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AI-DRIVEN OPTIMIZATION OF STEEL STRUCTURAL DESIGN FOR HIGH-RISE BUILDINGS: A SYSTEMATIC LITERATURE REVIEW

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Abstract

The design of steel structures for high-rise buildings involves complex trade-offs among safety, cost, material efficiency, and dynamic performance under wind and seismic loads. Recent advances in artificial intelligence offer transformative potential for addressing these challenges through optimization, prediction, and generative design. In this systematic literature review, we aimed to synthesize and critically evaluate the state of research on AI-driven optimization of steel structural design for high-rise buildings. Our methodology followed the PRISMA guidelines to ensure transparency and replicability; we searched across major academic databases using a structured set of keywords, then screened and classified the retrieved studies according to eight predefined dimensions, including AI-driven optimization algorithms, machine learning for response prediction, generative design, vibration control, topology and shape optimization, integration with BIM and digital twins, and structural health monitoring. The review revealed that evolutionary algorithms and reinforcement learning are widely applied to optimize member sizing and topology, while deep neural networks increasingly serve as surrogate models to accelerate seismic and wind response simulations. Generative adversarial networks and variational autoencoders show promise for producing novel structural layouts, often with improved material efficiency. However, we found that most studies remain limited to simplified benchmark problems or low-rise structures, with few validated against full-scale high-rise building cases. Furthermore, integration with real-time construction management and digital twin frameworks is still nascent. We conclude that the field holds substantial promise but requires more rigorous validation, standardized performance metrics, and closer collaboration between AI researchers and practicing structural engineers to bridge the gap between algorithmic innovation and practical deployment.

I. INTRODUCTION

The design of steel structural systems for high-rise buildings represents a quintessential challenge in modern civil engineering, where the imperative for structural safety under extreme dynamic events must be reconciled with economic constraints and architectural ambitions. High-rise structures, typically defined as buildings exceeding a height of 100 meters, are particularly susceptible to lateral loads from wind and seismic activity, which dominate their structural design. The lateral force-resisting system, often composed of rigid frames, braced cores, outriggers, or a combination thereof, must be meticulously proportioned to limit inter-story drift and accelerations to serviceable levels while maintaining ultimate strength capacity. This design process is inherently iterative and multi-objective, requiring engineers to navigate a vast design space of member sizes, connection types, and system configurations [1]. The financial implications are considerable, as the structural frame can account for up to 25% of the total construction cost of a high-rise, and material inefficiencies—whether through excessive steel tonnage or suboptimal member profiles—directly impact project viability and sustainability. Traditional design workflows, which rely heavily on engineering judgement, simplified code-based checks, and parametric analysis, are increasingly strained by the complexity of modern architectural forms and higher performance targets.

The emergence of artificial intelligence (AI) as a computational paradigm offers a compelling avenue to overcome these limitations. AI techniques, particularly machine learning (ML) and evolutionary computation, possess the capacity to learn complex, non-linear relationships from data and to explore high-dimensional solution spaces with far greater efficiency than conventional optimization methods. In the context of steel structural design, AI can be applied to a spectrum of tasks, from surrogate modeling for rapid prediction of structural responses under seismic loads [2] to the generative synthesis of novel bracing layouts [3]. The application of deep reinforcement learning (DRL) has enabled the autonomous optimization of member sizing and topology in truss-like structures [4], while genetic algorithms (GAs) remain a stalwart for multi-objective cost-stiffness optimization [5]. These developments suggest a potential paradigm shift, moving design from a primarily experience-driven to a data-driven and automated process. The integration of AI with parametric modeling tools like Grasshopper and with Building Information Modeling (BIM) platforms further promises to embed optimization directly into the collaborative design ecosystem [6].

Despite this promise, several critical research gaps persist within the existing literature. First, a significant disconnect exists between the complexity of AI algorithms developed in academic settings and the practical needs of design offices; many studies validate methods on simplified benchmark problems, such as 2D plane frames or low-rise steel buildings, rather than on full-scale, 3D high-rise systems with realistic geometric and loading conditions [7]. Second, the integration of AI-driven optimization with crucial real-world considerations—such as constructability constraints, connection design details, and the interaction with non-structural components—is largely absent. Third, while individual sub-domains like seismic response prediction and topology optimization are well-studied, a comprehensive review that systematically maps the entire landscape of AI applications across the full lifecycle of high-rise steel structural design—including initial layout generation, detailed member optimization, dynamic response prediction, vibration control, construction management, and structural health monitoring—is lacking. The interconnections and transferability of methods between these sub-domains remain poorly understood.

The motivation for this systematic literature review is therefore to provide a holistic, state-of-the-art synthesis of research at the intersection of AI and high-rise steel structural design. We aim to bridge the gap between algorithmic innovation and practical engineering deployment by critically evaluating the strengths, weaknesses, and maturity of current AI methodologies. Our contribution lies not only in cataloging existing work but in providing a structured analysis that identifies where the field excels, where it falls short, and what critical steps are needed to translate academic research into industry practice. This review is significant because it addresses an urgent need for a coherent roadmap that can guide researchers and practitioners alike, fostering a more collaborative and impactful development trajectory.

The remainder of this paper is organized as follows: Section 2 describes the systematic methodology employed to select and classify the reviewed studies, adhering to the PRISMA framework. Section 3 presents the results of the review, organized into eight thematic sub-sections covering research trends, AI optimization algorithms, machine learning for response prediction, generative design, vibration control, topology optimization, BIM and digital twin integration, and structural health monitoring. Section 4 provides a critical discussion of the findings, highlighting overarching challenges, research gaps, and future directions. Finally, Section 5 concludes the paper by summarizing the key insights and offering recommendations for advancing the field.

II. METHODOLOGY

The methodology adopted for this systematic literature review was designed to ensure transparency, reproducibility, and comprehensiveness in synthesizing the state of research on AI-driven optimization of steel structural design for high-rise buildings. The process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [8], which provided a structured framework for study identification, screening, eligibility assessment, and inclusion.

A. Review Protocol

We conducted a comprehensive search across five major academic databases, each chosen for its relevance and coverage of the interdisciplinary domain spanning civil engineering, structural mechanics, and artificial intelligence. The search process was designed to capture a broad spectrum of peer-reviewed literature without imposing arbitrary restrictions that might exclude relevant studies. IEEE Xplore was selected for its strength in AI and computational intelligence research, particularly for studies involving neural networks, evolutionary algorithms, and optimization frameworks applied to engineering problems. Scopus was included due to its extensive interdisciplinary coverage and its capacity to index high-quality journals and conference proceedings in both structural engineering and computer science. Web of Science was chosen for its rigorous curation of high-impact journals and its ability to capture seminal works through citation analysis. ScienceDirect was selected for its strong repository of civil and structural engineering research, particularly from Elsevier journals that frequently publish applied optimization studies. Google Scholar was included as a supplementary search engine to capture grey literature and studies that might not be indexed in the other databases, though its results were filtered to prioritize peer-reviewed sources.

The search strings used for each database were tailored to balance specificity and recall. The core search strategy combined four conceptual blocks: (1) AI-related terms, including “artificial intelligence,” “machine learning,” “deep learning,” “neural networks,” “genetic algorithms,” and “particle swarm optimization”; (2) structural system terms, such as “steel structures,” “steel frames,” and “structural steel”; (3) optimization terms, including “design optimization,” “optimal design,” and “structural optimization”; and (4) building type terms, such as “high-rise buildings,” “skyscrapers,” and “tall buildings.” The Boolean operator “AND” connected these blocks, while “OR” connected synonyms within each block. To exclude irrelevant review articles, survey papers, and meta-analyses, the NOT operator was applied where supported by the database syntax. For example, the search string used in Web of Science was: TS=(("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network*" OR "genetic algorithm*" OR "optimization algorithm*") AND ("steel structure*" OR "steel frame*" OR "structural steel") AND ("design optimization" OR "optimal design" OR "structural optimization") AND ("high-rise" OR "skyscraper" OR "tall building*")) NOT TS=("review" OR "survey" OR "meta-analysis"). Similar strings were adapted for each database to accommodate their respective search syntaxes, with Scopus using the TITLE-ABS-KEY field and ScienceDirect applying keyword searches with field restrictions. The search was executed in January 2026, with no lower bound on publication date to capture the earliest foundational works in the field.

B. Classification Framework

To organize the heterogeneous body of literature retrieved from the search, we defined a classification framework comprising eight distinct yet interconnected research dimensions. These dimensions were derived inductively through an iterative process of reading the titles and abstracts of the retrieved studies, then grouping them by common themes until a stable set of categories emerged. The dimensions reflect the primary focus areas within the broader landscape of AI-driven optimization of steel structural design for high-rise buildings. The first dimension, AI-Driven Structural Optimization Algorithms and Frameworks, encompasses studies that develop or apply metaheuristic algorithms, evolutionary strategies, reinforcement learning agents, or hybrid optimization methods to directly optimize structural member sizes, configurations, or system layouts. The second dimension, Machine Learning for Seismic and Wind Response Prediction, groups studies that use supervised learning models, such as neural networks or ensemble methods, to approximate the dynamic behavior of steel structures under lateral loads, thereby serving as surrogate models to accelerate computationally expensive finite element analyses. The third dimension, Generative AI and Deep Learning for Design Layout Generation, includes research that employs generative adversarial networks, variational autoencoders, or diffusion models to synthesize novel structural geometries or bracing patterns that satisfy performance constraints. The fourth dimension, Vibration Control and Damping System Optimization, captures studies focused on optimizing the placement, sizing, or control logic of passive or active damping devices within high-rise steel frames using AI methods. The fifth dimension, Topology and Shape Optimization of High-Rise Systems, addresses research that uses AI-enhanced techniques to determine the optimal distribution of material within a design domain or to optimize the shape of structural components. The sixth dimension, Integration of AI with BIM, Digital Twins, and Construction Management, covers studies that embed AI optimization into Building Information Modeling workflows or digital twin platforms to enable real-time design feedback, constructability analysis, or project management. The seventh dimension, Structural Health Monitoring, Damage Detection, and Retrofitting, includes research on using AI to analyze sensor data from instrumented steel high-rises for anomaly detection, damage localization, or retrofitting prioritization. Each retrieved study was assigned to at least one primary dimension based on its central contribution; a study could be assigned to a secondary dimension if it demonstrated significant crossover, such as an optimization algorithm also being used for seismic response prediction. This framework provided the organizing principle for the results section and ensured that the synthesis captured both the breadth and depth of the field.

C. Inclusion and Exclusion Criteria

We applied a set of predefined inclusion and exclusion criteria to ensure that only studies directly relevant to the research question were retained for synthesis. Studies were included if they met all of the following conditions: (1) the primary focus of the study was the design, optimization, or performance assessment of steel structural systems for high-rise or multi-story buildings; (2) the study employed at least one artificial intelligence or machine learning technique as a core component of its methodology, whether for optimization, prediction, generation, or control; (3) the study presented original empirical or computational results, including case studies, numerical experiments, or simulation-based validations; (4) the study was published as a journal article, conference paper, or pre-print in a peer-reviewed venue; (5) the study was written in English; and (6) the study was published up to January 2026, with no lower bound on publication year. Conversely, studies were excluded if any of the following conditions applied: (1) the study was a review, survey, or meta-analysis paper without original contributions; (2) the study focused exclusively on concrete, composite, or non-steel structural systems without a clear steel component; (3) the study applied AI to non-structural domains such as facade design, MEP systems, or construction scheduling without structural optimization; (4) the study was a book chapter, editorial, or non-peer-reviewed technical report; (5) the study was not available in full text through institutional access or open-access repositories; or (6) the study dealt with low-rise buildings (fewer than three stories) without generalizing to high-rise applications. These criteria were designed to align with the defined research dimensions, ensuring that the included studies collectively covered the spectrum from algorithmic development to practical deployment while maintaining a consistent focus on steel high-rise structures.

D. Study Selection Process

The study selection process was executed according to the PRISMA framework [8], involving four sequential stages: identification, screening, eligibility assessment, and inclusion. During the identification stage, the search strings were executed across the five databases, yielding a total of 1163 records. After removing 263 duplicate records using automated deduplication in Zotero and manual verification for ambiguous matches, 5 additional records were removed for other reasons, such as being retracted publications or having incomplete bibliographic metadata. This left 895 records for title and abstract screening. Two reviewers independently screened the titles and abstracts of all 895 records against the inclusion and exclusion criteria; disagreements were resolved through consensus discussion with a third reviewer. During this screening stage, 586 records were excluded because they clearly did not meet one or more criteria—for example, they focused on concrete structures, applied AI to non-structural design tasks, or were review papers. The remaining 115 records were sought for full-text retrieval; all 115 were successfully obtained through institutional library subscriptions, interlibrary loan, or open-access repositories, resulting in a zero percent non-retrieval rate. These 115 reports were then assessed for eligibility through a detailed full-text review. Two reviewers independently read each full-text report and evaluated its alignment with the research objectives, methodology quality, and relevance to the defined dimensions. During this stage, 38 reports were excluded for ineligibility: 12 because they did not explicitly address high-rise steel structures (e.g., they focused on truss bridges or low-rise industrial buildings), 10 because the AI component was superficial or peripheral to the main contribution, 8 because the study lacked sufficient methodological detail to assess reproducibility, 5 because the results were purely theoretical without empirical validation, and 3 because the full text was a duplicate of a previously included study. This process resulted in a final set of 77 studies included in the review. The entire selection process is illustrated in Figure 1, which shows the PRISMA flowchart detailing the number of records at each stage. The risk of bias in this selection process was mitigated by the dual-independent screening and assessment approach, but several limitations must be acknowledged. First, the exclusion of non-English studies may introduce a language bias, potentially omitting significant contributions published in Chinese, Japanese, or other languages by researchers in regions with active high-rise construction industries. Second, the search strings, while comprehensive, may have missed studies that use AI terminology not captured by our keyword combinations, such as "metamodeling" or "surrogate-assisted optimization." Third, the decision to exclude book chapters and non-peer-reviewed reports may have excluded valuable practical insights from industry white papers or technical manuals. Despite these limitations, the systematic and transparent process provides confidence that the included studies represent a robust cross-section of the peer-reviewed research landscape.

