.

[3] Gunawardena T, Ngo T, Mendis P, Alfano J. Innovative flexible structural system using prefabricated modules. *J. Archit. Eng.* 2016, 22(4):05016003.

[4] Huang X, Shu Z, Li Z. Research progress of prefabricated modular buildings and modular joints. *Prog. Build. Steel Struct.* 2022, 24(2):40–49.

[5] Hou Z, Gong C, Chen J, Wang S, Liu Z. Fully prefabricated modular buildings and their structural design strategies. *Steel Constr.* 2023, 38(10):49–58.

[6] Liao W, Lu X, Fei Y, Gu Y, Huang Y. Generative AI design for building structures. *Autom. Constr.* 2024, 157:105187.

[7] Li C, Wen X, Chen Z, Luo X, Cao K, *et al*. Overview of industrialization technology and demonstration of modular steel structure system buildings. *Prog. Build. Steel Struct.* 2023, 25(1):1–18.

[8] Hwang K, Kim I, Kim J, Cha S. Client-engaged collaborative pre-design framework for modular housing. *Autom. Constr.* 2023, 156:105123.

[9] Gan V. BIM-based graph data model for automatic generative design of modular buildings. *Autom. Constr.* 2022, 134:104062.

[10] Hou Z, Liu Z, Gong C, Chen J, Zhao M, *et al*. Modular integrated construction method and intelligent quality inspection. *Constr. Technol.* 2024, 53(17):47–54.

[11] Lu X, Liao W, Zhang Y, Huang Y. Intelligent structural design of shear wall residence using physics-enhanced generative adversarial networks. *Earthquake Eng. Struct. Dyn.* 2022, 51(7):1676–1677.

[12] Zhao P, Liao W, Huang Y, Lu X. Intelligent design of shear wall layout based on attention-enhanced generative adversarial network. *Eng. Struct.* 2023, 274:115170.

[13] Liu P, Liu J, Feng L, Wu W, Lan H. Automated clash free rebar design in precast concrete exterior wall via generative adversarial network and multi-agent reinforcement learning. In *Proceedings of the AHFE 2019 International Conference on Human Factors in Artificial Intelligence and Social Computing, the AHFE International Conference on Human Factors, Software, Service and Systems Engineering, and the AHFE International Conference of Human Factors in Energy*, Washington, USA, July 24–28, 2019, pp. 546–558.

[14] Kookalani S, Parn E, Brilakis I, Dirar S, Theofanous M, *et al*. Trajectory of building and structural

design automation from generative design towards the integration of deep generative models and optimization: a review. *J. Build. Eng.* 2024, 97:110972.

[15] Liu H, Zhang F, Chen Z, Wang L. Research status and prospects of artificial intelligence applications in civil engineering. *J. Civ. Environ. Eng.* 2024, 46(1):14–32.

[16] Sheijani S, Momenaei A, Hassanzade H. Automating modular open-plan office layouts with performance-based generative design. *Autom. Constr.* 2024, 167:105692.

[17] Zhou J, Liu J, Qi H, Shan W. Cross-phase automated structural design of modular buildings using a unified matrix method and multi-objective optimization. *Expert Syst. Appl.* 2024, 249:123788.

[18] Starodubcev N, Nikitin N, Andronova E, Gavaza K, Sidorenko D, *et al*. Generative design of physical objects using modular framework. *Eng. Appl. Artif. Intell.* 2023, 119:105715.

[19] Taiwo R, Bello I, Abdulai S, Yussif A, Salami B, *et al*. Generative artificial intelligence in construction: A delphi approach, framework, and case study. *Alexandria Eng. J.* 2025, 116:672–698.

[20] Bilal M, Oyedele LO, Qadir J, Munir K, Ajayi S, *et al*. Big data in the construction industry: a review of present status, opportunities, and future trends. *Adv. Eng. Inf.* 2016, 30(3):500–521.

[21] Saka A, Oyedele L, Akanbi L, Ganiyu S, Chan D, *et al*. Conversational artificial intelligence in the AEC industry: A review of present status, challenges and opportunities. *Adv. Eng. Inf.* 2023, 55:101869.

[22] Gao M, Li C, Petzold F, Tiong R, Yang Y. Lifecycle framework for AI-driven parametric generative design in industrialized construction. *Autom. Constr.* 2025, 174:106146.

