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AI-Enabled Performance-Based Structural Optimization of Steel Truss and Mezzanine Systems for Industrial Facilities

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Abstract

This study investigated AI-enabled, performance-based structural optimization of steel truss and mezzanine systems used in industrial facilities through a quantitative computational benchmarking design. Multiple optimization algorithms were evaluated under identical structural modeling assumptions, load combinations, and constraint conditions to determine their influence on material efficiency, serviceability control, stability adequacy, vibration response, and computational performance. The final analytic dataset consisted of 468 valid optimization runs derived from 16 standardized structural configurations, equally representing truss and mezzanine systems. Results demonstrated an overall mean weight reduction of 18.6% relative to baseline designs, with truss systems achieving higher reductions (20.1%) compared to mezzanine systems (17.0%). Differential Evolution and Hybrid Metaheuristic approaches produced significantly greater material savings than the reference Genetic Algorithm, with mean improvements exceeding 3.0 percentage points ($p < 0.001$). Dimensionality exerted the strongest influence on computational cost, as high-dimensional cases increased runtime by an average of 5.41 minutes and significantly raised convergence iterations ($p < 0.001$). The runtime regression model explained 56% of variance, while the weight reduction model explained 41% of variance. Feasibility performance remained stable across complexity levels, with an overall feasibility rate of 91.6%. No statistically significant differences were observed among algorithms for overall structural adequacy once feasible convergence was achieved, indicating consistent compliance with strength, serviceability, and stability requirements. Reliability analysis confirmed strong internal consistency for composite structural adequacy measures ($a = 0.88$) and acceptable consistency for optimization efficiency ($a = 0.74$), supporting inferential modeling validity. The findings demonstrated that algorithm selection and dimensional complexity significantly affected material efficiency and computational performance, while structural compliance remained consistently maintained. The study provided a statistically grounded benchmarking framework for evaluating AI-enabled optimization strategies in industrial steel structural systems.

Keywords

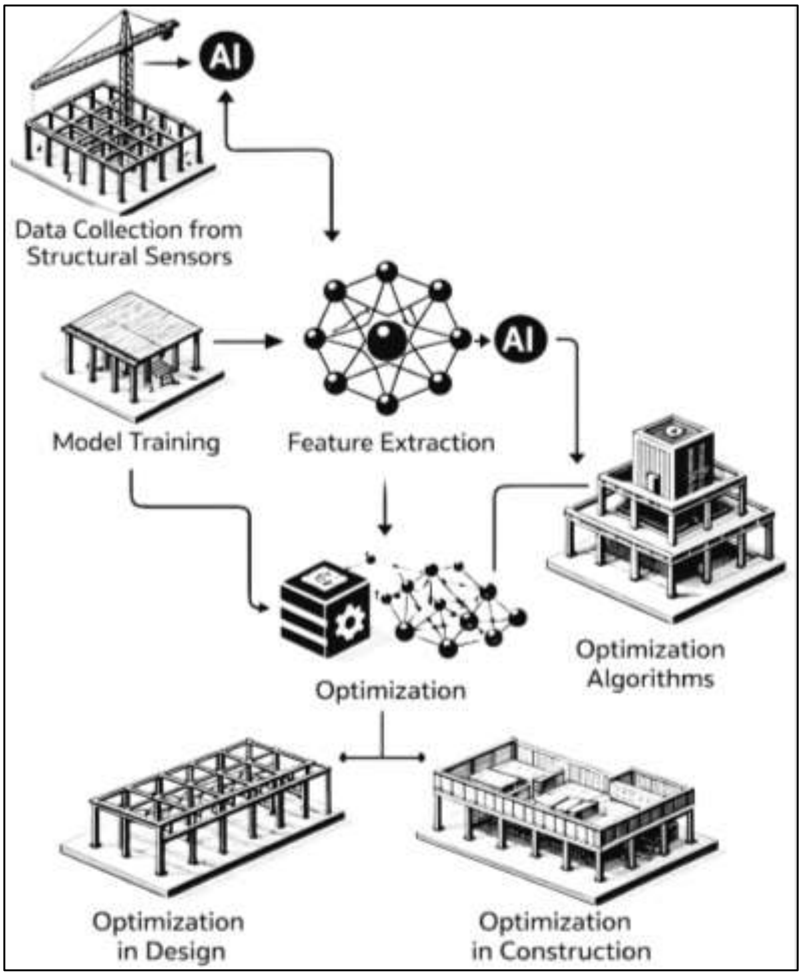
AI Optimization, Steel Structures, Performance-Based Design, Structural Benchmarking, Computational Engineering.

INTRODUCTION

Structural optimization refers to the systematic process of designing load-bearing systems to achieve optimal performance under specified constraints such as strength, stability, weight, cost, and serviceability. Within civil and industrial engineering, optimization techniques are used to determine the most efficient arrangement of structural elements, material distribution, and geometric configurations while satisfying safety codes and performance requirements (Jenis et al., 2023). Steel truss and mezzanine systems represent critical components in industrial facilities, offering adaptable, lightweight, and high-strength solutions for spanning large spaces and supporting dynamic loads. Artificial intelligence (AI), defined as the computational capability of machines to simulate intelligent decision-making processes, has increasingly been integrated into engineering optimization to enhance predictive accuracy and solution efficiency. AI-enabled optimization combines machine learning algorithms, evolutionary computation, and metaheuristic search strategies to analyze large design spaces and identify near-optimal or optimal structural configurations (Tapeh & Naser, 2023). In quantitative research, AI-driven structural optimization is evaluated through mathematical modeling, statistical performance metrics, and algorithmic benchmarking. The integration of AI with performance-based structural design frameworks supports data-driven decision-making processes that can process multidimensional variables, including load combinations, material properties, geometric constraints, and environmental influences. Internationally, industrial expansion, rapid urbanization, and infrastructure modernization have amplified the need for advanced optimization strategies that reduce material consumption while enhancing safety and operational efficiency. Global construction industries increasingly adopt performance-based design methodologies, which evaluate structures based on measurable performance indicators such as deflection limits, stress distribution, vibration control, and resilience under extreme conditions. The convergence of AI and structural optimization represents a quantitative paradigm in which computational intelligence augments traditional deterministic and probabilistic design methods (Chowdhary, 2020). This integration supports the systematic evaluation of steel truss and mezzanine systems within industrial facilities where operational continuity, load adaptability, and spatial efficiency are critical engineering priorities.