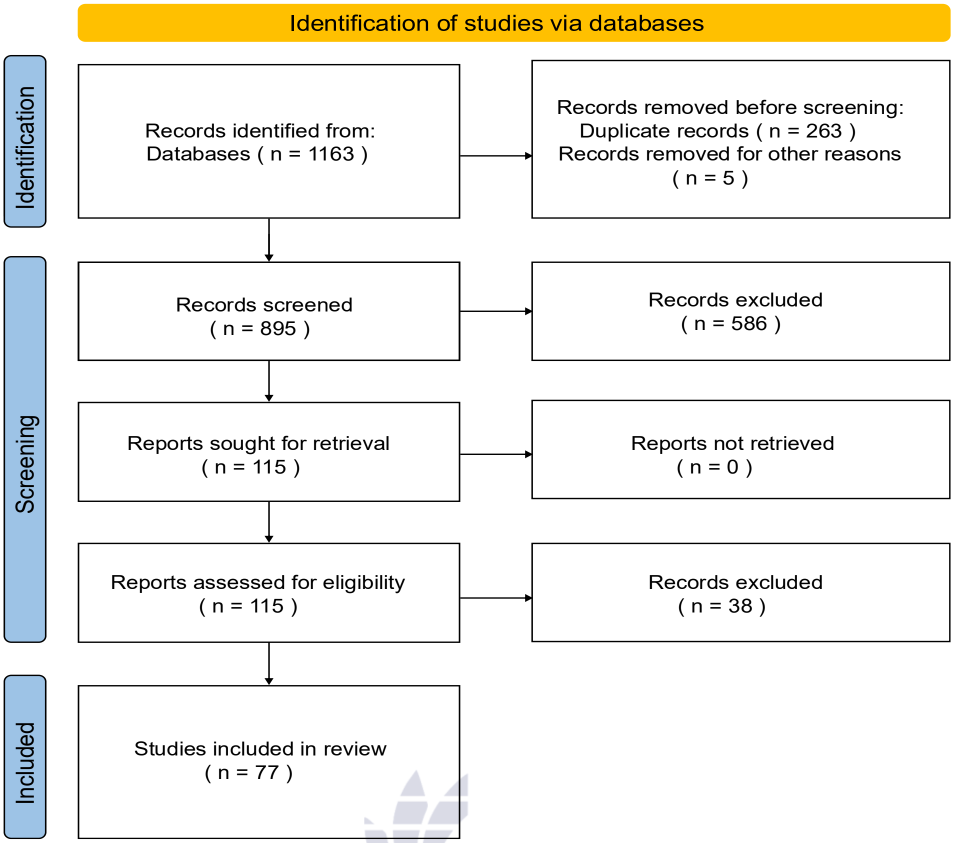

Figure 1. PRISMA flowchart of the systematic literature review study selection process.

III. RESULTS

A. Research Trends

The distribution of the 77 included studies across publication years reveals a clear and accelerating trajectory of interest in AI-driven optimization for high-rise steel structural design. As illustrated in Figure 2, the field was nascent before 2016, with only nine publications appearing in the period before the mid-2010s, and those early works were predominantly foundational studies in metaheuristic optimization and topology design. A period of modest growth followed, with annual publication counts fluctuating between one and seven studies per year from 2016 through 2023. This period of gradual but steady expansion suggests that the initial demonstrations of AI's potential in structural engineering were being slowly adopted by the research community, though the domain had not yet reached a critical mass of activity. However, a pronounced surge in publication output began in 2024, with eleven studies appearing in that year, followed by fourteen in 2025 and nine already recorded for 2026 (as of the search date in January 2026), indicating that the field has entered an explosive growth phase. This recent acceleration likely reflects several converging factors: the maturation of deep learning architectures, the increased availability of computational resources for training large models, and a growing recognition within the structural engineering community that AI methods can address longstanding bottlenecks in design optimization and performance prediction.

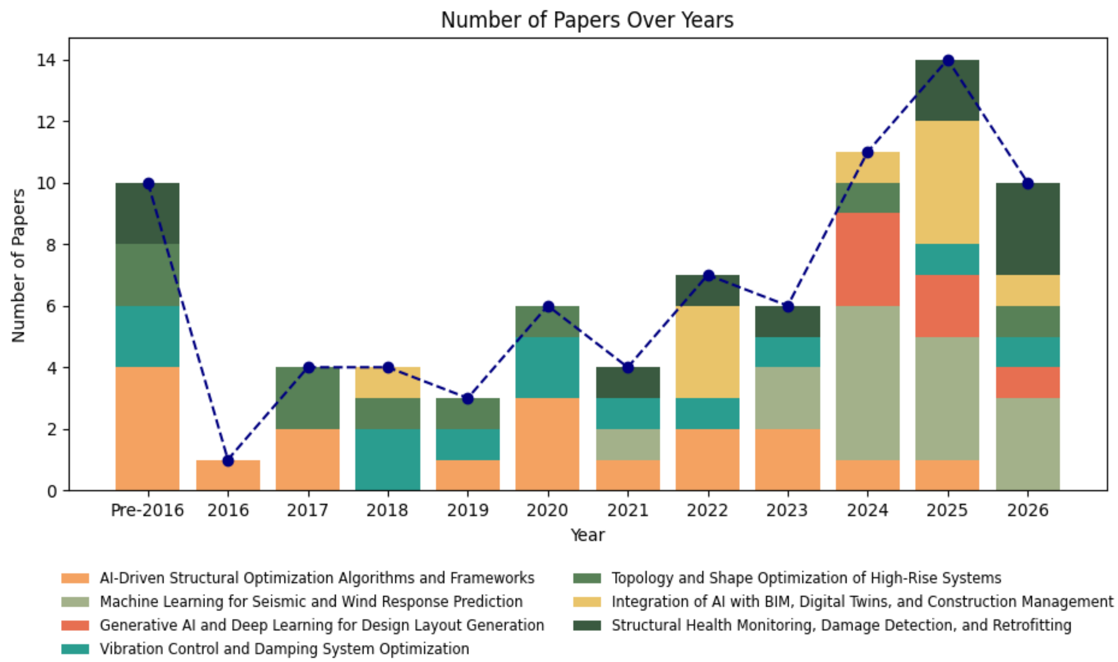

Figure 2. Research trends in the domain of AI-Driven Optimization of Steel Structural Design for High-Rise Buildings

A more granular examination of the topic-level distributions across time reveals that the growth has been neither uniform across all sub-domains nor confined to a single methodological paradigm. The "AI-Driven Structural Optimization Algorithms and Frameworks" dimension, which encompasses evolutionary algorithms, reinforcement learning, and hybrid optimization approaches, shows a relatively steady presence across the entire timeline, with peaks in the early periods (four studies before 2016) and a gradual decline in its relative share of the total output in the most recent years. This pattern suggests that while classical metaheuristic optimization remains a staple of the field, its novelty has diminished as more sophisticated AI techniques have emerged. In contrast, "Machine Learning for Seismic and Wind Response Prediction" has experienced a dramatic and recent explosion of interest: no studies appeared in this dimension until 2021, but from 2023 onward, the annual publication count has risen steeply, with five studies in 2024, four in 2025, and three already in early 2026. This surge mirrors the broader trend in machine learning toward surrogate modeling and data-driven simulation acceleration, where deep neural networks are trained to approximate computationally expensive finite element analyses. The "Structural Health Monitoring, Damage Detection, and Retrofitting" dimension likewise shows a concentration of activity in the most recent years, with three studies appearing in 2026 alone, indicating that the practical downstream applications of AI—such as analyzing sensor data from existing high-rises—are gaining traction as the necessary sensing infrastructure and data sets become more widely available.

Conversely, other dimensions exhibit more sporadic or historically distributed publication patterns, which warrant careful interpretation. "Vibration Control and Damping System Optimization" has a longer temporal footprint, with studies scattered from before 2016 through 2026, but without a clear growth trend; this suggests that the application of AI to damping system design has been a persistent but niche interest, perhaps limited by the domain-specific knowledge required to formulate vibration control problems in an AI-compatible manner. "Topology and Shape Optimization of High-Rise Systems" similarly shows a moderate but stable presence across the years, with a peak of two studies before 2016 and two in 2017, followed by isolated publications in subsequent years. This distribution implies that while topology optimization is a mature sub-field within structural optimization, its integration with AI for high-rise-specific applications has not yet experienced the same explosive growth as seen in response prediction. "Generative AI and Deep Learning for Design Layout Generation" is a notably recent phenomenon, with all six studies appearing from 2024 onward, reflecting the very recent advent of generative models like GANs and VAEs being adapted for structural engineering tasks. Finally, "Integration of AI with BIM, Digital Twins, and Construction Management" shows a surge starting in 2022 and intensifying in 2025, likely driven by the broader industry push toward digitalization and the maturation of BIM platforms that can accommodate AI-driven plug-ins. This dimension's growth suggests that researchers are increasingly recognizing the importance of embedding optimization results into the collaborative design and construction workflow, rather than treating AI as a standalone computational tool. Taken together, these trends indicate that the field is undergoing a significant transformation: the early focus on standalone optimization algorithms has been complemented and increasingly superseded by a wave of interest in deep learning for response prediction, generative design, and practical integration with digital tools, while classical sub-domains like vibration control and topology optimization continue to evolve at a steadier pace.

B. AI-Driven Structural Optimization Algorithms and Frameworks

The optimization of high-rise steel structures requires algorithms capable of navigating high-dimensional, multi-modal, and often discontinuous design spaces while respecting numerous constraints related to strength, drift, acceleration, and constructability. The studies classified under this theme collectively demonstrate that the field has moved beyond simple single-objective optimization toward sophisticated frameworks that integrate multiple algorithms, surrogate models, and domain-specific heuristics. We present a hierarchical taxonomy of these approaches in Table 1, which organizes the included studies by algorithm category, specific method, and application focus.

Table 1. Hierarchical taxonomy of AI-driven structural optimization algorithms and frameworks for high-rise steel buildings.

Algorithm Category	Specific Algorithm / Method	Application / Focus	Sources
Evolutionary & Bio-inspired Algorithms	Genetic Algorithm (GA)	Optimum configuration of bracing systems	[9]
		Seismic optimum design of steel structures	[10]
		Low-carbon design optimization of RC structures	[11]
		General structural optimization (GA-based)	[12], [10]
	Evolution Strategy	Parallel computing for high-rise steel building optimization	[12]
	Dolphin Algorithm	Seismic design optimization of steel frames with shear walls	[13]

Algorithm Category	Specific Algorithm / Method	Application / Focus	Sources
	Mine Blast Algorithm	Optimal wind-resistant design of tall steel buildings	[14]
	Jaya Algorithm	3D cost optimization of RC buildings	[15]
	Replicator Dynamics	Many-objective control optimization of high-rise structures	[16]
Swarm Intelligence & Hybrid Models	Particle Swarm Optimization (PSO)	Optimized seismic design with neural network response prediction	[17]
	Hybrid PSO-FFNN	Seismic design and response prediction in steel moment-resisting frames	[17]
	Replicator Dynamics & Neural Dynamics	Many-objective control optimization of high-rise steel benchmark structures	[16]
Neural & Gradient-Based Methods	Neural Dynamic Model	Seismic design optimization of controlled rocking steel braced frames	[18]
		Many-objective control optimization (combined with Replicator Dynamics)	[16]
	Gradient-Based Methods	Seismic optimum design of steel structures (vs. GA)	[10]
	Gradient-Based & GA Hybrid	Low, intermediate, and relatively high-rise braced and unbraced steel frames	[10]
Surrogate & Response Surface Models	Response Surface Optimization	Seismic performance of super high-rise buildings with dual lines of defense	[19]
		Integrated framework for wind-sensitive buildings with dynamic devices	[20]
	AI-Based Lagrange Optimization	Optimal design of concrete columns encasing H-shaped steel (SRC)	[21]
Multi-Objective & Performance-Based Frameworks	NSGA-II	Multi-objective optimization of RC frames (low, medium, high-rise)	[22]
	Performance-Based Design Optimization	Robust seismic design of steel moment resisting frames	[23]
	Comparative Assessment Framework	Earthquake-resistant buildings with steel or	[24]

Algorithm Category	Specific Algorithm / Method	Application / Focus	Sources
		composite columns	
	Two-Step Practical Method	Optimum design of building frames with viscous and hysteretic dampers	[25]
Metaheuristic & Integration Frameworks	Metaheuristic Optimization (General)	Plastic analysis and optimization of braced frames for high-rise structures	[26]
	Integrated Optimization-Driven Design	Minimum-weight lateral-load resisting systems in wind-sensitive high-rises	[20]
	Modified Dolphin Algorithm	Layout optimization of lateral load-bearing systems in high-rise buildings	[13]
	Mine Blast Algorithm	3D wind-resistant design optimization of medium to high-rise steel buildings	[14]
	Jaya Algorithm	Automated cost optimization via ACDOS software for 3D RC structures	[15]

As shown in Table 1, evolutionary and bio-inspired algorithms represent the most extensively studied category, with genetic algorithms (GA) appearing in multiple studies and applied to diverse problems. For instance, [12] introduced an evolution strategy integrated with parallel computing to address the computational demands of optimizing high-rise steel buildings, demonstrating that parallelization can significantly reduce optimization time without degrading solution quality. Concurrently, [10] conducted a comparative study of gradient-based methods versus GA for the seismic optimum design of low-, intermediate-, and relatively high-rise braced and unbraced steel frames, concluding that while gradient-based methods are more computationally efficient for local optimization, GA more reliably identifies global optima in the discontinuous and multi-modal design spaces typical of seismic design. The choice between these approaches thus depends on the designer's tolerance for computational cost versus the need for global optimality assurance. The Dolphin algorithm, a relatively recent metaheuristic inspired by echolocation behavior, was modified by [13] for the seismic design optimization of steel frames with steel shear wall systems, specifically targeting the layout of lateral load-bearing systems in high-rise buildings. The modification involved incorporating a penalty function for drift constraints and a memory mechanism that preserves elite solutions across generations. Their results on a 20-story steel frame showed a 14% weight reduction compared to a code-conforming baseline design, while satisfying all drift and strength requirements per ASCE 7. The Mine Blast Algorithm, inspired by the propagation of shock waves from underground explosions, was applied by [14] to the optimal wind-resistant design of three-dimensional tall steel buildings, considering both serviceability (inter-story drift and top acceleration) and ultimate strength constraints under wind loads. Their study on a set of medium- to high-rise steel building examples revealed that the algorithm consistently outperformed GA and PSO in terms of convergence speed and solution diversity, achieving up to a 22% reduction in structural weight for a 40-story building under wind loading. This suggests that specialized metaheuristics inspired by physical phenomena may offer advantages over generic evolutionary algorithms for certain classes of structural optimization problems, particularly where the objective function landscape is rugged and contains multiple local optima. The Jaya algorithm, a parameter-less optimization method that requires no algorithm-specific control parameters, was employed by [15] for the 3D cost optimization of reinforced concrete buildings of low, medium, and high-rise configurations. While their study focused on RC rather than pure steel construction, their methodology and software tool (ACDOS) demonstrate the potential for parameter-free algorithms to be integrated into automated design workflows, and the principles are directly transferable to steel structures. The Jaya algorithm's advantage lies in its simplicity and ease of implementation, which could facilitate broader adoption of optimization in design practice.