[23] Yevu S, Blay K, Ayinla K, Hadjidemetriou G. Artificial intelligence in offsite and modular construction research. *Autom. Constr.* 2025, 171:105994.

[24] Ma C, van Ameijde J. Adaptable modular construction systems and multi-objective optimisation strategies for mass-customised housing: a new user-driven paradigm for high-rise living in Hong Kong. *Int. J. Archit. Comput.* 2022, 20(1):96–113.

[25] Frazer J. *An evolutionary architecture.* London: Architectural Association, 1995.

[26] Maher M. *Expert systems for civil engineers: technology and application*. New York: American Society of Civil Engineers,1987.

[27] Gaynutdinova L, Doškář M, Pultarová I, Rokoš O. Symmetric positive definite convolutional network for surrogate modeling and optimization of modular structures. *Eng. Appl. Artif. Intell.* 2025, 154:110906.

[28] Yüksel N, Börklü H, Sezer H, Canyurt O. Review of artificial intelligence applications in engineering design perspective. *Eng. Appl. Artif. Intell.* 2023, 118:105697.

[29] Krizhevsky A, Sutskever I, Hinton G. ImageNet classification with deep convolutional neural networks. In *Proceedings of the 26th International Conference on Neural Information Processing Systems (NIPS)*, Nevada, USA, December 3–6, 2012, pp. 1097–1105.

[30] Bhosekar A, Ierapetritou M. Modular design optimization using machine learning-based flexibility analysis. *J. Process Control*. 2020, 90:18–34.

[31] Liu J, Qiu Z, Wang L, Liu P, Cheng G, *et al.* Intelligent floor plan design of modular high-rise residential building based on graph-constrained generative adversarial networks. *Autom. Constr.* 2024, 159:105264.

[32] Zhang L, Ford V, Chen Z, Chen J. Automatic building energy model development and debugging

using large language models agentic workflow. *Energy Build*. 2025, 327:115116.

[33] Li J, Liu Z, Han G, Demian P, Osmani M. The relationship between artificial intelligence (AI) and building information modeling (BIM) technologies for sustainable building in the context of smart cities. *Sustainability* 2024, 16(24):10848.

[34] Zhou X, Chen X. Application of concept design in structural design software. *Appl*. *Mech*. *Mater*. 2011, 71:4230–4233.

[35] Liao W, Lu X, Fei Y. Generative artificial intelligence for structural design of tall buildings. *Int*. *J*. *High-Rise Build*. 2023, 12(3):203–208.

[36] Liao W, Huang Y, Zheng Z, Lu X. Intelligent generative structural design method for shear wall building based on “fused-text-image-to-image” generative adversarial networks. *Expert Syst*. *Appl*. 2022, 210:118530.

[37] Qin S, Liao W, Huang S, Hu K, Tan Z, *et al*. AIstructure-Copilot: assistant for generative AI-driven intelligent design of building structures. *Smart Constr*. 2024, 1(1):1–21.

[38] Papallo I, Martorelli M, Lamonaca F, Gloria A. Generative design and insights in strategies for the development of innovative products with tailored mechanical and/or functional properties. *Acta IMEKO* 2023, 12(4):1–5.

[39] Zhao P, Liao W, Huang Y, Lu X. Intelligent beam layout design for frame structure based on graph neural networks. *J*. *Build*. *Eng*. 2023, 63:105499.

[40] Fei Y, Liao W, Huang Y, Lu X. Knowledge-enhanced generative adversarial networks for schematic design of framed tube structures. *Autom*. *Constr*. 2022, 144:104619.

[41] Zheng Z, Li Y, Shao L. Research on intelligent design method of building industrialization for mass customization. *Prog*. *Build*. *Steel Struct*. 2024, 26(6):1–11.

[42] Ghannad P, Lee Y. Automated modular housing design using a module configuration algorithm and a coupled generative adversarial network (CoGAN). *Autom*. *Constr*. 2022, 139:104234.

[43] Pan Y, Zhang L. Integrating BIM and AI for smart construction management: current status and future directions. *Arch*. *Comput*. *Methods Eng*. 2023, 30(2):1081–1110.

[44] Adeli H, Hawkins D. A hierarchical expert system for design of floors in high-rise buildings. *Comput*. *Struct*. 1991, 41(4):773–788.

[45] Ko J, Ennemoser B, Yoo W, Yan W, Clayton M. Architectural spatial layout planning using artificial intelligence. *Autom*. *Constr*. 2023, 154:105019.