Performance-based structural design is an engineering approach that defines structural adequacy in terms of explicit performance objectives rather than prescriptive code compliance alone. This methodology quantifies structural behavior under anticipated loading scenarios and evaluates measurable outcomes such as displacement, stress ratios, buckling resistance, fatigue life, and dynamic response. Steel truss systems, composed of interconnected triangular elements, provide high stiffness-to-weight ratios and efficient load transfer mechanisms suitable for industrial environments that demand long-span coverage (Duong et al., 2021). Mezzanine systems, defined as intermediate elevated platforms within industrial buildings, expand usable floor space without requiring full structural expansion, making them cost-effective solutions in logistics centers, manufacturing plants, and warehouses. Quantitative evaluation of these systems involves finite element modeling, load combination analysis, and optimization algorithms that assess performance metrics across multiple design scenarios. Internationally, industrial facilities must comply with global standards related to occupational safety, seismic performance, wind resistance, and fire resilience. Performance-based optimization enhances compliance by enabling engineers to simulate realistic operational loads, including equipment vibration, material handling impacts, and storage variability. AI-enabled analytical models allow for high-dimensional parametric studies in which thousands of structural configurations are evaluated efficiently. Such computational capacity supports global engineering practices seeking to reduce structural weight, minimize embodied carbon in steel production, and maintain structural integrity under variable environmental conditions. Quantitative performance metrics derived from AI algorithms include convergence rate, optimization accuracy, computational efficiency, and structural reliability indices (Kaveh, 2024). The international significance of this framework lies in its contribution to sustainable industrial development, economic efficiency, and infrastructure reliability across diverse geographic and climatic contexts. The integration of AI-driven optimization within performance-based structural design represents a structured quantitative approach to evaluating steel truss and mezzanine systems under realistic operational conditions.

Figure 1: Structural Optimization Using Artificial Intelligence

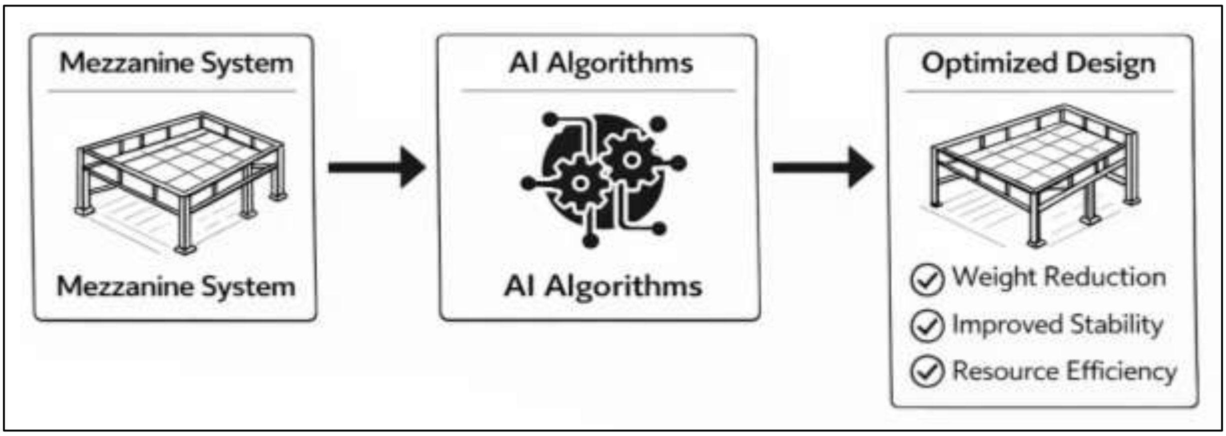


Steel truss systems are structural assemblies composed of linear members connected at nodes to form stable triangular configurations that distribute axial forces efficiently. These systems are widely used in industrial facilities for roof structures, conveyor supports, crane systems, and large-span frameworks (Bado et al., 2022). The structural behavior of steel trusses is governed by axial tension and compression forces, buckling stability, joint rigidity, and geometric nonlinearity. Quantitative optimization of truss systems involves variables such as cross-sectional area, member length, nodal coordinates, topology arrangement, and material grade. Objective functions typically include weight minimization, cost reduction, stiffness maximization, and stress uniformity. AI-enabled optimization methods such as genetic algorithms, particle swarm optimization, artificial neural networks, and hybrid metaheuristic models are applied to navigate complex design spaces. These algorithms iteratively evaluate candidate solutions using performance indicators derived from structural analysis models. International engineering research emphasizes lightweight design strategies to reduce transportation costs and environmental impact associated with steel production. Industrial facilities in seismic zones require optimized truss configurations that enhance ductility and energy dissipation capacity. Quantitative modeling integrates boundary conditions, load combinations, and material nonlinearities to simulate realistic structural responses (Riad et al., 2024). AI-based surrogate modeling techniques accelerate optimization by approximating finite element outputs, thereby reducing computational time. Performance metrics include structural reliability indices, utilization ratios, and constraint violation penalties. Globally, steel truss optimization supports large-scale industrial projects such as logistics hubs, manufacturing complexes, and distribution centers where structural efficiency directly influences operational productivity. AI-driven optimization provides scalable solutions adaptable to varying regulatory frameworks and climatic conditions. Through systematic parameter evaluation, steel truss systems can achieve balanced structural performance characterized by reduced material usage, improved safety margins, and optimized load transfer efficiency in industrial environments.

Mezzanine systems are semi-permanent elevated platforms constructed within industrial buildings to maximize vertical space utilization. Typically fabricated from steel beams, columns, decking systems, and bracing components, mezzanines support storage racks, production lines, and administrative spaces. Structural optimization of mezzanine systems focuses on load-bearing capacity, deflection control, vibration mitigation, and connection stability. Quantitative evaluation requires modeling static and dynamic loads, including distributed storage loads, concentrated equipment loads, and human occupancy loads (Lv et al., 2021). AI-enabled structural optimization techniques assess geometric parameters such as column spacing, beam depth, bracing configuration, and deck thickness to achieve optimal performance objectives. Industrial facilities worldwide face increasing demand for space efficiency due to supply chain expansion and e-commerce growth. Mezzanine systems offer flexible design adaptability that can be modified based on operational requirements. Performance-based evaluation ensures that mezzanine platforms meet safety standards for load capacity and serviceability. Quantitative metrics include allowable stress ratios, deflection limits relative to span length, natural frequency thresholds, and structural reliability probabilities. AI algorithms enable sensitivity analysis across numerous design scenarios, identifying parameter interactions that influence structural performance. Internationally, mezzanine optimization contributes to cost-effective industrial expansion without significant increases in building footprint (Sacks et al., 2020). Steel-based mezzanines align with modular construction practices that facilitate rapid installation and reconfiguration. Optimization frameworks integrate structural analysis software with AI learning models to enhance design precision. Through data-driven methodologies, mezzanine systems can achieve efficient material distribution, improved vibration performance, and reliable load-bearing capacity within industrial facilities characterized by variable operational demands.