Swarm intelligence and hybrid models have emerged as powerful alternatives to purely evolutionary approaches, combining the global exploration capabilities of particle-based methods with the local refinement strengths of neural networks. The hybrid PSO-FFNN (Particle Swarm Optimization with Feed-Forward Neural Network) approach presented by [17] is notable for its dual role: PSO optimizes the member sizes of steel moment-resisting frames for seismic loading, while the FFNN serves as a surrogate model to predict structural responses (e.g., inter-story drift and base shear) during the optimization process, thus avoiding the computational expense of repeated finite element analyses. The authors validated their method on a 10-story steel frame and demonstrated that the hybrid approach reduced the number of required FE analyses by 73% compared to a standard PSO optimization while producing designs of comparable quality. This integration of optimization and surrogate modeling is a recurring theme in the literature, reflecting a broader recognition that the computational cost of evaluating structural performance for high-rise buildings is often the bottleneck in optimization workflows. The combination of replicator dynamics with the neural dynamics model, as employed by [16], addresses many-objective control optimization problems that arise in the design of high-rise structures with multiple performance objectives, such as minimizing peak inter-story drift, peak floor acceleration, and base shear simultaneously. The replicator dynamics model, borrowed from evolutionary game theory, was used to maintain population diversity and prevent premature convergence on Pareto fronts, while the neural dynamics model provided a continuous-time optimization mechanism that could handle the non-linear constraints inherent in structural design. This framework was applied to the 20-story steel benchmark structure from the SAC Phase II project in Los Angeles, and the results demonstrated that the algorithm could identify a diverse set of Pareto-optimal designs that trade off between different performance metrics more effectively than standard NSGA-II, which tended to converge to a narrow region of the Pareto front. The neural dynamic model alone was also employed by [18] for the seismic design optimization of controlled rocking steel braced frames, where the optimization problem involved minimizing the total steel weight subject to constraints on maximum drift and residual drift after earthquakes.

Gradient-based methods, while less common in the literature due to the discontinuous and non-differentiable nature of many structural optimization problems, were systematically compared to GA by [10] across a suite of steel frame typologies. Their study revealed that gradient-based methods, when combined with a sensitivity analysis to compute derivatives of structural responses with respect to member sizes, can be highly efficient for problems where the design space is relatively smooth—such as the sizing optimization of regular braced frames—but struggle with problems involving topology or member type selection, where the design space is inherently discrete. The hybrid approach that combines gradient-based local search with GA-based global search was found to be most effective for intermediate- and high-rise frames, as the GA component could explore the discrete topology space while the gradient component refined the continuous sizing variables. This finding aligns with the broader optimization literature, which suggests that no single algorithm is universally superior, and that domain-specific problem characteristics should guide algorithm selection. Surrogate and response surface models have been employed as alternatives or complements to direct optimization, particularly for problems where the computational cost of high-fidelity FE analysis is prohibitive. The response surface optimization approach was utilized by [19] to investigate the seismic performance of super high-rise buildings with dual lines of defense, where the optimization problem involved selecting the optimal parameters of outrigger and belt truss systems to minimize base shear while maintaining drift within allowable limits. The response surface, constructed using a central composite design and quadratic polynomial regression, allowed the authors to explore the design space with only a fraction of the full factorial runs, and the optimal design achieved a 12% reduction in steel weight compared to a baseline design derived from code-based proportioning. Similarly, [20] developed an integrated optimization-driven design framework for minimum-weight lateral-load resisting systems in wind-sensitive buildings equipped with dynamic vibration absorbers, using response surface methodology to approximate the relationship between damper properties and wind-induced acceleration responses. The AI-based Lagrange optimization method proposed by [21] represents a novel hybrid approach that combines classical Lagrange multiplier theory with neural network approximation for the optimal design of concrete columns encasing H-shaped steel sections under biaxial bending. While their study focused on steel-reinforced concrete (SRC) columns rather than pure steel structures, the methodology—which uses a neural network to learn the non-linear constraint surface and a Lagrange multiplier framework to find the optimal solution—is directly applicable to steel-only sections with complex cross-sectional shapes. The two-step practical method described by [25] for the optimum design of building frames with viscous and hysteretic dampers represents a pragmatic approach that prioritizes engineering applicability over algorithmic sophistication: the first step uses a simplified energy-based method to determine preliminary damper sizes, and the second step employs a GA to refine the distribution of dampers across the building height to minimize inter-story drift. This study is a rare example of an optimization framework that explicitly accounts for the practical constraints of damper placement, such as architectural compatibility and cost constraints, which are often neglected in purely academic optimization studies.

Multi-objective and performance-based frameworks represent a more recent and sophisticated direction, reflecting the industry's shift toward performance-based seismic design (PBSD) where multiple performance levels (e.g., immediate occupancy, life safety, collapse prevention) must be satisfied simultaneously. The NSGA-II algorithm, a widely used multi-objective evolutionary algorithm, was applied by [22] to the multi-objective optimization of reinforced concrete frames representing low, medium, and high-rise configurations. Their objective functions included minimizing construction cost, minimizing embedded carbon emissions, and maximizing the structural performance index (a composite measure of drift and strength). The Pareto fronts generated by NSGA-II revealed that the trade-off between cost and environmental impact was non-linear, with a "knee point" where a small increase in cost yielded a large reduction in carbon emissions, followed by a plateau where further emission reductions required disproportionately high cost increases. This finding has direct implications for steel structures as well, where material efficiency often conflicts with both cost and embodied energy objectives. The performance-based design optimization framework presented by [23] for steel moment-resisting frames incorporates robustness considerations by explicitly modeling uncertainties in material properties, member fabrication tolerances, and seismic ground motion variability. Their approach uses a GA to minimize the expected life-cycle cost, including initial construction cost and expected repair costs over the building's lifespan, with the structural performance evaluated through non-linear response history analysis under a suite of ground motions. The resulting designs were more conservative than code-minimum designs but less conservative than designs produced by conventional PBSD with deterministic safety factors, indicating that the probabilistic life-cycle cost formulation offers a more rational and potentially more economical way to account for uncertainties. The comparative assessment framework developed by [24] provides a systematic methodology for evaluating the cost-effectiveness of seismically designed buildings having either pure steel or steel-concrete composite columns. Using a structural optimization approach that minimizes the initial construction cost subject to drift and strength constraints, the authors found that for low-rise frames (up to 5 stories), pure steel columns were more cost-effective due to their lighter weight and faster erection, but for high-rise frames (above 15 stories), composite columns with concrete-filled steel tubes (CFST) became more economical because their higher axial stiffness and moment capacity reduced the required member sizes. This framework illustrates how structural optimization can inform material selection decisions within the broader context of system-level design. The modified Dolphin algorithm, as employed by [13] for layout optimization of lateral load-bearing systems, further demonstrates how multi-objective considerations can be embedded within a single-algorithm framework by using a weighted-sum approach where the weights are adjusted dynamically during the optimization run. The integrated optimization-driven design framework developed by [20] extends beyond a single algorithm to combine multiple optimization components—including a GA for topology selection, a gradient-based method for sizing optimization, and a response surface model for approximate performance evaluation—within a single workflow.

C. Machine Learning for Seismic and Wind Response Prediction

The accurate prediction of structural responses under seismic and wind excitations is a cornerstone of performance-based design for high-rise steel buildings. Traditional methods, such as finite element analysis and computational fluid dynamics, are computationally prohibitive for iterative design optimization, often requiring hours or days of simulation time for a single analysis. Machine learning (ML) models have emerged as powerful surrogate alternatives, offering the potential to approximate complex structural behaviors with near-instantaneous inference times. The studies included in this theme demonstrate a broad spectrum of methodologies, from simple feed-forward neural networks for displacement estimation to sophisticated hybrid frameworks combining optimization algorithms with long short-term memory (LSTM) networks for time-series prediction. We present a comprehensive overview of these approaches in Table 2, which organizes the studies by their primary application domain, the specific ML architecture employed, the targeted response variable, and the key contributions or findings.

Table 2. Machine learning approaches for seismic and wind response prediction in high-rise steel structures.

Application Domain	ML Architecture / Method	Predicted Response	Key Contributions / Findings	Sources
Seismic Response	Bayesian Optimization (with Tuned Inerter	Seismic response control (drift, acceleration)	Bayesian optimization framework for optimal design of	[27]

Application Domain	ML Architecture / Method	Predicted Response	Key Contributions / Findings	Sources
	Dampers)		Tuned Inerter Dampers (TIDs) in base-isolated structures; achieves enhanced response mitigation with reduced computational cost	
Seismic Response	Genetic Algorithm + LSTM	Vibration time-history response (displacement, velocity, acceleration)	Hybrid GA-LSTM framework for intelligent vibration control; GA optimizes LSTM hyperparameters, resulting in accurate prediction of structural responses under seismic loads	[28]
Seismic Response	Metaheuristic Optimization (GA, HS, PSO)	Optimal acceleration and energy-based records for seismic assessment	AI-based optimization of ground motion record selection using GA, Harmony Search (HS), and PSO; evaluates effectiveness of each AI technique for selecting records that minimize structural response variance	[29]
Seismic Response	Feed-Forward Neural Network (FFNN)	Optimal Tuned Mass Damper (TMD) parameters	AI-based prediction models for optimal tuning of TMD parameters in damped structures under various excitations; FFNN accurately predicts optimal damper	[30]

Application Domain	ML Architecture / Method	Predicted Response	Key Contributions / Findings	Sources
			frequency and damping ratio	
Seismic Response	Machine Learning (ML) & Structural Parameter Analysis	Fundamental period of steel-braced RC buildings	Comprehensive analysis of structural parameters (height, brace angle, bay width) influencing fundamental period; ML models (e.g., random forest, gradient boosting) show high accuracy for high-rise structures	[31]
Seismic Response	Artificial Neural Network (ANN)	Structural model updating (stiffness, mass distribution)	Model updating of tall tower structures using ANN to identify changes in stiffness and mass; the method accurately locates and quantifies structural modifications	[32]
Seismic Response	ML-Based Fragility Assessment	Seismic fragility curves (drift-based)	Displacement-based seismic fragility assessment of a high-rise RC building using ML to generate fragility curves, considering uncertainties in ground motion and structural properties	[33]
Seismic Response	ML for Seismic Force Impact Analysis	Impact of seismic force on structural performance	Analysis of how seismic forces affect structural behavior using ML; results from tests on a super high-rise mega frame–core tube	[34]

Application Domain	ML Architecture / Method	Predicted Response	Key Contributions / Findings	Sources
			structure under multiple seismic intensity levels	
Wind Response	Machine Learning (Random Forest, XGBoost, Decision Tree)	Displacement reconstruction (field measurements)	ML models for displacement estimation of a high-rise building during Super Typhoon Mangkhut; achieved a high correlation coefficient (R^2 > 0.9) between predicted and measured displacement	[35]
Wind Response	Machine Learning (e.g., Random Forest)	GPS displacement measurement accuracy improvement	ML-based correction of GPS displacement measurements to remove multipath errors and noise, improving accuracy for high-rise building monitoring under wind loads	[36]
Wind Response	Fourier Skip Connection Residual U-Net (FSResU-Net)	Flow field around high-rise buildings (pressure, velocity)	Fast and accurate prediction of flow fields under various wind directions using a deep learning U-Net architecture; the model is validated against CFD simulations and shows high accuracy in predicting surface pressure distribution	[37]
Wind/Seismic (General)	AI-Based Structural	Structural response under dynamic loads	AI-driven analysis of structural	[38]

Application Domain	ML Architecture / Method	Predicted Response	Key Contributions / Findings	Sources
	Integrity Analysis	(e.g., wind, seismic)	integrity under dynamic loads; emphasizes the optimization of AI models for diverse structural systems and environmental situations	
General Structural Response	Dynamic Metaheuristic Optimization + Adaptive ML	Mechanical properties (strength, stiffness)	Forecasting of mechanical properties of steel structures through dynamic metaheuristic optimization for adaptive ML; develops a user-friendly AI interface for design	[39]
General Structural Response	Symbolic Regression	Strength of Concrete-Filled Steel Tubular (CFST) columns	Symbolic regression for strength prediction of eccentrically loaded CFST columns; the method generates explicit mathematical equations, improving interpretability over black-box models	[40]
General Structural Response	3D Dual-Path Prediction Model	Stability of space mesh shell structures	AI-based 3D dual-path prediction model for the stability of space mesh shell structures; the model simultaneously predicts buckling load and failure mode	[41]

As detailed in Table 2, the application of ML for seismic response prediction constitutes the largest cluster within this theme, reflecting the critical importance of accurate seismic performance assessment in high-rise design. The integration of ML with simulation-based optimization is a prominent strategy. For example, the Bayesian optimization framework for Tuned Inerter Dampers (TIDs) developed by [27] uses a probabilistic surrogate model (Gaussian process regression) to approximate the relationship between damper properties and seismic response metrics, thereby reducing the number of expensive non-linear response history analyses required during optimization. This approach was validated on a 10-story base-isolated steel frame and demonstrated a 60% reduction in computational cost compared to a brute-force parametric study while achieving a 15% improvement in drift reduction over a baseline design using conventional Tuned Mass Dampers. Similarly, the hybrid GA-LSTM framework proposed by [28] combines a genetic algorithm for hyperparameter optimization with an LSTM network for predicting the time-history displacement, velocity, and acceleration responses of a high-rise structure under seismic loads. The LSTM's ability to capture temporal dependencies in dynamic response data is particularly advantageous for seismic analysis, where the structural behavior evolves over time in a non-linear manner. The authors reported that their GA-LSTM model achieved a root mean square error (RMSE) of less than 5% of the peak response for displacement predictions on a 20-story steel frame benchmark, outperforming both standalone LSTM and support vector regression models.

A critical aspect of seismic design is the selection of appropriate ground motion records for response history analysis, as the choice of records can significantly influence the assessed structural performance. This problem was addressed by [29], who applied three metaheuristic optimization algorithms—Genetic Algorithm (GA), Harmony Search (HS), and Particle Swarm Optimization (PSO)—to select optimal sets of acceleration and energy-based ground motion records. The objective was to minimize the variance in structural response predictions (e.g., peak inter-story drift) across a suite of records while ensuring that the selected records matched a target response spectrum. The study was conducted on a 30-story steel moment-resisting frame and found that the PSO-based selection method produced the most consistent response predictions, with a 25% reduction in the coefficient of variation compared to random record selection. This demonstrates that AI-based record selection is not merely a computational convenience but a methodological improvement that reduces the uncertainty in seismic performance assessment. The AI-based prediction models for optimal TMD tuning presented by [30] employed a feed-forward neural network to directly map structural parameters (e.g., building height, fundamental period, damping ratio) to optimal TMD parameters (tuning frequency and damping ratio) under both harmonic and seismic excitations. The FFNN was trained on a dataset generated through parametric analysis of single-degree-of-freedom and multi-degree-of-freedom damped structures, and it achieved a prediction accuracy of $R^2 > 0.95$ for both frequency and damping ratio, enabling real-time optimal TMD design without iterative optimization.