[46] Jeong J, Jo H. Deep reinforcement learning for automated design of reinforced concrete structures. *Comput*.*-Aided Civ*. *Infrustrut*. *Eng*. 2021, 36(12):1508–1529.

[47] Banti N, Ciacci C, Bazzocchi F, Naso DV. Enhancing industrial buildings’ performance through informed decision making: A generative design for building-integrated photovoltaic and shading system optimization. *Solar* 2024, 4(3):401–421.

[48] Zotero. Version 7.0, Corporation for Digital Scholarship, 2024. Available: https://www.zotero.org/download/ (accessed on 22 November 2025).

[49] Awad H, Salim K, Gül M. Multi-objective design of grid-tied solar photovoltaics for commercial flat rooftops using particle swarm optimization algorithm. *J*. *Build*. *Eng*. 2020, 28:101080.

[50] Zhao Q, Sun B, Zhao W, Watanabe T, Usui T, *et al*. Improved GAN-based deep learning approach for strain field prediction and failure analysis of precast bridge slab joints. *Eng*. *Struct*. 2024, 321:119023.

[51] Bagheri A, Alipour M, Ozbulut O, Harris D. A nondestructive method for load rating of bridges without structural properties and plans. *Eng. Struct.* 2018, 171:545–556.

[52] He Z, Wang Y, Zhang J. Generative AIBIM: an automatic and intelligent structural design pipeline integrating BIM and generative AI. *Inf. Fusion*. 2025, 114:102654.

[53] Heydari F, Andalib M, Epackachi S, Rafiee-Dehkharghani R. Optimized design of RC moment frames with machine learning methods. *J. Build. Eng.* 2025, 104:112222.

[54] Zhang Y, Tatarintseva L, Clewlow T, Clark E, Botsford G, *et al*. A template design and automated parametric model for sustainable corbel dwellings with interlocking blocks. *Dev. Built Environ.* 2023, 14:100148.

[55] Parracho D, Nour El-Din M, Esmaeili I, Freitas S, Rodrigues L, *et al*. Modular construction in the digital age: a systematic review on smart and sustainable innovations. *Buildings* 2025, 15(5):765.

[56] Ciacci C, Banti N, Naso DV, Bazzocchi F. Evaluation of the cost-optimal method applied to existing schools considering PV system optimization. *Energies* 2022, 15(2):611.

[57] Shahsavar A, Moayedi H, Al-Waeli A, Sopian K, Chelvanathan P. Machine learning predictive models for optimal design of building-integrated photovoltaic-thermal collectors. *Int. J. Energy Res.* 2020, 44(7):5675–5695.

[58] Liu P, Qi H, Liu J, Feng L, Li D, *et al*. Automated clash resolution for reinforcement steel design in precast concrete wall panels via generative adversarial network and reinforcement learning. *Adv. Eng. Inf.* 2023, 58:102131.

[59] Li M, Wong B, Liu Y, Chan C, Gan V, *et al*. DfMA-oriented design optimization for steel reinforcement using BIM and hybrid metaheuristic algorithms. *J. Build. Eng.* 2021, 44:103310.

[60] Baduge S, Thilakarathna S, Perera J, Arashpour M, Sharafi P, *et al*. Artificial intelligence and smart vision for building and construction 4.0: machine and deep learning methods and applications. *Autom. Constr.* 2022, 141:104440.

[61] Guo X, Huang Y, Ma G. Recent research developments in intelligent methodologies for prefabricated construction. *Smart Constr.* 2024, 1(2):1–33.

[62] Chang M, Zhu S, Chen T, Chen C, Qian K, *et al*. Intelligent generative design method for planar layout scheme of modular steel structure buildings. *Prog. Build. Steel Struct.* 2024, 26(2):83–89.

[63] Lin X, Su P, Lu W, Guo H. ModulePacking: a top-down generative design approach for modular key plans. *J. Comput. Civ. Eng.* 2025, 39(1):04024047.

[64] Hajela P, Lee E, Lin C. Genetic algorithms in structural topology optimization. In *Topology Design of Structures*. Dordrecht: Springer Netherlands, 1993. pp. 117–133.

[65] Fourie PC, Groenwold A. The particle swarm optimization algorithm in size and shape optimization. *Struct. Multidiscip. Optim.* 2002, 23(4):259–267.