Artificial intelligence techniques applied to structural optimization encompass supervised learning, unsupervised learning, reinforcement learning, and metaheuristic search algorithms (Ebid, 2021). Genetic algorithms simulate evolutionary processes through selection, crossover, and mutation to identify high-performing structural designs. Particle swarm optimization models collective intelligence behavior to explore solution spaces efficiently. Artificial neural networks function as predictive models capable of approximating nonlinear relationships between design variables and performance outcomes. Reinforcement learning algorithms adaptively refine structural configurations based on reward-based performance feedback. Quantitative evaluation of these AI methods involves convergence speed, solution stability, computational complexity, and optimization accuracy. Industrial structural systems, including steel trusses and mezzanines, involve nonlinear constraints and multiple objective functions, making them suitable candidates for AI-driven optimization. International research demonstrates that hybrid algorithms combining machine learning with finite element analysis enhance predictive accuracy while reducing computational time (Lukyanenko et al., 2022). Surrogate modeling techniques enable rapid approximation of structural responses, facilitating large-scale parametric optimization. Performance-based design objectives are integrated within AI frameworks to ensure compliance with strength, serviceability, and stability requirements. AI-enabled optimization supports real-time decision-making during design iterations, allowing engineers to compare alternative structural configurations efficiently. Quantitative validation methods include statistical error metrics, cross-validation techniques, and reliability-based performance indices. Globally, AI integration in structural engineering reflects broader digital transformation trends within the construction industry. The adoption of computational intelligence enhances engineering precision, supports resource-efficient construction practices, and contributes to standardized performance benchmarking across international industrial projects (Alhamrouni et al., 2024).

Figure 2: Structural Performance Optimization Using AI



Quantitative structural optimization relies on mathematical modeling, statistical evaluation, and algorithmic benchmarking to measure system performance. Finite element analysis provides numerical simulation of stress distribution, displacement patterns, and buckling behavior under various load conditions. Objective functions in AI-enabled frameworks may include weight minimization, cost efficiency, structural reliability maximization, and environmental impact reduction. Constraint equations ensure compliance with design standards related to allowable stresses, deflection limits, and stability criteria (Schmitt, 2023). Performance metrics used to evaluate optimization effectiveness include convergence rate, computational time, solution robustness, and sensitivity coefficients. Reliability-based design approaches integrate probabilistic load modeling and material variability into performance assessment. Steel truss and mezzanine systems in industrial facilities must account for operational uncertainties such as equipment loads, storage variability, and dynamic vibrations. AI algorithms enable multi-objective optimization where trade-offs between cost, safety, and structural efficiency are quantitatively analyzed. Statistical validation techniques assess model accuracy by comparing predicted performance with analytical or simulation-based benchmarks (Banh & Strobel, 2023). Internationally, performance-based optimization aligns with sustainability metrics by reducing steel consumption and embodied energy. Digital modeling environments integrate structural analysis software with AI computational platforms, enhancing reproducibility and scalability. Quantitative research in this domain emphasizes data integrity, algorithm transparency, and statistical reliability to ensure replicable findings. The structured evaluation of steel truss and mezzanine systems through AI-driven quantitative frameworks strengthens engineering accuracy, operational efficiency, and global competitiveness in industrial infrastructure development.

The global industrial sector relies on efficient structural systems to support manufacturing, warehousing, logistics, and energy production facilities (Luckey et al., 2020). Steel truss and mezzanine systems form the backbone of many industrial infrastructures due to their adaptability, strength-to-weight efficiency, and modular design characteristics. AI-enabled performance-based structural optimization addresses the increasing demand for material efficiency, safety enhancement, and rapid project delivery. International construction markets prioritize cost-effective design strategies that reduce material waste and optimize load-bearing capacity. Quantitative AI-driven frameworks enable engineers to evaluate thousands of potential configurations within reduced computational timeframes. Industrial facilities operating in diverse climatic and seismic conditions require adaptable structural systems capable of maintaining stability under varying environmental stresses. AI optimization supports resilience-oriented design by incorporating multi-scenario load analysis and probabilistic reliability assessment. Global sustainability initiatives encourage the reduction of carbon emissions associated with steel manufacturing, reinforcing the importance of weight-efficient structural solutions. Digital transformation in engineering practices integrates computational intelligence into building information modeling and automated design workflows(Harandizadeh et al., 2021). Quantitative

research methodologies validate AI optimization models through statistical performance metrics, ensuring objective evaluation of structural efficiency. The international significance of AI-enabled optimization lies in its contribution to standardized engineering excellence, enhanced structural safety, and economic efficiency across industrial sectors. Through systematic quantitative analysis, steel truss and mezzanine systems can achieve optimized configurations that align with global engineering standards, operational demands, and performance-based design principles.
This quantitative study aims to develop and evaluate an AI-enabled, performance-based structural optimization framework for steel truss and mezzanine systems used in industrial facilities by translating structural performance requirements into measurable objective functions and computational decision rules. The first objective is to formalize a performance-based optimization model that simultaneously captures strength, stiffness, and stability constraints through quantifiable indicators such as member utilization ratios, nodal displacement limits, global and local buckling checks, and serviceability thresholds relevant to industrial operations. The second objective is to implement an AI-driven optimization engine capable of exploring high-dimensional design spaces by varying structural topology and sizing parameters, including member cross-sectional properties, truss geometry, panel lengths, chord-web arrangements, column spacing, beam depths, and bracing layouts for mezzanine framing. The third objective is to construct a simulation-integrated evaluation pipeline in which each candidate design is assessed using numerical structural analysis outputs and standardized performance metrics, enabling objective comparison across competing configurations under multiple load combinations representative of industrial facility demands, including distributed storage loads, concentrated equipment loads, and dynamic effects from material handling activities. The fourth objective is to quantify optimization effectiveness using statistical and computational performance indicators such as convergence behavior, computational runtime, constraint satisfaction rate, and variability of solution quality across repeated runs, thereby supporting reproducible benchmarking of alternative AI strategies. The fifth objective is to examine multi-objective trade-offs between material efficiency and performance adequacy by measuring changes in total steel weight, estimated structural cost proxies, stiffness indices, and stability margins while maintaining fixed safety and serviceability constraints. The sixth objective is to test model robustness through sensitivity analysis by perturbing key inputs such as load magnitudes, boundary conditions, and material properties to evaluate the stability of optimized solutions and identify the most influential parameters affecting truss and mezzanine performance. The final objective is to produce a validated quantitative basis for comparing conventional deterministic optimization with AI-enabled approaches in terms of achieved performance outcomes and computational efficiency, using consistent evaluation rules and reporting structures suitable for industrial engineering decision contexts.