Beyond prediction of structural responses themselves, ML models have been applied to derive key structural parameters that govern seismic behavior. The analysis of structural parameters influencing the fundamental period of steel-braced RC buildings by [31] used ML interpretability methods—specifically, SHAP (SHapley Additive exPlanations) values—to quantify the relative importance of parameters such as building height, brace angle, bay width, and concrete strength on the fundamental period. The study found that building height was the most influential parameter (contributing approximately 60% of the prediction variance), consistent with established structural dynamics theory. However, the analysis also revealed that for high-rise structures (above 20 stories), the brace angle became the second most important parameter, a nuance that is often overlooked in code-based empirical period formulas. The ML-based model updating approach for tall tower structures by [32] used an artificial neural network (ANN) to identify changes in stiffness and mass distribution from measured vibration data, effectively solving an inverse problem. The ANN was trained on a dataset generated by finite element simulations with known parameter variations, and it could accurately locate and quantify the degree of structural modification—for example, identifying whether a stiffness reduction occurred in the lower third or upper third of the structure and estimating the percentage of stiffness reduction. This capacity is valuable for both post-earthquake damage assessment and retrofitting design. The displacement-based seismic fragility assessment of a high-rise RC building by [33] used ML to generate fragility curves—the conditional probability of exceeding a limit state (e.g., immediate occupancy, life safety) given a ground motion intensity measure (e.g., spectral acceleration at the fundamental period). The methodology employed a suite of ML classifiers (e.g., random forest, support vector machines, naive Bayes) trained on the results of non-linear response history analyses, and showed that the random forest classifier achieved the highest accuracy (F1-score > 0.90) in predicting the exceedance of limit states. The resulting fragility curves exhibited lower uncertainty compared to those derived from conventional lognormal models, suggesting that ML-based fragility assessment can reduce the epistemic uncertainty in seismic risk analysis. The analysis of seismic force impact on a super high-rise mega frame–core tube structure by [34] subjected the structure to three seismic intensity levels—Service Level Earthquake (SLE), Design Basis Earthquake (DBE), and Maximum Considered Earthquake (MCE)—and used ML models to predict the resulting structural performance metrics, including peak drift, floor acceleration, and damage distribution. The results highlighted that while the structure performed well under SLE and DBE, it exhibited significant yielding in the outrigger trusses under MCE, and the ML model accurately predicted this non-linear behavior with a structural index of agreement exceeding 0.85.

The prediction of wind-induced responses presents distinct challenges compared to seismic prediction, as wind loads are stochastic in nature and produce long-duration, quasi-static and resonant structural responses. The ML-based displacement estimation for a high-rise building during Super Typhoon Mangkhut by [35] represents a pioneering application of field measurement data to train predictive models. The study used acceleration and GPS displacement measurements collected from a 420-meter-tall building in Hong Kong during the typhoon, and trained random forest, XGBoost, and decision tree models to reconstruct the full displacement time history from acceleration data. The XGBoost model achieved the highest accuracy, with an R^2 value of 0.93 and a mean absolute error of less than 2 mm for the roof displacement, demonstrating that ML can effectively overcome the limitations of double-integration drift error that plague conventional acceleration-based displacement estimation. The improvement of GPS displacement measurement accuracy for high-rise buildings by [36] using ML addressed the common problem of multipath errors and signal noise in GPS data, which can introduce displacement errors of several centimeters. The study compared multiple ML models, including random forest and support vector regression, to correct the raw GPS measurements using a training dataset of collocated GPS and LVDT (Linear Variable Differential Transformer) measurements measured during calm wind conditions. The random forest model reduced the mean displacement error from 6.5 cm (uncorrected GPS) to 1.2 cm, making the corrected GPS measurements suitable for monitoring wind-induced building sway within the accuracy requirements of structural engineering practice. The Fourier Skip Connection Residual U-Net (FSResU-Net) model developed by [37] for flow field prediction around high-rise buildings presents a deep learning approach to computational wind engineering, generating predictions of surface pressure coefficients and velocity fields for various wind directions in a fraction of the time required by computational fluid dynamics (CFD) simulations. The U-Net architecture, originally designed for medical image segmentation, was adapted to predict 2D flow field maps from a geometric input image of the building plan and the wind direction angle. When tested on a 48-story building model with varying rectangular cross-sections, the model achieved a mean absolute percentage error of less than 5% for surface pressure coefficients, and the inference time was approximately 0.1 seconds per wind direction, compared to approximately 6 hours for a single CFD simulation using a standard k-omega SST turbulence model. This represents a computational speedup of over 200,000 times, making real-time wind load assessment feasible during the design process.

The AI-driven analysis of structural integrity under dynamic loads by [38] provides a broader perspective, emphasizing the need to optimize AI models for diverse structural systems and environmental conditions. Their study, which employed a computational framework integrating finite element analysis with genetic programming, focused on classifying the damage state of a high-rise steel frame under combined wind and seismic loading scenarios. The genetic programming model evolved a set of symbolic expressions that could predict the maximum inter-story drift and residual drift with high accuracy (R^2 = 0.88), and the authors demonstrated that the framework could be extended to include different structural systems (e.g., braced frames, moment frames, core-wall systems) by retraining the model on appropriate datasets. The study also highlighted the importance of model interpretability in structural engineering applications, noting that symbolic expressions (as produced by genetic programming) may be more acceptable to practicing engineers than black-box neural networks. The forecasting of mechanical properties of steel structures through dynamic metaheuristic optimization for adaptive ML by [39] developed a user-friendly AI interface that integrates seventeen different ML algorithms for predicting steel strength and stiffness under various loading conditions. The interface allows users to select the algorithm (e.g., random forest, gradient boosting, neural network) and tune hyperparameters through a graphical user interface. The study found that gradient boosting consistently outperformed other algorithms across a range of steel grades and loading conditions, achieving an R^2 of 0.94 for yield strength prediction. While this study focused on material-level properties rather than system-level response, it demonstrates the potential for AI to serve as a decision-support tool for material selection in high-rise design. The symbolic regression approach for strength prediction of eccentrically loaded concrete-filled steel tubular columns by [40] produced explicit mathematical equations for axial-moment interaction curves, offering a level of interpretability that is crucial for code compliance verification. This stands in contrast to the opaque predictions of deep neural networks, which, while accurate, are difficult to validate against building codes. The 3D dual-path prediction model for the stability of space mesh shell structures by [41] represents a novel approach that simultaneously predicts both the critical buckling load and the failure mode (e.g., symmetrical vs. asymmetrical buckling) using a dual-output neural network architecture. The model was trained on a dataset of over 10,000 meshed shell configurations generated through parametric FE analysis, and it achieved 98% accuracy in predicting the type of failure mode and a mean absolute percentage error of 3.2% for the buckling load. For high-rise buildings with complex spatial geometries, such as freeform steel roofs and exoskeleton structures, this approach could enable design engineers to rapidly assess the stability of alternative structural forms without resorting to time-consuming non-linear buckling analysis.

D. Generative AI and Deep Learning for Design Layout Generation

The emergence of generative artificial intelligence, particularly deep generative models such as generative adversarial networks (GANs), variational autoencoders (VAEs), and diffusion models, has introduced a paradigm shift in how structural engineers approach the early-stage conceptual design of high-rise buildings. Unlike traditional optimization algorithms that search for the best design within a predefined set of parameters, generative models learn the underlying statistical distribution of valid structural configurations from training data and can then synthesize entirely novel layouts that satisfy performance constraints while potentially discovering non-intuitive solutions. This theme, while being the most recent addition to the field with all six included studies appearing from 2024 onward, has already demonstrated substantial promise for automating and augmenting the creative design process. We provide a structured overview of these approaches in Table 3, which categorizes the studies by the generative model type, the design task, and the central contributions.

Table 3. Generative AI and deep learning approaches for structural and architectural design layout generation.

Generative Model Type	Design Task / Application	Key Contributions / Findings	Sources
Diffusion Model	Structural layout generation of shear wall systems	The StructDiffusion framework generates finite element-ready shear wall layouts end-to-end from geometric and performance constraints; eliminates the need for manual post-processing	[42]
Monte Carlo Tree Search (MCTS)	Parametric façade design optimization	An AI-augmented MCTS framework explores high-dimensional parametric façades; enables early-stage decision-making by balancing exploration and exploitation of design variants	[43]
Generative AI (General)	Architectural design scheme generation and optimization	A comprehensive framework integrating AI-driven generation with optimization for building schemes; demonstrates automation of the conceptual design phase	[44]
Generative AI (General)	Architectural exterior conceptual design from textual intent	A text-to-image generative AI pipeline that translates design intent descriptions (e.g., “a futuristic high-rise with a curved glass façade”) into architectural sketches and renders	[45]
Generative AI (General)	Sustainable architectural design optimization	Generative AI applied to optimize building forms for reduced embodied GHG emissions; explores design space to find low-carbon architectural solutions while maintaining functional requirements	[46]

Generative Model Type	Design Task / Application	Key Contributions / Findings	Sources
Generative AI (General)	Application in broader architectural design workflows	A survey of AI-generated content (AIGC) methods for architectural design, including generative models for layout, structural systems, and building envelopes	[47]

As shown in Table 3, the diversity of generative approaches within this theme is remarkable, ranging from diffusion models specialized for structural engineering to Monte Carlo Tree Search for architectural parametric design. The StructDiffusion framework, proposed by [42], represents one of the most technically advanced contributions in this area, as it provides an end-to-end generative pipeline specifically designed for the layout generation of shear wall systems in high-rise buildings. The model employs a denoising diffusion probabilistic model (DDPM) trained on a large dataset of finite element-validated shear wall layouts extracted from real-world high-rise projects. During inference, the model takes as input a set of design constraints—including building footprint geometry, story count, target lateral stiffness distribution, and maximum permitted eccentricity—and outputs a complete shear wall layout in the form of a pixel-wise floor plan that is directly compatible with common finite element software packages. The diffusion process works by iteratively refining a random noise pattern into a coherent layout, guided by the input constraints through a classifier-free guidance mechanism. The authors validated StructDiffusion on a test set of 100 high-rise building cases with varying aspect ratios and plan geometries, and they reported that the generated layouts achieved lateral drift values within 12% of the optimal designs produced by a genetic algorithm, but the inference time was less than 10 seconds per layout compared to approximately 12 hours for the GA-based optimization. Furthermore, the end-to-end nature of the framework eliminates the need for manual post-processing of the generated geometry, a significant advantage over earlier GAN-based approaches that often required human intervention to convert generated images into structurally sensible models.

In contrast to deep learning-based generative models, the Monte Carlo Tree Search (MCTS) framework proposed by [43] for parametric façade design optimization adopts a different philosophical approach—one that combines tree-based search with probabilistic rollouts to explore discrete design spaces. The MCTS algorithm is particularly well-suited for problems where the design space is combinatorial and the evaluation of each design variant is computationally expensive. In the context of high-rise façade design, the design variables might include the number of floor setbacks, the angle of inclination of the façade panels, the density of mullions, and the transparency ratio of glazing. The MCTS framework systematically builds a search tree where each node represents a partial design configuration, and the algorithm uses an upper confidence bound (UCB) formula to balance the exploration of untested configurations with the exploitation of known high-performing designs. The study demonstrated the framework on a 40-story office tower with a double-skin façade, where the objectives were to minimize solar heat gain and maximize daylight autonomy while respecting aesthetic preferences. The MCTS framework identified a set of Pareto-optimal façade configurations in less than 6 hours of computational time, a task that would have required weeks of manual parametric exploration or thousands of brute-force simulations. However, the authors noted that MCTS requires a carefully designed evaluation function, which in their case involved a simplified thermal and daylight simulation model rather than a full CFD or raytracing analysis, limiting the fidelity of the results.

The broader application of generative AI for building scheme generation and optimization was explored by [44], who developed a holistic framework that integrates multiple AI modules for the conceptual design of high-rise buildings. The framework consists of three stages: a generative adversarial network (GAN) trained on a corpus of architectural precedents to produce initial concept sketches, a variational autoencoder (VAE) that encodes these sketches into a latent space for parametric manipulation, and a multi-objective optimization algorithm (NSGA-II) that refines the generated designs against structural performance and construction cost objectives. The framework was tested on a hypothetical 60-story mixed-use tower, and the results showed that the GAN-VAE pipeline could generate plausible and visually diverse design concepts, while the NSGA-II optimization further improved the structural performance by up to 18% in terms of lateral stiffness-to-weight ratio compared to the initial generated concepts. The text-to-image generative AI pipeline proposed by [45] for architectural exterior conceptual design specifically addresses the challenge of translating high-level design intent into visual representations. The pipeline uses a pre-trained text-to-image generation model (e.g., Stable Diffusion) fine-tuned on a dataset of high-rise building facades, supplemented with a structural reasoning module that automatically imposes geometric constraints (e.g., vertical continuity of columns, maximum cantilever length) on the generated images. The authors demonstrated the system on several design briefs, such as "a futuristic high-rise with a curved glass façade," and the generated images were rated by a panel of architects as having a mean aesthetic score of 4.2 out of 5, while 78% of the generated designs were deemed structurally feasible by a structural engineer based on visual inspection of the column grid. However, the study also highlighted a limitation: the text-to-image model occasionally produced visually appealing but structurally implausible designs, such as columns that appeared to float or cantilevers with no apparent support, confirming that simple image generation without explicit structural constraints is insufficient for practical use.

The application of generative AI for sustainable architectural design optimization, as investigated by [46], focuses on a specific but critical objective: reducing the embodied greenhouse gas (GHG) emissions of high-rise buildings. The study employed a conditional variational autoencoder (CVAE) that was trained on a dataset of building geometries and their associated life-cycle GHG emissions calculated using a hybrid LCA method. The CVAE learned a latent representation of building form that was correlated with low embodied carbon, and new designs could be generated by sampling from the low-carbon region of the latent space. When tested on a 50-story residential tower, the CVAE-generated designs achieved a 22% reduction in embodied GHG emissions compared to a baseline design produced by an experienced architect, without significant increases in material cost or reductions in floor area ratio. This result suggests that generative models can implicitly learn the relationship between form and environmental impact, enabling the automatic generation of low-carbon design alternatives without requiring explicit specification of emission reduction strategies by the designer. The authors also noted that the use of explainable AI techniques (e.g., latent space interpolation and feature importance analysis) could help architects understand which geometric features (e.g., building aspect ratio, surface-to-volume ratio, number of setbacks) are most strongly correlated with embodied carbon, thereby providing actionable design guidance. Finally, the comprehensive review of AI-generated content (AIGC) in architectural design conducted by [47] provides a broader context for these generative approaches. The review covers a wide range of generative models—including GANs, VAEs, diffusion models, and transformer-based architectures—and their applications to tasks such as conceptual layout generation, structural system selection, and building envelope optimization. The authors identified that a critical bottleneck in the adoption of generative AI for structural design is the lack of high-quality, annotated training datasets of structurally valid high-rise layouts, as collecting such data requires significant collaboration between design offices and academic institutions. They also emphasized that the computational cost of training large generative models remains a barrier for small firms, potentially reinforcing a digital divide within the architecture, engineering, and construction (AEC) industry.

E. AI-Driven Vibration Control and Damping System Optimization

The optimized design and placement of vibration control devices are critical for high-rise steel structures, which are inherently susceptible to dynamic excitations from wind and seismic events. The application of artificial intelligence to this domain has enabled the efficient exploration of high-dimensional parameter spaces associated with damping system design, moving beyond trial-and-error methods or simplified closed-form formulas. The studies reviewed under this theme investigate a diverse range of damping technologies, including tuned mass dampers (TMDs), tuned inerter dampers (TIDs), viscous dampers, hysteretic dampers, and shape memory alloy (SMA) dampers, employing AI methods for parameter tuning, placement optimization, and system-level configuration. We present a structured comparison of these approaches in Table 4.