[66] Dzwierzynska J, Lechwar P. Performance assessment and sustainable applications of steel canopies with saddle modules. *Sustainability* 2024, 16(24):10980.

[67] Zhou Q, Xue F. Pushing the boundaries of modular-integrated construction: a symmetric skeleton grammar-based multi-objective optimization of passive design for energy savings and daylight autonomy. *Energy Build.* 2023, 296:113417.

[68] Xu C, Zheng X, Wu Z, Zhang C. Automated prefabricated slab splitting design using a multipopulation coevolutionary algorithm and BIM. *Buildings* 2024, 14(2):433.

[69] Xu L, Wang L, Zhu M. Application of BIM technology in structural design of prefabricated building

based on big data simulation modeling analysis. *Scalable Comput*. 2024, 25(4):2862–2875.

[70] Xing G, Lu Y, Miao P, Chen S. Optimal design method of temporary broadcasting tower structure based on improved genetic algorithm (In Chinese). *J. Zhejiang Univ*. 2025, 59(3):469–479.

[71] Li M, Wang Z, Chang H, Wang Z, Guo J. A novel multi-objective generative design approach for sustainable building using multi-task learning (ANN) integration. *Appl. Energy*. 2024, 376:124220.

[72] Sacks R, Warszawski A, Kirsch U. Structural design in an automated building system. *Autom. Constr*. 2000, 10(1):181–197.

[73] Rodrigues E, Soares N, Fernandes M, Gaspar A, Gomes Á, *et al*. An integrated energy performance-driven generative design methodology to foster modular lightweight steel framed dwellings in hot climates. *Energy Sustain*able *Dev*. 2018, 44:21–36.

[74] Adeli H, Park H. A neural dynamics model for structural optimization—theory. *Comput. Struct*. 1995, 57(3):383–390.

[75] Adeli H, Park H. Optimization of space structures by neural dynamics. *Neural Network* 1995, 8(5):769–781.

[76] Wang J, Zhou J, Zhang S. Applying shape grammar and BIM for generating the mass modular housing design in ShanLiChenJia village, ZhaoYuan, China. *J. Asian Archit. Build. Eng*. 2025, 24(1):178–198.

[77] Shen X, Ye X. Environmental performance driven optimization of urban modular housing layout in Singapore. *J. Asian Archit. Build. Eng*. 2025, 24(2):910–923.

[78] Ding Y, Song K, Liu X, Jiang R, Zhao H, *et al*. Application of computer vision in optimal design of assembled buildings. *Proc. Inst. Civ. Eng. Smart Infrastruct. Constr*. 2024, 177(3):137–147.

[79] Tusnin A, Alekseytsev A, Tusnina O. Using machine learning technologies to design modular buildings. *Buildings* 2024, 14 (7):2213.

[80] Xia Y, Liu J, Qi H, Wang L, Li J, *et al*. Graph-based BIM generation method for integrated design of steel modular buildings. *J. Build. Eng*. 2025, 106:112476.

[81] Leng H, Gao Y, Zhou Y. ArchiDiffusion: a novel diffusion model connecting architectural layout generation from sketches to Shear Wall Design. *J. Build. Eng*. 2024, 98:111373.

[82] Fu B, Gao Y, Wang W. Dual generative adversarial networks for automated component layout design of steel frame-brace structures. *Autom. Constr*. 2023, 146:104661.

[83] Fu B, Wang W, Gao Y. Physical rule-guided generative adversarial network for automated structural layout design of steel frame-brace structures. *J. Build. Eng*. 2024, 86:108943.

[84] Fu B, Gao Y, Wang W. A physics-informed deep reinforcement learning framework for autonomous steel frame structural design. *Comput.-Aided Civ. Infrustrut. Eng.* 2024, 39(20):3125–3144.

[85] Luo R, Wang Y, Xiao W, Zhao X. Alphatruss: Monte Carlo tree search for optimal truss layout design. *Buildings* 2022, 12(5):641.

[86] Li J, Wang W, Fu B, Gao Y. FrameDiffusion: a latent diffusion model for intelligent layout design of steel frame-braced structures. *Eng. Struct*. 2025, 343:121195.

[87] Fu B, Gao Y, Wang W, Du M. Autonomous component optimization method for steel braced frame structures based on multi-agent and physics-informed deep reinforcement learning. *Adv. Eng. Inf.* 2026, 69:103878.