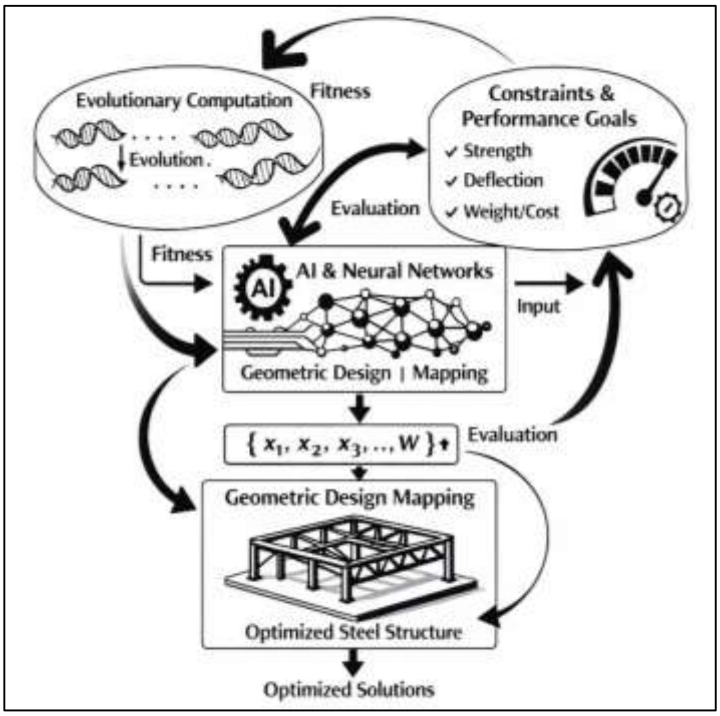
LITERATURE REVIEW

This Literature Review synthesizes quantitative research underpinning AI-enabled, performance-based structural optimization of steel truss and mezzanine systems in industrial facilities (Badini et al., 2023). The review is structured to progressively connect mathematical optimization theory, structural performance metrics, advanced numerical modeling, and artificial intelligence algorithms within a unified quantitative framework. Emphasis is placed on measurable variables, objective function formulation, constraint modeling, algorithmic efficiency indicators, and validation metrics commonly used in structural engineering optimization studies. The literature is organized to reflect how steel truss and mezzanine systems are modeled, how performance-based design criteria are translated into quantifiable limit states, and how AI-driven methods are benchmarked using statistical and computational indicators (Priyadarshi, 2024). Each subsection adopts a highly specific quantitative orientation, focusing on analytical formulations, parameter sensitivity structures, computational scalability, and performance evaluation standards relevant to industrial structural systems.

Multi-Objective Structural Optimization Problems for Steel Systems

The quantitative foundations of multi-objective structural optimization in steel systems are grounded in the systematic translation of engineering performance goals into measurable and computationally assessable criteria. Structural optimization research initially concentrated on minimizing structural weight as an indicator of material efficiency and cost reduction, particularly in steel frameworks where self-weight significantly influences member sizing and foundation demand. Over time, optimization objectives expanded to incorporate structural compliance reduction, stiffness enhancement, and cost proxies that reflect fabrication complexity, connection detailing, and constructability efficiency (Foresti et al., 2020). Multi-objective optimization frameworks emerged to address the reality that steel structures must simultaneously satisfy strength, serviceability, durability, and economic criteria. Within these frameworks, competing objectives are evaluated collectively, enabling designers to identify balanced configurations that achieve acceptable trade-offs between material reduction and performance reliability. The literature consistently emphasizes that clearly defined quantitative performance indicators are essential for ensuring objective comparison among design alternatives (Trakadas et al., 2020). In steel truss and industrial framing systems, performance quantification commonly includes global displacement behavior, internal force distribution uniformity, and utilization consistency across members. Optimization studies also recognize the importance of scalability in handling large numbers of design variables, particularly in high-dimensional truss systems where geometric and sectional parameters interact . The integration of structured evaluation metrics has contributed to the development of reproducible computational workflows, enabling systematic benchmarking of design efficiency across varied structural typologies (Sun et al., 2024).

Figure 3: Structural Optimization Using Artificial Intelligence



Constraint modeling represents a central component of structural optimization research, ensuring that candidate designs remain within acceptable safety and serviceability boundaries. In steel systems, constraints are typically derived from allowable stress limits, displacement thresholds, buckling capacity requirements, and vibration performance criteria associated with operational safety. The literature emphasizes that constraint definition directly influences the shape and boundaries of the feasible design space, which contains all structurally acceptable configurations. Accurate characterization of this feasible region is essential for preventing optimization algorithms from converging toward impractical or unsafe solutions (Truong et al., 2024). Studies on steel truss optimization frequently incorporate axial stress limits for tension and compression members, global stability checks for slender elements, and serviceability-based deflection controls tied to span length ratios. In industrial applications, vibration constraints are particularly relevant for mezzanine systems and elevated platforms subjected to human occupancy or machinery-induced dynamic effects. Research has also highlighted the importance of constraint-handling mechanisms that effectively balance feasibility enforcement with computational efficiency. Methods such as penalty-based adjustment strategies and adaptive constraint prioritization have been widely discussed in optimization literature (Pereira et al., 2022). These approaches ensure that optimization algorithms explore high-performing regions of the solution space while systematically reducing constraint violations. Through structured constraint modeling, researchers establish a controlled search environment that maintains structural integrity and operational reliability across diverse steel system configurations.