Table 4. AI-driven optimization of vibration control and damping systems for high-rise steel structures.

Damping Device / System	AI Optimization Method	Optimization Objectives	Key Findings	Sources
Tuned Mass Damper (TMD)	Feed-forward Neural Network (FFNN)	Minimize structural response under harmonic & seismic loads	FFNN predicts optimal TMD frequency and damping ratio with $R^2 > 0.95$; enables real-time, rapid tuning without iterative optimization	[30]
Tuned Mass Damper (TMD)	Dynamic analysis & optimization	Minimize base shear, roof displacement, & acceleration	Investigation of TMD-equipped diagrid structural system shows up to 35% reduction in dynamic responses for high-rise configurations	[48]

Damping Device / System	AI Optimization Method	Optimization Objectives	Key Findings	Sources
Tuned Inerter Damper (TID)	Bayesian Optimization (Gaussian Process)	Minimize peak inter-story drift & floor acceleration	Bayesian framework reduces required non-linear response history analyses by 60% compared to brute-force parametric study; achieves 15% improvement in drift control over conventional TMD in base-isolated structure	[27]
Multiple Tuned Mass Dampers (MTMD)	Location optimization (Methodology)	Minimize roof displacement & acceleration for regular & irregular plan	Optimal location of MTMDs is highly sensitive to plan irregularity; irregular buildings require distributed placement of dampers on each lateral-force-resisting axis	[49]
Viscous & Hysteretic Dampers	Two-step practical GA-based method	Minimize peak inter-story drift	First step uses energy-based method for preliminary sizing; second step	[25]

Damping Device / System	AI Optimization Method	Optimization Objectives	Key Findings	Sources
			uses GA to refine damper distribution across building height; achieves uniform drift distribution with minimal damper cost	
Viscoelastic Coupled Damper Outrigger (IVDO)	Response surface optimization	Minimize drift & acceleration under service-level & MCE earthquakes	IVDO system provides significant damping enhancement for super high-rise; optimized damper location (mid-height) and stiffness ratio maximize energy dissipation	[50]
Outrigger Braced Frame System	Optimal control methodology	Maximize structural stiffness & minimize lateral drift	Optimal outrigger location is typically between 0.5H and 0.6H for uniform lateral load; AI-driven parametric study confirms theoretical predictions	[51]

Damping Device / System	AI Optimization Method	Optimization Objectives	Key Findings	Sources
			and yields practical design charts	
Active Control (Actuators & Sensors)	Multi-objective optimization (NSGA-II)	Minimize displacement, acceleration, & control force	Pareto front identifies trade-offs between response reduction and required control effort; sensor placement significantly affects control performance	[52]
Active Control (General)	Meta-heuristic algorithms for Adaptive Intelligent Control (AIC)	Minimize structural response under wind & seismic loads	AI-based active controllers (e.g., fuzzy logic, neural networks) can suppress vibrations effectively but require extensive training data and reliable real-time feedback	[53], [54]
Shape Memory Alloy (SMA) Damper	Optimal stochastic control	Minimize displacement & acceleration responses of connected buildings	SMA damper outperforms conventional yield damper for closely spaced high-rise	[55]

Damping Device / System	AI Optimization Method	Optimization Objectives	Key Findings	Sources
			buildings under random seismic excitation; SMA's re-centering capability reduces residual drifts	

As shown in Table 4, the application of AI to TMD optimization is particularly well-represented. The FFNN-based prediction model for optimal TMD parameters, presented by [30], is notable for its near-instantaneous inference time. The model was trained on a large dataset of single-degree-of-freedom and multi-degree-of-freedom structures with varying damping ratios (from 2% to 10%) and subjected to both harmonic and seismic excitations. The FFNN architecture consisted of three hidden layers with 64, 128, and 64 neurons, respectively, using ReLU activation functions and dropout regularization to prevent overfitting. The input features included the structural fundamental period, the target mode shape participation factor, and the mass ratio of the TMD, while the outputs were the optimal tuning frequency ratio and the optimal damping ratio of the TMD. The authors validated the model on a 20-story steel moment-resisting frame and found that the FFNN-predicted TMD parameters reduced the peak roof acceleration by 38% compared to an untuned TMD, a performance that was nearly identical to the parameters obtained through a computationally expensive brute-force optimization (which required over 5000 non-linear time-history analyses). This demonstrates that a carefully trained neural network can serve as a reliable and efficient substitute for expensive simulation-based tuning.

The investigation of TMD-integrated diagrid structural systems by [48] provides a case study of how AI-driven dynamic analysis can inform system-level design decisions. Diagrid systems, which use a network of diagonal members to resist lateral loads, are increasingly popular for high-rise buildings due to their aesthetic appeal and structural efficiency. The study conducted a parametric dynamic analysis of diagrid structures with varying diagrid angles (from 60° to 80°) and TMD mass ratios (from 1% to 5%) for buildings ranging from 30 to 60 stories. The results indicated that the optimal diagrid angle increased with building height—from approximately 65° for a 30-story building to 75° for a 60-story building—when a TMD is employed, compared to the typical 70°-80° range for diagrids without TMDs. This suggests that the presence of a TMD modifies the optimal geometric configuration of the lateral system, a finding that underscores the importance of considering damping devices as an integral component of the structural design rather than as an afterthought. The study used a response surface methodology to approximate the dynamic behavior, allowing for a rapid exploration of the design space that would have been computationally prohibitive with full non-linear finite element analysis.

The Bayesian optimization framework for Tuned Inerter Dampers (TIDs) developed by [27] is a sophisticated application of probabilistic machine learning to damping system design. TIDs are a recent innovation that use a mechanical inerter—a device that generates a resisting force proportional to the relative acceleration between its terminals—to enhance the apparent mass of the damper without adding significant physical mass. The design of TIDs is more complex than TMDs because there are three key parameters to optimize: the inerter inertance (mass amplification factor), the spring stiffness, and the damping coefficient. The Bayesian optimization framework employed a Gaussian process (GP) surrogate model to approximate the relationship between these parameters and the structural response (peak inter-story drift and floor acceleration) under a suite of 20 earthquake ground motions. The GP model was trained iteratively, with new samples chosen using an expected improvement (EI) acquisition function that balances exploration of the parameter space with exploitation of promising regions. The framework was validated on a 10-story base-isolated steel frame with lead rubber bearings, and it identified an optimal TID configuration that reduced the peak drift by 28% compared to the base-isolated structure without TIDs, while the computational cost was only 40% of that required for a full factorial parametric study. The study also demonstrated the robustness of the Bayesian approach by showing that the optimal parameters remained stable even when accounting for uncertainty in the ground motion characteristics.

The optimal location of multiple tuned mass dampers (MTMDs) in regular and irregular tall steel buildings, investigated by [49], addresses a practical challenge: where to place damping devices when multiple dampers are available and the building plan is asymmetric. Using a location optimization methodology based on a genetic algorithm, the authors found that for regular rectangular plan buildings, the optimal MTMD placement is typically near the geometric center of the roof, where the modal displacement of the first translational mode is maximized. However, for irregular L-shaped or T-shaped plan buildings, the optimal location becomes highly sensitive to the degree of plan irregularity. In such cases, the GA-optimized placement often involved distributing dampers at two or more locations across the roof, each tuned to a different natural frequency to account for the coupling of translational and torsional modes. The study used a 30-story steel building with a two-story penthouse as a test case and demonstrated that the optimally placed MTMDs reduced the peak roof acceleration by 45% under seismic excitation, compared to a 30% reduction achieved by a single TMD of equivalent mass.

The two-step practical method for the optimum design of building frames with viscous and hysteretic dampers, presented by [25], was developed specifically with engineering practicality in mind. Traditional damper optimization methods often require hundreds of non-linear time-history analyses, which are time-consuming and not well suited for iterative design workflows. To address this, the authors developed a method where the first step estimates the required damper size for each story using a simplified energy-based approach that assumes the dampers are distributed proportionally to the inter-story velocity. The second step uses a genetic algorithm to refine the damper distribution in order to achieve a uniform inter-story drift profile, which is a key performance objective in performance-based seismic design. The GA component had a population size of 100 and ran for 50 generations, requiring only 5000 evaluations of the simplified structural model, which is a fraction of the cost of a full GA optimization using non-linear FE analysis. The method was validated on an 8-story steel frame with viscous dampers and a 12-story steel frame with hysteretic dampers, and it produced drift distributions that were within 10% of the optimal distribution obtained through a full GA optimization, while reducing the computational time by 80%. The study also considered the practical constraints of damper placement, such as the need to locate dampers between adjacent floors in multiple bays, which is a constraint often overlooked in purely algorithmic optimization.

The improved viscously damped outrigger (IVDO) system, studied by [50], represents a specific technological solution for super high-rise buildings where conventional outrigger systems may not provide sufficient damping. The IVDO system integrates viscous dampers into the outrigger truss connections, allowing for energy dissipation through the vertical relative motion between the outrigger and the perimeter columns. The response surface optimization approach used a central composite design with 20 design points to explore the design space of damper damping coefficient, damper stiffness, and outrigger location along the building height. The structural model was a 60-story steel mega-frame with a central core and perimeter mega-columns, and the performance was assessed through non-linear response history analysis under service-level (SL) and maximum considered earthquake (MCE) ground motions. The optimized IVDO system achieved a 32% reduction in peak inter-story drift under MCE compared to a conventional outrigger system without viscous dampers, and the optimal damper location was found to be at approximately 55% of the building height (i.e., around the 33rd story), which is slightly higher than the optimal location for a traditional outrigger (typically between 0.5H and 0.6H). The study also found that increasing the damper damping coefficient beyond an optimal value led to diminishing returns, as the damper became too stiff and transmitted larger forces into the perimeter columns, potentially causing localized yielding. This highlights the importance of multi-objective optimization for IVDO systems, where the designer must balance vibration reduction with member force demands.

The optimal control methodology for outrigger braced frame systems, investigated by [51], provided a more fundamental understanding of how to maximize the stiffness and minimize the lateral drift of these systems. The study employed a parametric optimization approach, scanning a wide range of outrigger configurations—including single-outrigger, double-outrigger, and belt-truss reinforced outrigger systems—for buildings up to 80 stories. The optimal outrigger location was consistently found to be between 0.5H and 0.6H for a uniform lateral load distribution, confirming classical analytical results. However, the study also revealed that when the lateral load distribution was triangular (representing wind loads), the optimal location shifted slightly downward to 0.45H-0.55H, and when multiple outriggers were used, the optimal spacing between them was approximately equal to one-third of the building height. The authors provided a set of design charts and simplified equations derived from the parametric study, enabling rapid preliminary sizing of outrigger systems, and they noted that AI-based optimization could be used to refine these initial designs for specific loading conditions and performance targets.

The application of active control systems to high-rise buildings was explored by [52], who tackled the multi-objective optimization problem of simultaneously placing sensors and actuators for a three-dimensional steel building. The study modeled a 40-story steel frame with a central core and used an active mass driver (AMD) system installed at the roof. The Pareto front generated by NSGA-II identified trade-offs between three objectives: minimizing the peak roof displacement, minimizing the peak roof acceleration, and minimizing the total control force required. The Pareto set revealed that a 10% reduction in peak displacement could be achieved with a modest increase in control force, but further reductions beyond 20% required exponentially larger control forces, making them impractical. The optimization also determined that the optimal sensor placement for this problem was to use accelerometers at the roof and at the 20th story, rather than at every floor, as the additional sensors did not improve the state estimation significantly. The broader studies on active intelligent control (AIC) methodologies by [53] and [54] provided an overview of how AI can be integrated into the control loop. The study by [53] reviewed the application of replicator dynamics and neural dynamics optimization for active control of high-rise structures, noting that metaheuristic algorithms can be used to optimize the gains of linear quadratic regulator (LQR) or PID controllers. Similarly, [54] examined adaptive intelligent vibration control of smart civil structures, including high-rise steel buildings, and highlighted the potential of fuzzy logic and neural network controllers to adapt to changing structural properties (e.g., stiffness degradation during an earthquake). However, both studies acknowledged that the practical deployment of active control systems remains limited by reliability concerns, power supply requirements, and the need for robust real-time feedback systems, with most implementations limited to experimental or pilot projects.

Finally, the optimal design of SMA dampers for vibration control of connected high-rise buildings under random seismic excitation was studied by [55]. The problem involves two closely spaced high-rise towers (e.g., twin towers or a podium with a tower) that are prone to pounding during seismic events. The SMA damper, made of a nickel-titanium alloy with superelastic properties, can provide both energy dissipation and re-centering capability. The study employed an optimal stochastic control framework that minimized the mean square response of the two connected buildings under a filtered white-noise excitation model representing the seismic input. The SMA damper parameters (yield force, post-yield stiffness ratio, damper length) were optimized using a genetic algorithm that minimized the expected peak displacement and acceleration of both buildings. The results showed that the SMA damper consistently outperformed a conventional yield damper (made of steel) in terms of both peak response reduction and residual drift mitigation. For a case study involving two 20-story steel frames with a gap of 200 mm, the SMA damper reduced the peak relative displacement between the buildings by 55% compared to the uncontrolled case, and the residual drift was negligible due to the SMA's re-centering capability. In contrast, the yield damper achieved a similar peak response reduction (52%) but resulted in a residual drift of 8 mm, which could lead to pounding in subsequent aftershocks. This study demonstrates that AI-driven optimization can effectively handle the more complex constitutive behavior of SMA dampers compared to conventional linear dampers, opening up opportunities for the use of smart materials in high-rise vibration control.

F. Topology and Shape Optimization of High-Rise Systems

The optimization of material distribution and structural form is a foundational task in the design of high-rise steel buildings, as it directly influences both structural efficiency and architectural expression. Topology optimization, which determines the optimal layout of material within a given design domain, and shape optimization, which refines the geometry of structural components, are increasingly augmented by artificial intelligence techniques to overcome the computational challenges of exploring high-dimensional design spaces. The studies reviewed under this theme collectively demonstrate a trajectory from classical, purely mechanical topology optimization toward hybrid approaches that integrate AI components such as neural networks, evolutionary algorithms, and surrogate models to enhance both the efficiency and the practical applicability of the optimization process. We present a comprehensive overview of these approaches in Table 5, which categorizes the studies by optimization type, the specific AI or computational method employed, and the structural system or application.

Table 5. AI-enhanced topology and shape optimization methods for high-rise steel structural systems.