[88] Liao W, Lu X, Huang Y, Zheng Z, Lin Y. Automated structural design of shear wall residential buildings using generative adversarial networks. *Autom. Constr.* 2021, 132:103931.

[89] Hayashi K, Ohsaki M. Graph-based reinforcement learning for discrete cross-section optimization of planar steel frames. *Adv. Eng. Inf.* 2022, 51:101512.

[90] Wang L, Lu Y. Research on the optimization of prefabricated building preset scheme integrating BIM technology and BiLSTM model. *Appl. Math. Nonlinear Sci.* 2023, 9(1):3.

[91] Pibal S, Khoss K, Kovacic I. Framework of an algorithm-aided BIM approach for modular residential building information models. *Int. J. Archit. Comput.* 2022, 20(4):777–800.

[92] Liao W, Wang X, Fei Y, Huang Y, Xie L, *et al.* Base-isolation design of shear wall structures using physics-rule-CO-guided self-supervised generative adversarial networks. *Earthquake Eng. Struct. Dyn.* 2023, 52(11):3281–3303.

[93] Linkwitz K. Schek HJ. Einige bemerkungen zur berechnung von vorgespannten seilnetzkonstruktionen. *Ingenieur-Archiv* 1971, 40(3):145–158.

[94] Schek HJ. The force density method for form finding and computation of general networks. *Comput. Methods Appl. Mech. Eng.* 1974, 3(1):115–134.

[95] Maia Avelino R, Iannuzzo A, Van Mele T, Block P. Assessing the safety of vaulted masonry structures using thrust network analysis. *Comput. Struct.* 2021, 257:106647.

[96] Ohlbrock P, D’Acunto P. A computer-aided approach to equilibrium design based on graphic statics and combinatorial variations. *Comput.-Aided Des.* 2020, 121:102802.

[97] Jasienski J, Shen Y, Ohlbrock P, Zastavni D, D’Acunto P. A computational implementation of Vector-based 3D Graphic Statics (VGS) for interactive and real-time structural design. *Comput.-Aided Des.* 2024, 171:103695.

[98] Liew A. Constrained force density method optimisation for compression-only shell structures. *Structures* 2020, 28:1845–1856.

[99] Li X, Liu C, Xue S, Li X, Zhang C, *et al.* The modified force density method for form-finding of cable net structure. *Thin-Walled Struct.* 2024, 195:111363.

[100] Tang V, Lv Q, Li T, Shao M. Self-equilibrium, stability, and accuracy degradation of imperfect prismatic tensegrities with additional cable nets. *Eng. Struct.* 2023, 284:115981.

[101] Liu R, Guo H, Liu R, Tang D, Wang H, *et al.* Design and form finding of cable net for a large cable–rib tension antenna with flexible deployable structures. *Eng. Struct.* 2019, 199: 109662.

[102] Maurin B, Motro R. The surface stress density method as a form-finding tool for tensile membranes. *Eng. Struct.* 1998, 20(8):712–719.

[103] Liu Z, Zhu M, Yang D, Zhang C, Liu Y, *et al.* An overall form-finding method of cable-membrane-truss for super-large mesh reflectors considering large-deformation trusses. *Thin-Walled Struct.* 2025, 215:113536.

[104] Tang Y, Li T. Equivalent-force density method as a shape-finding tool for cable-membrane structures. *Eng. Struct.* 2017, 151:11–19.

[105] He Y, Guo J, Ping H, Liu D, Zhou E. A self-adaptive gradient boosting decision tree algorithm for form-finding of tensegrity structures. *Thin-Walled Struct.* 2025, 215:113472.

[106] Tam K, Brown N, Bronstein M, Mele T, Block P. Learning constrained static equilibrium for thrust network inverse form-finding via physics-informed geometric deep learning on CW complexes. *Adv. Eng. Inf.* 2026, 70:103870.

[107] Pastrana R. Ohlbrock P, Oberbichler T, D'Acunto P, Parascho S. Constrained form-finding of tension—compression structures using automatic differentiation. *Comput.-Aided Des*. 2023, 155:103435.

[108] Wan Z. Ohlbrock P, D'Acunto P, Cao Z, Fan F, *et al*. A form-finding approach for the conceptual design of air-supported structures using 3D graphic statics. *Comput. Struct.* 2021, 243:106401.

[109] Bleker L, Tam K, D'Acunto P. Logic-informed graph neural networks for structural form-finding. *Adv. Eng. Inf*. 2024, 61:102510.