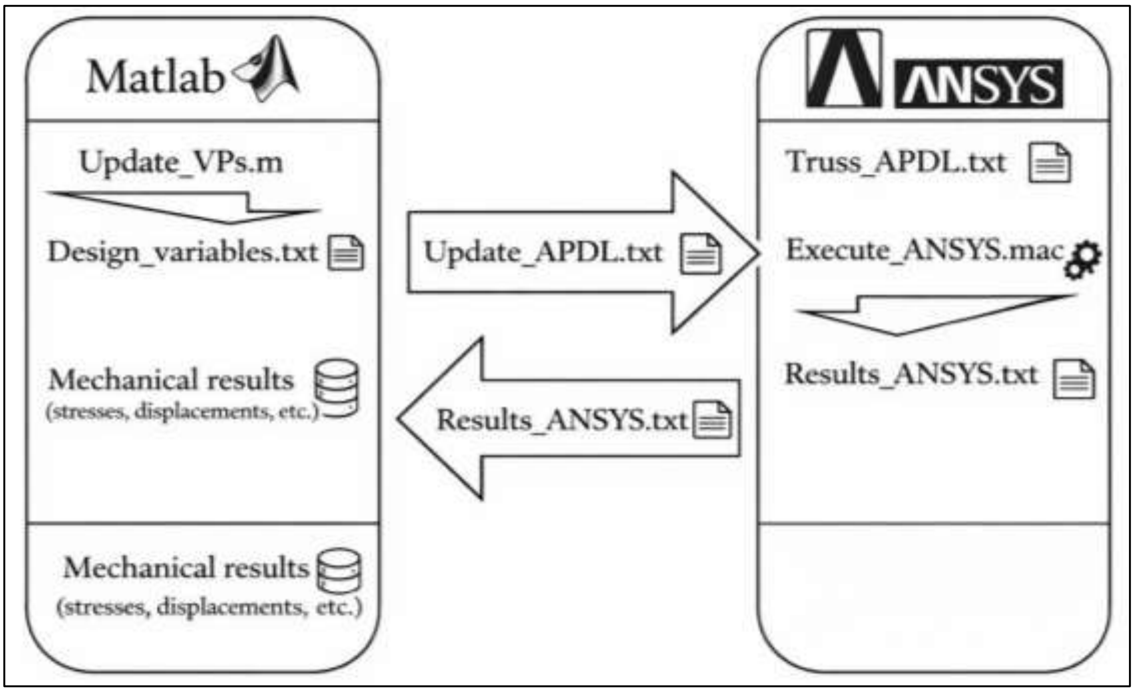
Structural optimization research distinguishes between deterministic and reliability-based approaches in modeling uncertainty and safety margins within steel systems. Deterministic models treat loads, material properties, and geometric parameters as fixed quantities, focusing on optimizing structural performance under predefined conditions (Mathern et al., 2021). This approach has been widely used due to its computational efficiency and straightforward implementation in engineering practice. However, the literature increasingly recognizes that steel structures in industrial environments are subject to variability in load intensity, fabrication tolerances, and material strength. Reliability-based optimization frameworks address this variability by incorporating probabilistic descriptions of uncertainties into performance evaluation. Instead of merely satisfying deterministic constraints, reliability-oriented approaches quantify the probability of failure or safety index levels associated with structural components. This shift toward probabilistic modeling enables more refined control over safety margins and risk distribution across members. Studies comparing deterministic and reliability-based frameworks demonstrate that probabilistic integration often leads to more balanced material distribution and improved structural consistency under uncertain conditions (Crespino et al., 2024). Calibration of safety indices and load factors plays a crucial role in aligning optimization outputs with recognized engineering standards. The literature also discusses computational trade-offs between deterministic simplicity and probabilistic robustness, noting that reliability-based methods demand additional sampling or statistical evaluation procedures. Nonetheless, reliability-informed optimization enhances decision-making transparency and supports risk-aware structural design in complex industrial settings.

Multi-objective structural optimization research emphasizes the importance of trade-off analysis in evaluating competing design goals within steel systems (Tu et al., 2020). Rather than producing a single optimal solution, multi-objective frameworks generate a spectrum of non-dominated alternatives that represent different balances among objectives such as weight reduction, stiffness control, and reliability enhancement. The concept of Pareto optimality is central to this approach, providing a structured method for identifying solutions where no objective can be improved without compromising another. In steel truss and mezzanine optimization studies, trade-off analysis allows designers to assess the implications of incremental material savings relative to serviceability or stability performance. The literature highlights visualization techniques and ranking metrics used to interpret sets of competing solutions in high-dimensional design spaces (Shan et al., 2024). Computational solution strategies have evolved to address the complexity of multi-objective problems, particularly in large-scale steel systems characterized by numerous design variables and nonlinear constraints. Algorithm efficiency is frequently evaluated based on convergence behavior, solution diversity, computational runtime, and scalability with increasing problem dimensionality. Research also explores adaptive parameter control mechanisms that enhance exploration and exploitation balance during optimization. Through structured trade-off evaluation and performance benchmarking, multi-objective optimization research provides a quantitative foundation for systematically comparing alternative steel structural configurations within industrial design contexts (Gholizadeh & Fattahi, 2021).

Industrial Steel Truss and Mezzanine Structures

Performance-based structural design in industrial steel truss and mezzanine systems is grounded in the explicit definition of measurable structural objectives that reflect strength, serviceability, and stability requirements under operational loading conditions (Resende et al., 2024). Unlike prescriptive design approaches that rely primarily on standardized member sizing tables and fixed safety factors, performance-based frameworks translate structural expectations into quantifiable response indicators that can be analytically verified. Research in industrial facility design emphasizes that steel truss systems and mezzanine platforms are subjected to varied load patterns, including distributed storage loads, concentrated equipment forces, and repetitive operational impacts associated with logistics and manufacturing activities (Liu et al., 2022). The literature consistently identifies strength limit states, serviceability criteria, and global stability thresholds as the core pillars of performance evaluation. Strength-related assessments focus on axial capacity, bending resistance, and connection adequacy, while serviceability assessments prioritize deflection control and vibration comfort in elevated working platforms. Stability considerations examine global frame behavior, lateral bracing effectiveness, and susceptibility to buckling under compressive forces. Studies demonstrate that performance-based approaches improve transparency in structural evaluation by linking design decisions directly to measurable behavioral outcomes. Within industrial contexts, this framework enhances adaptability to varying occupancy patterns and equipment layouts, enabling systematic comparison of structural configurations using standardized performance indicators (Kaveh & Dadras Eslamlou, 2020). As a result, performance-based design has become central to quantitative optimization research involving steel systems in complex industrial environments.