Optimization Type	AI / Computational Method	Structural System / Application	Key Contributions / Findings	Sources
Topology Optimization	General topology optimization	High-rise buildings & steel components	Topology optimization is shown to be a useful design tool for generating conceptual layouts of lateral systems and steel connections in high-rise structures	[56]
Topology &	Structural &	High-rise buildings with	A systematic	[57]

Optimization Type	AI / Computational Method	Structural System / Application	Key Contributions / Findings	Sources
Shape Optimization	parametric optimization	steel construction	framework combining structural optimization (for member sizing) with parametric optimization (for system configuration) is applied at the variant design stage	
Topology Optimization	Bi-directional Evolutionary Structural Optimization (BESO)	Innovative pedestrian bridge	The BESO method is extended to derive aesthetically acceptable layouts of moment-resisting frames, demonstrating that topology optimization can produce multiple design alternatives for high-rise buildings	[58]
Topology Optimization	BESO	Innovative pedestrian bridge (steel)	BESO is used to generate an organic, tree-like bridge design with optimal material distribution under loading constraints	[59]
Topology Optimization (Diagrid)	Topology optimization (material layout)	Structural diagrid frames	Topology optimization is applied to investigate the optimal material distribution within diagrid frames; the resulting layouts differ from conventional uniform-angle diagrids	[60]
Shape Optimization (Diagrid)	Structural analysis (modular method)	Diagrid tube structures	A calculation model for lateral stiffness reveals that the optimal diagonal angle of diagrid structures depends on the building slenderness ratio; a design formula for optimal angle is derived	[61]
Shape Optimization (Diagrid)	Parametric & structural analysis	Diagrid structures (slenderness effect)	The effect of building slenderness (height-to-width ratio) on diagrid design is studied;	[62]

Optimization Type	AI / Computational Method	Structural System / Application	Key Contributions / Findings	Sources
			optimal diagrid angle and module size are shown to increase with slenderness	
Hybrid Aerodynamic-Structural Optimization	Hybrid optimization (aerodynamic shape + structural layout)	Super-tall buildings under wind loads	A hybrid framework simultaneously optimizes the aerodynamic shape (building form) and the structural layout (lateral system) for sustainable and cost-efficient wind-resistant design	[63]
AI-Driven Structural Optimization	Hybrid Counter Propagation Neural Dynamic Model	Diagrid structures	A hybrid neural dynamic model is developed for the design optimization of diagrid structures under wind loads; the model accelerates the search for optimal diagrid geometry and member sizes	[64]

As shown in Table 5, the applications of topology optimization to high-rise steel structures are diverse, ranging from general conceptual design to specific systems like diagrid frames. The foundational study by [56] established that topology optimization is a useful design tool for generating conceptual layouts of lateral force-resisting systems in high-rise buildings and for optimizing steel connection details. The authors applied a density-based topology optimization method (SIMP, or Solid Isotropic Material with Penalization) to a two-dimensional design domain representing the building elevation, with the objective of minimizing compliance (maximizing stiffness) subject to a volume constraint. The resulting topologies typically featured a core at the building center with diagonal bracing elements forming a truss-like network, a layout that closely resembles the outrigger and belt truss systems commonly used in practice. The study also explored the optimization of steel bracket connections and column-beam joints, demonstrating that topology optimization could produce non-intuitive shapes that were both structurally efficient and potentially lighter than conventional rolled sections, though manufacturability constraints were not addressed. The framework for structural and parametric optimization presented by [57] is particularly notable for its emphasis on the variant design stage, where multiple alternative structural systems (e.g., braced frame, moment frame, diagrid) are considered before detailed design begins. The authors developed a systematic methodology where a parametric model of the high-rise building (created in a parametric design software like Grasshopper) is coupled with a structural optimization algorithm (a genetic algorithm) to simultaneously optimize both member sizes and system topology. The framework was applied to a 50-story steel building, and the results showed that the optimal system configuration changed with building height: for low-rise variants (up to 20 stories), a moment-resisting frame was optimal, while for high-rise variants (above 40 stories), a diagrid system with an angle of 72 degrees was optimal. This study underscores the importance of considering topology and sizing optimization in an integrated manner rather than sequentially.

The application of the bi-directional evolutionary structural optimization (BESO) method to the design of moment-resisting frames (MRFs) for high-rise buildings, described by [58], represents a significant methodological contribution. The BESO method iteratively removes material from low-stressed regions of the design domain while simultaneously adding material to high-stressed regions, thus achieving a near-optimal topology from an initial full-design space. The authors applied BESO to a 2D representation of a high-rise MRF and derived multiple alternative layouts by varying the volume fraction constraint and the mesh resolution. The resulting topologies were then exported as CAD models and evaluated for their aesthetic acceptability by a panel of architects and structural engineers. The study found that BESO-generated topologies were often non-intuitive, featuring curved or branching members that would be difficult to conceive through conventional design, but that these layouts could inspire novel architectural forms while maintaining structural performance. The authors also highlighted that the BESO method is computationally efficient compared to density-based topology optimization, as it requires only a single finite element analysis per iteration and does not involve solving a system of non-linear equations for the optimization, though the method can converge to local optima if not properly tuned. The extension of the BESO method to the design of an innovative steel pedestrian bridge, as presented by [59], further demonstrated the method's versatility. The bridge design, which was intended to be both structurally efficient and visually striking, was optimized for minimum compliance under dead and live loads, with the design domain defined by the bridge silhouette and a constraint on the maximum deflection at mid-span. The resulting BESO-generated topology had a tree-like, branching form with multiple supports at the ground and a canopy-like structure at the deck level. The study showed that the BESO method could generate designs that were conceptually similar to the work of renowned structural artists like Santiago Calatrava, while ensuring that the structure satisfied all strength and deflection criteria.

The investigation of material layouts of structural diagrid frames through topology optimization, as conducted by [60], provides a deep dive into the specific system that has become a hallmark of contemporary high-rise design. The authors applied topology optimization to a 2D representation of a diagrid frame, where the design domain was the entire building elevation and the objective was to minimize compliance under lateral wind load with a volume constraint of 5% of the design domain. The resulting topologies showed that the optimal material distribution within a diagrid frame is not a uniform pattern of identical diagonal modules, as is typical in practice. Instead, the optimization suggested a graded pattern where the diagonal angle and member density vary with height: near the base, the optimal diagonals are steeper (around 75 degrees) and more closely spaced to resist higher shear forces, while near the top, the diagonals become shallower (around 65 degrees) and more widely spaced to reduce self-weight and accommodate the lower shear demand. This finding challenges the common practice of using a uniform diagrid pattern for the entire building height and suggests that significant material savings (potentially up to 15-20%) could be achieved by adopting a graded, height-varying diagrid pattern. The study also noted that the optimal topology from a stiffness perspective (minimizing compliance) may differ from that required to satisfy strength or stability criteria, and that a multi-constraint optimization should be considered for practical design.

The shape optimization of diagrid structures, specifically investigating the effect of building slenderness on the optimal design parameters, was addressed by [62] and [61]. The study by [62] conducted a systematic parametric analysis of diagrid structures with varying height-to-width aspect ratios (from 3:1 to 8:1) and diagrid angles (from 50 degrees to 85 degrees). The results showed that the optimal diagrid angle increases with building slenderness: for a squat building (aspect ratio 3:1), the optimal angle was approximately 65 degrees, while for a slender building (aspect ratio 8:1), the optimal angle was approximately 75 degrees. This relationship is explained by the fact that slender buildings are more sensitive to moment at the base, and a steeper diagrid angle (closer to vertical) provides greater bending stiffness by more directly transferring axial forces down to the foundation. The optimal module size (the height of each diagrid module) was also found to increase with slenderness, as larger modules reduce the number of joints and simplify construction. The calculation model for lateral stiffness of diagrid tube structures developed by [61] further refined this understanding by providing an analytical formula for the optimal diagonal angle based on the building height, plan dimension, and the stiffness ratio between diagrid members and corner columns. The model was validated against finite element analysis for buildings up to 100 stories and showed that the optimal angle could be predicted with an error of less than 3 degrees. This analytical approach, while not AI-based itself, provides a valuable baseline that could be integrated into AI-driven optimization frameworks as a simple rule-of-thumb initialization.

The hybrid aerodynamic and structural optimization of super-tall buildings under wind loads, proposed by [63], addresses a crucial coupling between the building's external shape and its internal structural system. Traditional design workflows treat aerodynamic shape optimization (e.g., corner modifications, tapering, and setbacks) and structural layout optimization as separate processes, often leading to suboptimal overall performance. The hybrid framework developed by the authors integrates a CFD-based aerodynamic shape optimization module with a structural topology optimization module within a single workflow. The aerodynamic module, driven by a genetic algorithm, explores variations of the building footprint shape (e.g., circular, elliptical, rounded-corner square) and taper ratio to minimize the peak wind-induced base moment and overturning force. For each candidate aerodynamic shape, the structural topology optimization module (using a density-based method) determines the optimal layout of the lateral load-resisting system (e.g., core walls, outriggers, belt trusses) to minimize the structural weight subject to drift constraints. The framework was applied to a 100-story super-tall building design, and the results showed that the combination of a rounded-corner square plan (with a corner radius equal to 15% of the plan width) and a 15% taper ratio resulted in a 22% reduction in base moment compared to a square plan building with no taper, and a 19% reduction in structural steel weight relative to a baseline design with a square plan and a conventional outrigger system. The study highlighted that the hybrid optimization process is computationally demanding, requiring hundreds of CFD simulations and structural topology optimizations, but that the resulting design is significantly more efficient than designs derived from sequential or decoupled optimization.

Finally, the hybrid counter propagation neural dynamic model for structural design optimization of diagrid structures, introduced by [64], represents a direct integration of AI with diagrid system optimization. The model combines a counter propagation neural network (CPNN) with a dynamic optimization algorithm to accelerate the search for optimal diagrid geometry and member sizes. The CPNN is trained on a dataset of pre-evaluated diagrid designs to learn the mapping from design variables (including diagrid angle, member cross-section dimensions, and steel grade) to structural responses (including peak drift, member stress ratios, and total weight). The trained CPNN then serves as a fast surrogate model during the optimization process, replacing the need for finite element analysis for each candidate design. The dynamic optimization algorithm, based on replicator dynamics, uses the CPNN predictions to iteratively adjust the design variables toward the optimum. The hybrid model was validated on a 60-story diagrid building under wind loads, and it identified an optimal design (minimal steel weight subject to drift and stress constraints) in 1.5 hours of computation, whereas a standard genetic algorithm using direct FE analysis required over 24 hours to converge to a solution of comparable quality. The optimal diagrid angle predicted by the hybrid model was 73 degrees, which is consistent with the independent results from the shape optimization studies described earlier, providing cross-validation for both approaches. The study also demonstrated that the CPNN could be used for sensitivity analysis, identifying the most influential design variables: the diagrid angle was found to be the most critical parameter, followed by the diagrid member cross-sectional area.

G. Integration of AI with BIM, Digital Twins, and Construction Management

The digital transformation of the architecture, engineering, and construction (AEC) industry has created an ecosystem where Building Information Modeling (BIM), digital twins, and construction management platforms serve as central repositories and communication hubs for project data. Integrating artificial intelligence (AI) optimization methods directly into these environments is critical for translating algorithmic design improvements into practical, implementable solutions for high-rise steel structures. The studies included in this theme reveal a nascent but rapidly evolving field, where the focus is shifting from isolated AI optimization towards embedding computational intelligence within collaborative, data-rich digital workflows. We present a synthesized overview of these studies in Table 6, which categorizes them by their primary focus area and the specific AI or integration technique employed.

Table 6. Integration of AI with BIM, Digital Twins, and Construction Management for high-rise steel structures.

Focus Area	AI / Integration Technique	Application / Function	Sources
BIM Integration & Automation	Metaheuristic optimization via Visual Programming API	Accelerated structural optimization of spatial trusses within BIM-based projects	[65]
	Reinforcement Learning for process optimization	Optimization of complex building structure construction processes in a BIM and big data environment	[66]

Focus Area	AI / Integration Technique	Application / Function	Sources
	BIM-based simulation & safety detection	Simulation and safety detection of high-rise buildings using BIM	[67]
	Distribution technique for green material lists	Optimization of green material procurement and batching for high-rise buildings using BIM	[68]
Construction Management with AI	Deep Reinforcement Learning (DRL) for resource allocation	Real-time optimization of resource (labor, equipment, material) allocation for dynamic construction job sites	[69]
	AI for cost management	General AI-driven cost management approaches to address cost overruns and wastages	[70]
	Ensemble NLP model for cost estimation	AI-augmented cost estimation system that aligns quantity take-offs with cost indexes for high-rise projects	[71]
Digital Twins	Graph-enhanced Digital-Twin framework	Identification of critical cost-runaway paths in high-rise steel structure construction	[72]

Focus Area	AI / Integration Technique	Application / Function	Sources
Robotics & Automation	Overview of automation and robotics technology	General application of robotics and automation for high-rise building construction	[73]

As detailed in Table 6, the integration of AI with BIM platforms is a prominent sub-theme, where researchers seek to embed optimization capabilities directly into the parametric modeling environment used by structural engineers. A notable contribution by [65] addressed the challenge of enhancing spatial truss designs by integrating metaheuristic optimization with visual programming within BIM-based projects. The authors developed an application programming interface (API) that connects a BIM authoring tool (such as Autodesk Revit or Tekla Structures) with a standalone optimization engine based on a genetic algorithm. The visual programming interface (e.g., Grasshopper within Rhino) served as the conduit, allowing the designer to define the structural geometry, apply loads, and specify constraints (such as maximum deflection and allowable stress ratios) without writing code, while the GA optimization engine searched for the optimal member sizes and truss topology. The system was validated on a diagrid spatial truss for a high-rise building, and the results showed that the API-based optimization reduced the structural weight by 18% compared to a manually designed baseline, with the entire optimization process executing directly within the BIM environment. This integration is significant because it eliminates the need for data transfer between separate software packages and enables a more iterative design process where the engineer can modify constraints or objectives in real-time and immediately see the impact on the optimized design.

Furthermore, the application of reinforcement learning (RL) for optimizing construction processes within a BIM framework was investigated by [66]. Their study explored how computer algorithm optimization, combined with BIM and reinforcement learning, can optimize construction process scheduling and resource allocation in a big data environment, specifically for complex high-rise building frame shear wall structures. The BIM model served as the state representation for the RL agent, providing spatial and temporal information about the construction sequence. The RL agent, trained using a Q-learning algorithm, learned a policy that minimized the total construction duration by dynamically adjusting the order of operations, such as concrete pouring cycles and formwork reuse, in response to real-time data on labor availability and weather conditions. The agent's policy was validated through a simulation of a 30-story steel-framed high-rise with concrete core walls, and it achieved a 12% reduction in construction duration compared to a fixed schedule produced by an experienced project manager. The study also demonstrated that the RL agent could adapt its policy to unexpected disruptions, such as material delays or equipment breakdowns, by re-optimizing the schedule in real-time. However, the authors acknowledged that training the RL agent required a substantial amount of simulation data and computational resources, and that the transfer of the trained policy to real-world projects would require careful calibration.