Figure 4: Performance-Based Steel Structural Design



The literature on quantitative structural metrics highlights the importance of clearly defined evaluation parameters for both strength and serviceability performance in steel truss and mezzanine structures. Strength performance is commonly assessed using member utilization ratios, capacity-to-demand comparisons, and stability checks that ensure structural elements operate within acceptable stress boundaries (Wasse et al., 2024). Researchers emphasize that uniform force distribution across truss members enhances structural efficiency and reduces localized overstressing. In mezzanine systems, beam and column performance is evaluated in terms of load-bearing adequacy under combined vertical and lateral forces generated by storage systems and mechanical installations. Serviceability performance has been extensively studied in relation to deflection limits, particularly for long-span truss members and mezzanine beams supporting human activity (Keskin et al., 2021). Excessive deflection can compromise operational functionality, affect equipment alignment, and reduce occupant comfort. Vibration performance is also critical in industrial platforms, where repetitive motion from machinery or foot traffic may induce dynamic responses that require frequency-based evaluation criteria. Studies examining industrial steel floors identify acceptable vibration thresholds based on occupancy type and operational sensitivity. Slenderness considerations for compression members further contribute to performance verification, ensuring resistance against instability phenomena. By integrating these quantitative metrics, researchers establish consistent benchmarks for comparing alternative structural configurations within optimization-driven design frameworks (Minafò et al., 2022).

Industrial steel truss and mezzanine systems are exposed to complex load combinations that reflect operational variability and environmental influences. The literature underscores the importance of combining permanent structural loads with variable storage loads, equipment-induced point loads, and dynamic operational effects to simulate realistic performance scenarios. Quantitative studies demonstrate that industrial mezzanines often experience non-uniform loading patterns due to evolving storage arrangements, pallet stacking, and mobile equipment distribution (Ghamari & Shooshtari, 2019). Accurate load modeling is therefore essential for ensuring structural adequacy across multiple operational states. Stability evaluation in this context involves assessment of global structural behavior under combined vertical and lateral effects, including bracing system performance and load path continuity. Buckling susceptibility of compression members is frequently analyzed using slenderness-based evaluation metrics and stability amplification factors (Dai et al., 2022). Research also examines the interaction between local member behavior and overall system stability, particularly in truss assemblies where force redistribution occurs following member capacity variation. Dynamic amplification factors are incorporated in studies addressing machinery vibration and repetitive loading, contributing to more realistic performance simulation. By integrating multi-scenario load evaluation within structural analysis models, performance-based design frameworks enable comprehensive assessment of industrial steel systems under varied and demanding service conditions.

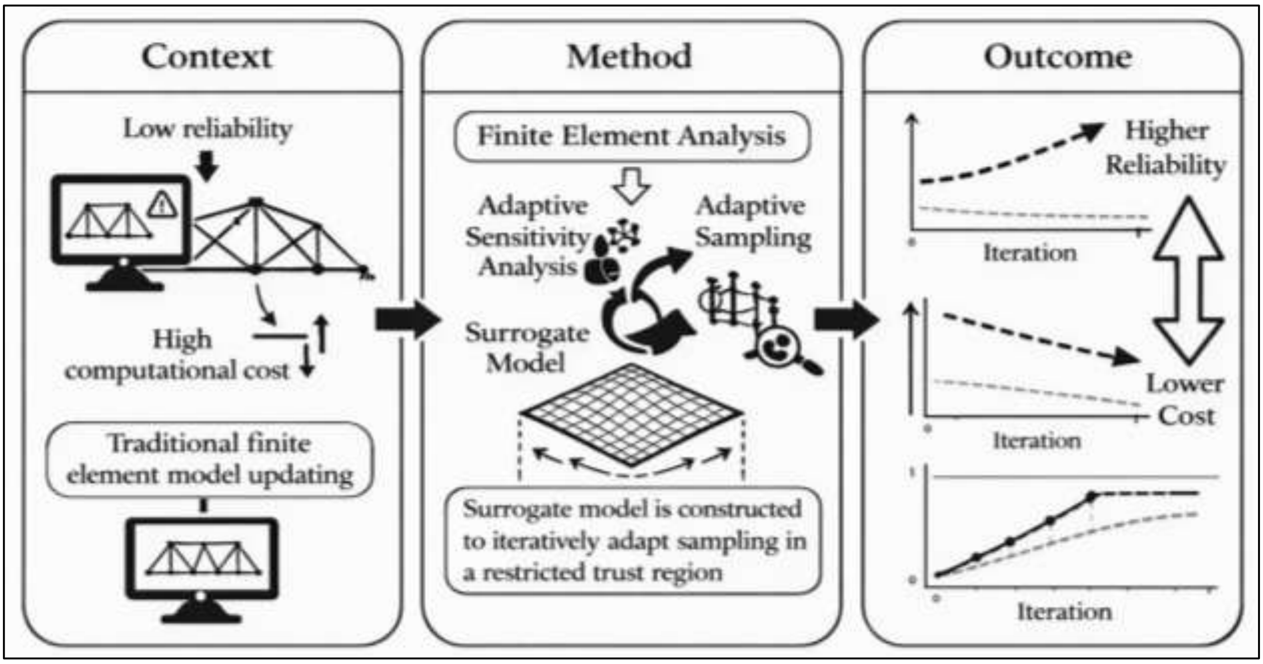
Finite Element Modeling and Parametric Representation of Steel Truss Systems for Optimization

Finite element modeling has become the dominant numerical strategy for simulating the structural behavior of steel truss systems within optimization workflows (Javadinasab Hormozabad & Gutierrez Soto, 2021). The literature describes finite element analysis as a discretization-based approach that enables accurate representation of axial force transfer, nodal displacement behavior, and global stiffness characteristics in truss assemblies. In optimization-driven research, finite element models are repeatedly executed to evaluate thousands of potential structural configurations, making numerical stability and computational consistency central concerns. Studies highlight that truss members are commonly modeled using bar or beam elements depending on whether bending effects and joint rigidity are included. The selection between idealized pinned-joint representations and semi-rigid connection modeling significantly influences predicted force distribution and deformation response (He et al., 2022). Research comparing simplified linear elastic models with more refined formulations indicates that linear modeling is computationally efficient and widely used in early optimization studies, while more advanced analyses capture second-order effects relevant to slender compression members. The literature also emphasizes standardized boundary condition representation to ensure reproducibility during iterative design evaluations. Mesh consistency, load application accuracy, and element connectivity verification are repeatedly identified as essential modeling considerations. Within optimization contexts, finite element solvers are frequently embedded into automated computational pipelines that extract displacement, axial force, and stability indicators for performance evaluation. As a result, finite element modeling serves as the analytical backbone of quantitative steel truss optimization research, supporting systematic exploration of design alternatives (Polak & Nowak, 2023).