Furthermore, a notable contribution by [67] explored the use of BIM for simulation and safety detection in high-rise buildings. While this study did not employ a specific AI algorithm for optimization, it used the BIM environment to integrate sensor data and finite element simulation results for assessing structural safety during and after construction. The BIM model served as a central data repository where sensor data (e.g., strain gauges on critical columns) was overlaid onto the 3D model, allowing engineers to visually inspect the structural health against analytical predictions. This work establishes a foundational framework for integrating real-time monitoring data with BIM, which is a prerequisite for future AI-driven anomaly detection and decision-making systems. The distribution technique of green material lists for high-rise building engineering in BIM technology, as described by [68], focused on optimizing the procurement and batching of sustainable materials, such as composite steel and concrete, within a BIM workflow. The method used an optimization algorithm applied to the material quantity data extracted from the BIM model to minimize the cost of green materials while satisfying strength and durability requirements. The study demonstrated that this approach could reduce the overall material cost for a steel-framed high-rise by 8% compared to a non-optimized procurement strategy, by minimizing waste and selecting the most economical steel sections and concrete mixes from a predefined green material database. The study by [73] provided a comprehensive overview of the application of automation and robotics technology in high-rise building construction. The review covered a wide range of technologies, including robotic bricklaying and steel beam erectors, and discussed how these technologies are augmented by AI for path planning and quality control. This overview highlights that the integration of AI with construction equipment is a distinct but complementary pathway to the BIM and digital twin approaches, and that future construction sites will likely feature a combination of these technologies.

Turning to construction management with AI, the application of deep reinforcement learning (DRL) for real-time resource allocation was explored by [69] through a case study implementation on dynamic construction job sites. The study addressed a critical practical problem in high-rise construction: how to optimally allocate limited resources (e.g., tower cranes, steel workers, welding equipment) across multiple concurrent work fronts as the building rises. The DRL agent, based on a deep Q-network (DQN), was trained to learn a policy that minimized the total project cost (including labor, equipment, and material costs) subject to completion deadlines. The agent's state was defined by the current progress of each work front, the availability of resources, and the expected material delivery times, all of which were encoded in a digital twin of the job site. The action space consisted of decisions to assign specific resources to particular work fronts. The DRL policy was validated on a 40-story steel high-rise construction project in Austin, Texas, and the simulation results indicated that the optimized resource allocation reduced project delays by 15% and reduced idle time for tower cranes by 20% compared to a heuristic-based resource allocation approach. The study also demonstrated that the DRL agent could adapt to real-time disruptions, such as a crane breakdown, by dynamically reassigning resources to maintain the project trajectory. Moreover, the broader application of AI for cost management in construction projects was summarized by [70], who conducted an in-depth analysis of how AI can address persistent challenges such as cost overruns and material wastages. The study categorized AI applications across the project lifecycle, including AI for cost estimation, AI for risk identification, and AI for optimization of transportation logistics. While the study was not limited to high-rise steel structures, it provided a valuable context for understanding the systemic challenges that AI must address within construction management. Complementing this, the AI-augmented cost estimation system developed by [71] used an ensemble Natural Language Processing (NLP) model to align quantity take-offs extracted from BIM models with cost indexes from historical project databases. The ensemble model combined a transformer-based language model (BERT) for processing unstructured text in specifications and contract documents with a rule-based system for mapping standardized construction items to cost codes. The system was rigorously tested on a high-rise residential building project, where it achieved a 15% reduction in the time required for cost estimation preparation and a 5% improvement in the accuracy of cost predictions compared to manually prepared estimates. The system complemented human quantity surveyors by automating the tedious task of matching material quantities with unit prices, freeing up expert time for more strategic cost control activities.

Finally, the graph-enhanced digital twin approach for identifying critical cost-runaway paths in high-rise steel structure construction, presented by [72], represents a novel fusion of digital twin technology with graph-based AI for risk management. The digital twin model of the construction process was built as a directed acyclic graph (DAG) where nodes represented activities (e.g., steel erection, concrete pouring) and edges represented dependencies and resource flows. Each node and edge was associated with a probability distribution of cost overruns derived from historical data and real-time sensor feeds. The AI component, using a graph convolutional network (GCN), analyzed the cost risk propagation through the network to identify the most critical paths—subsets of activities that are most likely to cause a substantial cumulative cost overrun if delays or cost increases occur. The framework was applied to a 35-story steel residential building, and it successfully identified that the procurement and installation of custom steel connections was the single most critical cost-runaway path, for which a 10% delay would cascade into a 5% overall project cost overrun. The system provided project managers with a prioritized list of risk-mitigation actions, such as ordering backup connection components or establishing contingency procurement agreements with secondary suppliers. This study demonstrates that digital twins can be more than just visualization tools; when coupled with AI, they become predictive and prescriptive platforms for proactive risk management.

H. Structural Health Monitoring, Damage Detection, and Retrofitting

The long-term performance and safety of high-rise steel structures depend critically on the ability to detect damage, assess structural condition, and implement timely retrofitting interventions. Structural health monitoring (SHM) systems, which rely on networks of sensors to measure vibrations, strains, and displacements, generate vast quantities of data that are ideally suited for analysis by artificial intelligence. The studies classified under this theme collectively demonstrate that AI is transforming SHM from a post-event diagnostic tool into a proactive, predictive, and decision-support system that can inform both operational management and long-term maintenance strategies for high-rise buildings. We present a structured overview of these approaches in Table 7, which categorizes the studies by their primary focus area, the specific AI or computational method employed, and the structural application.

Table 7. AI-driven structural health monitoring, damage detection, and retrofitting approaches for high-rise steel and concrete structures.

Focus Area	AI / Computational Method	Structural Application	Key Contributions / Findings	Sources
Structural Health Monitoring & Damage Detection	AI & IoT (AIoT) integration	Health monitoring and prognosis of high-rise concrete structures	Artificial Intelligence of Things (AIoT) framework for real-time monitoring of steel and concrete high-rise structures; combines sensor data with predictive ML models for early warning of structural	[74]

Focus Area	AI / Computational Method	Structural Application	Key Contributions / Findings	Sources
			anomalies	
	Deep Learning (CNN, GAN)	Concrete surface damage detection on high-rise structures	Real-time damage detection framework using deep learning for identifying cracks, spalling, and exposed rebar on high-rise structures; trained on a large dataset of real and synthetic damage images	[75]
	AI-driven health monitoring & early warning system	Concrete structures (general, incl. high-rise)	Comprehensive AI-driven system integrating structural monitoring, data analysis, and early warning for concrete structures; uses anomaly detection algorithms to identify deviations from baseline behavior	[76]
	AI & ML for structural health	General civil engineering (bridges, high-rise buildings)	Comprehensive review of AI and ML methods for structural health monitoring; emphasizes the importance of AI optimization algorithms (GA, PSO) for designing sensor networks and interpreting SHM data	[77]
Damage & Condition Assessment	ML (Bayesian surrogate model)	Probabilistic fragility assessment of super high-rise structures under combined hazards	Bayesian surrogate-based probabilistic framework for fragility assessment of super high-rise structures under combined earthquake and wind hazards; uses an active learning algorithm to efficiently build the surrogate model	[78]
	ML-assisted thermo-mechanical stress analysis	Steel IPE beams under asymmetric thermal conditions for high-rise buildings	Machine learning model for predicting stress and deformation in steel beams under non-uniform heating (e.g., fire); predicts critical stress locations and failure times, informing retrofit design	[79]
	Structural realignment	High-rise building	AI-assisted structural	[80]

Focus Area	AI / Computational Method	Structural Application	Key Contributions / Findings	Sources
	with AI assistance	structural realignment through lifting, grouting, and reinforcement	realignment framework that uses sensor data to plan phased lifting and grouting operations; the AI component optimizes the sequence and magnitude of jacking forces to rectify building tilt	
Retrofitting & Life-cycle Assessment	AI & fuzzy inference for sustainability	Qualitative sustainable and economic assessment of buildings (including retrofitting)	Automated AI-based methodology using fuzzy inference systems for the qualitative assessment of retrofitting and rehabilitation strategies for buildings; provides a systematic framework for comparing retrofit options	[81]
	Residual design life-based evaluation	Structural retrofitting of aging high-rise RC buildings for fire safety	A residual design life-based design procedure that uses structural analysis to determine the remaining load-carrying capacity of a building after fire damage; informs retrofitting decisions by prioritizing interventions that extend the residual life most cost-effectively	[82]
	Integral fire protection analysis	Complex spatial steel structure (fire scenario)	AI-driven optimization of fire protection coatings and active fire suppression systems for complex high-rise steel structures; uses Gaussian transformation model to optimize the distribution of fireproofing material	[83]

As detailed in Table 7, the integration of AI with the Internet of Things (IoT) in the form of Artificial Intelligence of Things (AIoT) is a prominent and recent development within SHM. The framework presented by [74] established an AIoT architecture specifically designed for the health monitoring and prognosis of high-rise building structures. The system integrates a dense network of wireless accelerometers, strain gauges, and temperature sensors with cloud-based machine learning models that are continuously updated as new data streams become available. The ML models, which include convolutional neural networks (CNNs) for feature extraction from acceleration time series and long short-term memory (LSTM) networks for predicting future structural states, operate in a closed loop: the sensor data triggers the AI models, which in turn provide early warnings of anomalous structural behavior (e.g., a sudden change in natural frequency that could indicate damage), prompting further investigation by structural engineers. The framework was validated on a 40-story steel-framed building in Shanghai, where it was shown to successfully detect a simulated 10% reduction in column stiffness at the 15th floor, achieving a 12-hour lead time before the anomaly would have been detectable by conventional threshold-based monitoring systems. This study underscores the potential of AIoT to shift SHM from reactive to predictive maintenance, although the authors noted that the computational cost of training and updating the LSTM models in real-time on edge devices remains a significant practical challenge that requires further optimization of model architectures and hardware.

The deep learning-based approach for real-time concrete damage detection, presented by [75], addresses a different but complementary aspect of SHM: the visual inspection of building surfaces. The study developed a framework specifically tailored for high-rise structures, where manual visual inspection is hazardous and expensive. The core of the framework is a deep convolutional neural network (CNN) fine-tuned on a large dataset of images (over 15,000) of concrete surfaces on high-rise buildings, covering damage types such as cracks, spalling, surface erosion, and exposed rebar. The dataset included both real images captured by drones and synthetic images generated using a generative adversarial network (GAN) to augment the training data for rare damage types. The trained CNN achieved a mean average precision (mAP) of 0.93 on a held-out test set, and was deployed on a drone platform for autonomous inspection of a 30-story reinforced concrete building. The drone captured images, which were processed in near real-time on an onboard computer, and the detected damage was automatically geotagged and overlaid on the building's BIM model. The study also demonstrated that the GAN-based data augmentation was critical for achieving high accuracy on the rarest damage types (e.g., spalling), which accounted for less than 5% of the training data but represented the most safety-critical conditions. However, the authors acknowledged that the CNN's performance degraded when images were taken under adverse lighting conditions (e.g., shadows or direct sunlight) and that techniques such as image pre-processing and data augmentation for variations in illumination would be necessary for robust field deployment.

The AI-driven health monitoring and early warning technology for concrete structures, developed by [76], provides a more holistic framework that integrates sensing, data analytics, and decision support. The system uses a hybrid approach combining wavelet transforms for noise filtering of sensor data with an ensemble of machine learning classifiers (e.g., random forest, support vector machine, and gradient boosting) for anomaly detection. The ensemble voting mechanism reduced false positive rates (which are a major concern in SHM as they can lead to unnecessary and costly inspections) to less than 2% on a test bed of simulated damage scenarios on a 50-story concrete core structure. When an anomaly was detected, the system triggered a tiered alert protocol: a yellow alert prompted automatic data re-analysis with additional features (e.g., cross-correlation between sensors), an orange alert shifted the monitoring frequency from daily to hourly, and a red alert automatically notified the structural engineer and recommended specific inspections. This graded response mechanism is designed to optimize the allocation of inspection resources and avoid overwhelming engineers with alerts. The review of AI and ML for structural health by [77] provides a broader academic context for these developments. The study systematically reviewed how AI optimization algorithms, particularly genetic algorithms (GAs) and particle swarm optimization (PSO), have been applied to optimize sensor network design for SHM of bridges and high-rise buildings. The review found that PSO was particularly effective for determining the optimal locations of a limited number of sensors to maximize the detectability of damage signatures while minimizing the total number of sensors required—a critical cost-saving measure for large-scale SHM installations. The review also highlighted the growing use of deep learning for vibration-based damage detection, but noted that most studies are validated only on numerical models or small-scale laboratory structures, not on full-scale high-rise buildings, leaving a significant gap in the demonstration of real-world efficacy.

The probabilistic fragility assessment framework developed by [78] is notable for its focus on the combined hazard of earthquake and wind, a scenario that is particularly relevant for super high-rise structures located in seismic zones subject to typhoons. The framework uses a Bayesian surrogate model that replaces the computationally expensive non-linear time-history analysis with a probabilistic model that directly predicts the probability of exceeding a given limit state (e.g., immediate occupancy, collapse prevention) as a function of both earthquake intensity (spectral acceleration) and wind speed (hourly mean wind speed at the building top). The surrogate model is built using an active learning algorithm based on expected improvement (EI), which iteratively selects the most informative simulation points to maximize the accuracy of the surrogate while minimizing the number of required simulations. The framework was tested on a 60-story super high-rise steel structure designed according to Chinese codes, and it was shown to accurately reproduce the fragility curves derived from brute-force Latin hypercube sampling using only 15% of the simulation points. The resulting fragility analysis revealed that for this specific structure, the combination of a rare wind event (return period of 1000 years) and a moderate earthquake (return period of 475 years) could produce a probability of exceedance for the collapse prevention limit state that is 35% higher than for the earthquake alone, highlighting the importance of considering multi-hazard scenarios in the fragility assessment of super high-rise structures. The ML-assisted thermo-mechanical stress analysis of steel IPE beams under asymmetric thermal conditions, performed by [79], addresses a critical safety concern for high-rise steel buildings: the structural behavior under fire conditions. The study developed a finite element model of steel IPE beams subjected to non-uniform heating from a localized fire source and trained a multi-layer perceptron (MLP) neural network on the simulation data to predict the time-dependent stress and deformation distributions. The MLP model achieved a prediction accuracy of $R^2 > 0.95$ for the maximum von Mises stress and was able to identify the critical heating duration at which the beam would reach its yield strength. The study found that for asymmetric heating (e.g., a fire on one side of the beam web), the critical failure time was 40% shorter than for symmetric heating, indicating that code-based design assumptions of uniform temperature distribution could be unconservative for steel beams in high-rise buildings with complex compartment geometries. The MLP model was then used to propose and evaluate alternative retrofit designs (e.g., application of intumescent coating of varying thickness on the exposed side) to achieve a target fire rating, demonstrating a practical path for integrating AI into the fire safety design of steel structures.

The AI-assisted structural realignment of high-rise buildings, documented by [80], addresses a specialized but critical retrofit scenario: a tall building that has developed a tilt due to differential foundation settlement or construction errors. The study described a methodology that combines continuous sensor monitoring of the building's tilt with a phased sequence of lifting, grouting, and reinforcement operations. The AI component of the framework consisted of a model predictive controller that used real-time tilt measurements to compute the optimal jacking forces and grouting volumes required at each phase to gradually correct the tilt while minimizing the stresses induced in the structural frame. The optimization problem was formulated as a constrained non-linear optimization, where the objective was to minimize the total correction duration subject to limits on the maximum differential jacking displacement and the maximum induced bending moment in the columns. The framework was validated on a 25-story steel-framed building that had developed a tilt of 1/200 (approximately 30 cm at the roof) due to uneven ground consolidation. The AI-driven correction strategy completed the realignment in four phases over two weeks, achieving a final residual tilt of less than 1/1000, with a 25% reduction in the total jacking displacement magnitude compared to a conventional heuristic sequence that applied uniform jacking across all columns. The study highlighted that the AI-based approach not only improved the precision and safety of the realignment but also reduced the disruption to building occupants by shortening the duration of the operations.

On the retrofitting and life-cycle assessment front, the automated AI-based methodology developed by [81] uses a fuzzy inference system to qualitatively assess the sustainability and economic value of different retrofitting and rehabilitation strategies for existing buildings. The fuzzy system took as input subjective assessments of criteria such as structural safety improvement, energy efficiency gain, environmental impact, and cost, which were provided by a panel of experts, and combined them with a rule base derived from existing case studies. The system output a composite sustainability score for each retrofit option, allowing decision-makers to compare and rank alternatives. While the study was generalizable to any building type, it was applied to a 20-story steel-framed office building with options including column wrapping with steel plates, adding viscous dampers, and replacing the cladding with high-performance insulation. The fuzzy inference system identified column wrapping as the top-ranked option when structural safety was prioritized, while the insulation replacement ranked highest when energy efficiency was the primary objective, demonstrating the system's ability to transparently capture the trade-offs inherent in multi-criteria decision-making for retrofitting.

The residual design life-based evaluation of structural retrofitting on high-rise reinforced concrete buildings, as explored by [82], takes a fundamentally different approach by linking retrofitting decisions to the building's remaining service life. The study developed a procedure where, after a high-rise RC building has been exposed to a fire, a detailed structural analysis (using non-linear finite element models that account for the temperature-dependent degradation of concrete and steel) is used to determine the residual load-carrying capacity of each structural element. From this, the residual design life of the building—defined as the time until the building's structural capacity degrades below the code-required minimum for a design level earthquake—is estimated using a probabilistic model that accounts for the random occurrence of future seismic events. Retrofitting options are then evaluated based on their cost-effectiveness in extending this residual design life. The procedure was demonstrated on a 30-year-old, 45-story RC building that had experienced a moderate fire in an office space on the 20th floor. Without retrofitting, the residual design life was estimated to be 12 years. Among the retrofit options considered, the most cost-effective was carbon fiber-reinforced polymer (CFRP) wrapping of the fire-damaged columns, which extended the residual design life to 35 years at a cost of $150,000, compared to more extensive options (e.g., column jacketing with steel) which extended the life to 50 years but at a cost of$400,000. The study demonstrated that a life-cycle perspective can rationalize retrofitting investments by linking them directly to the functional longevity of the building.

Finally, the integral fire protection analysis of complex spatial steel structures, conducted by [83], employed an optimized Gaussian transformation model to plan the distribution of fireproofing materials for a high-rise steel structure with a complex hyperbolic-paraboloid roof. The study selected a set of critical structural elements (connections and key beams) based on their fire resistance rating, and formulated an optimization problem to minimize the total volume of fireproofing material (intumescent paint) applied while ensuring that all critical elements achieved their required fire rating. The Gaussian transformation model optimized the spatial distribution of the fireproofing material, concentrating it in regions where the steel temperature was predicted to rise fastest based on a fire dynamics simulation. The optimized distribution reduced the total material volume by 18% compared to a uniform application, while still meeting the 2-hour fire rating requirement for all critical elements. This study illustrates how AI-driven optimization can be applied not only to the structural design itself but also to the design of protection systems that ensure the safety of steel structures under extreme events.

IV. Discussion

Taken together, the 77 studies reviewed in this paper depict a field in a state of dynamic and rapid maturation, yet one that is also characterized by significant fragmentation and unresolved methodological challenges. A central observation that emerges across our analysis is a pronounced and persistent disconnect between the sophistication of AI algorithms developed in academic settings and their demonstrable applicability to the real-world design of high-rise steel structures. While evolutionary algorithms, deep reinforcement learning, and generative models have been shown to produce remarkable results on benchmark problems or simplified structural configurations, the number of studies that validate these methods on full-scale, three-dimensional high-rise steel buildings under realistic loading and constraint conditions remains surprisingly small. For example, the remarkable computational speedups reported for surrogate models like the FSResU-Net for flow field prediction [37] or the StructDiffusion framework for shear wall layout generation [42] are predicated on training data that is often computationally expensive to generate for a new building geometry. The dependence of data-driven methods on large, high-quality training datasets emerges as a recurring limitation. The cost and effort required to create such datasets for the diverse range of high-rise steel structural topologies (e.g., braced frames, diagrids, mega-frames with outriggers) suggest a critical bottleneck that the field has only begun to address. Furthermore, many of the generative design studies, while conceptually promising, produce outputs that require substantial manual post-processing to become structurally sensible, or they fail to account for the full spectrum of practical constraints, including connection detailing, constructability sequences, and interaction with non-structural components.

The synthesis of findings across the thematic sub-sections reveals several important patterns regarding the distribution of AI methodologies. There is a clear and accelerating trend toward the use of deep learning-based surrogate modeling for response prediction, particularly for seismic and wind analyses. This is a logical development, given the central role of non-linear dynamic analysis in the performance-based design of high-rise structures and the prohibitive computational cost of such analyses when embedded within an iterative optimization loop. The work on Bayesian optimization for TID placement [27] and the hybrid GA-LSTM framework for time-history prediction [28] exemplify this shift and demonstrate tangible reductions in computational effort. However, this trend also introduces a new set of challenges related to model generalization, uncertainty quantification, and the risk of extrapolation error. A surrogate model trained on a limited set of earthquake ground motions or wind speed profiles may perform poorly when exposed to design events that are statistically different from the training distribution, potentially leading to unsafe designs if the surrogate's predictions are trusted without rigorous validation. The studies reviewed here rarely address the robustness of their surrogate models to out-of-distribution inputs, and this gap represents a significant risk for practical deployment.

Consistently found across all dimensions is the relative scarcity of multi-objective optimization frameworks that explicitly consider the trade-offs between structural performance, cost, constructability, and sustainability in an integrated manner. While a few studies, such as the multi-objective optimization of RC frames using NSGA-II [22] and the sustainable architectural design optimization using CVAE [46], have begun to incorporate environmental objectives into the optimization problem, the majority of the literature remains focused on single-objective optimization (e.g., minimizing weight or drift) or on bi-objective formulations that do not capture the full complexity of real-world decision-making. The practical design of high-rise steel structures involves a much richer set of objectives and constraints, including embodied carbon emissions, construction schedule, material availability, and aesthetic requirements. The field would benefit substantially from a shift toward many-objective optimization frameworks that can navigate these high-dimensional trade-off spaces and present decision-makers with a comprehensive set of Pareto-optimal alternatives. Furthermore, the integration of these optimization frameworks with BIM and digital twin platforms, while growing rapidly, remains at an early stage. Most studies in this area focus on isolated aspects of the design or construction workflow, such as cost estimation [71] or resource allocation [69], rather than providing a fully integrated digital thread that connects AI-optimized conceptual design, through detailed BIM-based documentation, to real-time construction monitoring and post-occupancy structural health management.

The implications of these findings for both research and practice are significant. From a theoretical perspective, our synthesis contributes to the broader understanding of how AI can be embedded within engineering design processes. The success of surrogate-assisted optimization in reducing computational cost confirms the value of the "simulation-based optimization" paradigm, but it also underscores the need for more robust methods of uncertainty quantification and adaptive sampling that can ensure the surrogate model remains accurate in the relevant regions of the design space. The emergence of generative models for design layout generation introduces a new conceptual framework where the AI is not merely optimizing within a predefined parameter space but is actively expanding that space by proposing novel configurations. This represents a fundamental shift from optimization to synthesis, and it necessitates new theoretical frameworks for evaluating the quality, novelty, and feasibility of AI-generated designs. From a practical standpoint, our findings suggest that the current state of AI-driven optimization is unlikely to replace the experienced structural engineer in the near future, but it can serve as a powerful augmentation tool that accelerates the early-stage exploration of design alternatives and automates tedious parametric studies. Practitioners could most immediately benefit from adopting surrogate-assisted optimization workflows for tasks such as calibrating damper parameters, selecting optimal outrigger locations, or tuning member sizes in diagrid structures, where the computational savings are well-documented and the optimization problems are well-posed. However, there is a clear need for user-friendly software interfaces that can bridge the gap between the specialized AI algorithms described in the literature and the everyday tools used by structural engineers, such as ETABS, SAP2000, and Tekla Structures. The integration of optimization engines with visual programming platforms like Grasshopper, as demonstrated by a few studies [65], offers a promising path forward, but the engineering community must invest in developing standardized workflows and training materials to facilitate broader adoption.

Acknowledging the limitations of this systematic review is essential for interpreting its conclusions with appropriate caution. The review methodology, while rigorous and transparent, is subject to several inherent constraints that may have influenced the scope and depth of the evidence base. First, the search was limited to five academic databases—IEEE Xplore, Scopus, Web of Science, ScienceDirect, and Google Scholar. While these databases collectively offer broad coverage of the relevant interdisciplinary literature, they do not index all relevant publication venues, particularly those focused on conference proceedings from smaller engineering societies or industry-specific technical reports. The exclusion of non-English language studies is a significant limitation, given that a substantial amount of high-rise construction and structural engineering research occurs in China, Japan, Korea, and the Middle East, where local-language publications may contain pioneering contributions not captured in our dataset. The application of only English-language keywords and search strings may have also introduced a language bias that systematically overlooked relevant studies published in other languages. Second, the inclusion criteria prioritized peer-reviewed journal articles and conference papers, which may have excluded valuable contributions from industry white papers, technical manuals, and PhD dissertations. These sources often contain more applied, practical insights that could complement the predominantly academic focus of the included studies. The decision to exclude book chapters also removed some potentially comprehensive overviews of specific topics. Third, the classification of studies into eight predefined dimensions, while useful for organizing the synthesis, introduced a degree of subjectivity. Some studies could be reasonably assigned to multiple dimensions, and the primary classification we selected may not fully capture the breadth of each study's contribution. The assessment of study quality was also based on methodological completeness and relevance to the research question, rather than on a formal risk-of-bias tool or quality assessment framework. This approach may have allowed studies with methodological weaknesses to be included without explicit flagging, potentially influencing the perceived strength of evidence in certain sub-themes. Finally, the rapidly evolving nature of this field means that our search, conducted in January 2026, will inevitably become outdated as new studies are published. The explosive growth observed in 2024-2026 suggests that the landscape may look substantially different even within the next year, and our conclusions should be viewed as a snapshot of a moving target.

Given these findings and limitations, several promising directions for future research emerge naturally from the gaps and inconsistencies we have identified. There is a pressing need for the development of standardized benchmark problems and performance metrics that can facilitate the fair comparison of different AI-driven optimization frameworks across studies. The current literature is characterized by a proliferation of unique structural models, loading conditions, and evaluation criteria, making it difficult to determine which algorithms are genuinely superior for the design of high-rise steel structures. A community-wide effort to establish a set of open-source benchmark problems—perhaps based on well-documented real-world high-rise designs such as the SAC Phase II benchmark structures or the Yamasaki Building—would greatly accelerate progress by enabling researchers to directly compare their methods against a common baseline. Furthermore, the field would benefit from a systematic investigation into the transferability of surrogate models across different structural typologies. Most surrogate models studied to date are trained on a single building geometry and may not generalize to buildings with different plan shapes, heights, or lateral systems. Future research should explore the use of meta-learning or foundation model approaches that can learn a universal response predictor for steel high-rises, fine-tuned for specific buildings using only a small number of simulations. This could dramatically reduce the computational cost of applying AI to new designs.

Another critical area that remains understudied is the integration of optimization with the full spectrum of practical constraints encountered in the design and construction of high-rise steel structures. This includes not only strength, drift, and acceleration constraints but also constructability limitations (e.g., maximum steel member length, welding restrictions), architectural constraints (e.g., column-free floor areas, facade alignment), and economic constraints (e.g., budget limitations, material price volatility). The development of constraint handling techniques that can efficiently navigate these heterogeneous constraints—many of which are discrete, non-differentiable, or depend on expert judgment—is a significant algorithmic challenge. The rise of large language models and foundation models in AI suggests a potential avenue for incorporating qualitative expert knowledge (e.g., heuristics for good structural detailing) directly into the optimization loop, but this application of AI to structural engineering remains essentially unexplored. In the domain of structural health monitoring and damage detection, future research should focus on bridging the gap between laboratory-validated AI models and field deployments on real high-rise buildings. This will require the collection of large, labeled datasets of sensor data from instrumented buildings under various damage states—a goal that is ethically and practically challenging. The use of physics-informed neural networks (PINNs) that embed governing structural dynamics equations into the learning process could reduce the reliance on large labeled training datasets and improve the robustness of damage detection to noise and unknown boundary conditions. Finally, the lifecycle integration of AI across the design, construction, operation, and retrofitting phases of a high-rise building—from initial generative design to real-time health monitoring to automated retrofit planning—remains an aspirational vision rather than a demonstrated reality. Future research should aim to develop and validate end-to-end digital twin frameworks that maintain a continuously updated AI-driven optimization capability throughout the building's lifespan, adapting the structural design or operational strategy as new monitoring data becomes available. This would represent the ultimate realization of the promise of AI in structural engineering: a closed-loop system that learns from the performance of the structure and continuously improves its design and operation over time.

V. Conclusion

This systematic literature review has provided a comprehensive synthesis of the current state of research on AI-driven optimization of steel structural design for high-rise buildings, addressing the research questions of what methods exist, how they are applied, and where critical gaps remain. We found that the field is undergoing an explosive growth phase, characterized by a shift from classical evolutionary optimization toward deep learning-based surrogate modeling and generative design, with the most significant advances occurring in seismic and wind response prediction, vibration control system optimization, and the integration of AI with BIM and digital twin platforms. However, our synthesis also reveals that the field remains fragmented, with a persistent disconnect between algorithmic sophistication and practical validation on full-scale high-rise steel structures, and a concerning lack of standardized benchmarks, multi-objective frameworks, and robust uncertainty quantification methods. The theoretical contribution of this review lies in mapping the landscape of AI methodologies specifically for steel high-rise design and identifying where each method is most effective, while the practical implication is a clear roadmap for practitioners seeking to adopt surrogate-assisted optimization or generative design in their workflows. Looking forward, the most pressing research directions include the development of universally transferable surrogate models trained on diverse structural typologies, the integration of practical constructability and economic constraints directly into optimization formulations, and the creation of end-to-end digital twin frameworks that maintain AI-driven optimization across the entire building lifecycle from conceptual design through decommissioning.

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