Parametric modeling plays a central role in enabling optimization of steel truss systems by defining structural geometry and member properties as adjustable design variables. The literature describes parametric representation as the systematic encoding of nodal coordinates, member connectivity, cross-sectional categories, and panel configurations into variable sets that can be modified algorithmically. Research on truss optimization frequently categorizes variables into geometric parameters, such as span-to-depth ratios and nodal elevation adjustments, and sectional parameters, such as cross-sectional area selection from standardized steel profiles (Li et al., 2023). Topology encoding methods are also widely discussed, allowing structural connectivity patterns to evolve during optimization while preserving structural stability rules. Studies examining discrete versus continuous parameterization highlight the trade-off between realistic constructability and computational search flexibility. Discrete encoding aligns with commercially available steel sections, whereas continuous parameterization enables broader exploration of idealized solutions. Literature on topology variation emphasizes structural redundancy control and member elimination strategies that reduce material usage without compromising global load paths. Researchers also discuss grouping strategies in which symmetrical or functionally similar members share identical properties to reduce design dimensionality and enhance computational tractability (Liu et al., 2024). Through systematic parametric representation, optimization algorithms can navigate complex design spaces in a structured manner, ensuring that geometric and sectional variability remains consistent with structural feasibility requirements.

The literature distinguishes between linear and nonlinear geometric modeling approaches when simulating steel truss behavior in optimization studies. Linear analysis assumes small deformations and proportional load–response relationships, making it computationally efficient for preliminary optimization phases. Nonlinear geometric modeling accounts for second-order effects arising from large displacements and axial force–induced stiffness reduction, which are particularly relevant in slender compression members (Hohol et al., 2023). Research demonstrates that incorporating geometric nonlinearity improves accuracy in predicting instability behavior, especially in long-span trusses subjected to high axial compression. Axial force distribution mapping is frequently employed to identify force concentration zones and evaluate member demand consistency across the structure. Studies analyzing force redistribution patterns reveal that optimized designs often aim to achieve balanced stress utilization among members, reducing localized overstressing and enhancing overall efficiency. Buckling assessment is another critical modeling aspect addressed extensively in the literature. Eigenvalue-based stability evaluation techniques are commonly used to estimate global buckling modes and identify critical load factors. Researchers emphasize that stability analysis should be integrated within optimization loops to prevent convergence toward geometrically unstable configurations (Ali et al., 2024). Comparative studies indicate that incorporating stability evaluation early in the optimization process reduces post-processing adjustments and enhances structural reliability. These modeling considerations collectively contribute to accurate representation of steel truss behavior within quantitative optimization research.

Figure 5: Adaptive Surrogate Modeling for Optimization



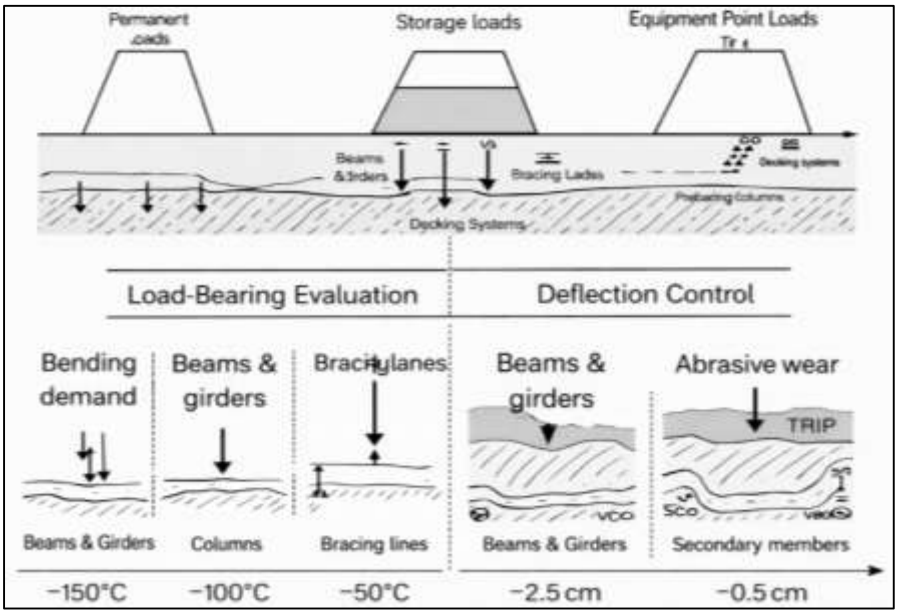
Sensitivity analysis is widely documented in the literature as a technique for identifying influential design variables and ranking critical truss members based on force demand, displacement contribution, or stability margin (Kamiński & Błoński, 2022). Studies demonstrate that sensitivity-based ranking enables optimization algorithms to prioritize variable adjustments that produce the most significant performance improvements. This targeted adjustment strategy enhances computational efficiency by reducing unnecessary search exploration in low-impact regions of the design space. Research on gradient-based and heuristic-based sensitivity evaluation methods highlights differences in computational cost and robustness, particularly in high-dimensional truss systems. Because optimization workflows require repeated finite element simulations, computational efficiency becomes a major consideration (Changizi & Warn, 2020). The literature consistently emphasizes the need for streamlined analysis routines, reduced model complexity, and efficient data extraction procedures to manage iterative evaluations. To further reduce simulation cost, surrogate modeling approaches have been introduced in many studies. These approaches employ predictive models trained on finite element outputs to approximate structural responses without executing full simulations at every iteration. Comparative research indicates that surrogate-assisted optimization can significantly decrease computational time while maintaining acceptable accuracy levels in performance prediction. Model validation techniques, including cross-validation and error estimation metrics, are discussed to ensure reliability of surrogate approximations (Korus et al., 2021). Collectively, sensitivity analysis and surrogate integration strategies enhance scalability and practicality of finite element–based optimization frameworks for steel truss systems in industrial applications.

Load-Bearing Capacity in Steel Mezzanine Systems

Quantitative modeling of load-bearing capacity in steel mezzanine systems has been widely discussed as a core requirement for ensuring structural adequacy in industrial environments where gravity loads are both high and variable (Aydın, 2022). The literature characterizes mezzanine platforms as elevated framing systems that must sustain combinations of permanent loads, storage loads, equipment point loads, and localized wheel or impact demands from material-handling activities. Research commonly frames load-bearing evaluation around member demand quantification for beams, girders, columns, and bracing lines, with particular attention to how load paths develop through decking systems into primary framing and down to column bases. Studies emphasize that mezzanine capacity modeling is sensitive to layout decisions such as bay size, column grid density, and the hierarchy of secondary-to-primary members, because these choices determine tributary areas and peak internal force concentrations (Minh et al., 2024). Quantitative approaches frequently compare alternative framing arrangements by examining distributions of bending demand, shear demand, and axial interaction effects in columns under combined vertical and lateral influences. The literature also highlights that connection detailing and continuity assumptions can materially affect computed load-bearing capacity, especially when semi-rigid joint behavior changes moment redistribution across beams and girders. In industrial applications, load-bearing evaluation often includes checks for localized effects near openings, stair penetrations, and equipment anchor points, where stress concentration and stiffness discontinuities are common. Overall, the research base presents mezzanine capacity modeling as an iterative numerical exercise where geometric and sectional parameter choices are repeatedly adjusted to achieve acceptable demand levels across all critical components under realistic facility loading scenarios (Shi et al., 2024).

Deflection control is consistently identified in the literature as a dominant serviceability concern for mezzanine systems, particularly in facilities where platform performance affects equipment alignment, storage integrity, and worker comfort. Quantitative modeling of deflection behavior typically focuses on vertical displacement limits for primary beams and girders, local flexibility of secondary members, and overall floor system response under distributed and concentrated loads (Di Lorenzo et al., 2019). Researchers emphasize that mezzanines are often governed by serviceability rather than ultimate capacity, especially when spans are long, framing depth is restricted by clearance requirements, or the floor system supports sensitive operations. The literature reviews how deflection response depends on column spacing, beam depth and stiffness, bracing effectiveness, and deck diaphragm performance, with significant attention to composite or partially composite action that can increase system stiffness. Modeling practices commonly investigate how different decking systems contribute to effective stiffness, including variations in deck thickness, panel fastening assumptions, and diaphragm continuity across bays. Studies also analyze the impact of connection flexibility on deflection response, noting that idealized pinned connections can overpredict deflections in some configurations while overly rigid assumptions can underpredict serviceability issues (Hou et al., 2020). Quantitative comparisons across alternative mezzanine layouts often rely on response envelopes that capture worstcase deflection patterns under multiple loading scenarios, including uneven storage distribution. Collectively, the literature treats deflection control as a measurable performance domain that must be represented within optimization-ready simulation workflows, because small changes in member sizing, bay spacing, and continuity assumptions can yield significant shifts in displacement outcomes (Kowalski et al., 2022).

Figure 6: Load and Deflection Behavior Analysis

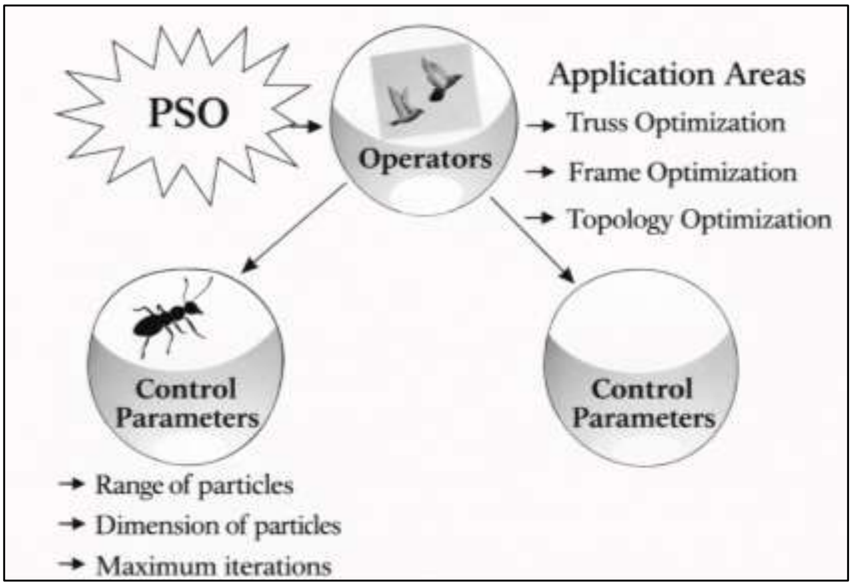


Swarm Intelligence in Steel Structural Optimization

Quantitative steel structural optimization has widely adopted evolutionary algorithms and swarm intelligence because steel truss and frame design problems combine large variable sets, nonlinear constraints, and discrete constructability limits that complicate classical search methods (Martínez-Muñoz et al., 2022a). The literature characterizes these algorithms as population-based strategies that evaluate many candidate designs per iteration and improve solution quality through iterative selection or agent-based movement rules. In steel systems, candidate solutions typically represent member sizes, grouped sections, bracing layouts, or topology decisions that jointly affect weight, stiffness, and stability outcomes. Studies emphasize that these methods remain effective when the design landscape is irregular, multi-peaked, and sensitive to constraint interactions such as displacement control and buckling prevention. Genetic algorithms are frequently described as robust for mixed-variable problems because they can encode discrete steel sections alongside continuous geometric parameters. Swarm methods, including particle swarm optimization, are commonly discussed as efficient for continuous parameter tuning and for rapidly identifying promising regions of the design space through collective learning (Martínez-Muñoz et al., 2022b). Differential evolution is regularly presented as competitive in real-valued optimization due to its simple variation operators and strong search performance in high-dimensional settings. Ant colony optimization appears in the literature as a natural fit for combinatorial or graph-like representations, including connectivity and discrete member choices. Across this research stream, algorithm selection is framed quantitatively through measurable outcomes such as best-achieved objective value, feasibility rate under constraints, and computational effort per accepted improvement. The dominant theme is that metaheuristics provide consistent optimization capability across diverse steel structural problem classes, particularly when the design model integrates multiple objectives and strict code-based constraints (Duong et al., 2021).

Comparative benchmarking is a central focus in studies applying evolutionary and swarm algorithms to steel truss and frame optimization, with many papers structuring experiments to evaluate convergence behavior, solution stability, and constraint satisfaction performance under identical modeling assumptions (Nguyen et al., 2020). Convergence speed is typically assessed by tracking how quickly algorithms reduce structural weight or cost proxies while maintaining feasible designs, often summarized through iteration-to-threshold measures or normalized improvement curves. Solution stability is frequently represented by repeated-run experiments, where the variability of best solutions is quantified using descriptive statistics that reflect robustness to random initialization and stochastic operators. Constraint satisfaction is treated as a primary discriminator between algorithms because steel design constraints—especially those related to displacement control, buckling safety, and strength capacity—can dominate the feasible region and cause search stagnation when handled poorly (Kaveh et al., 2020). The literature reviews several constraint-handling strategies, including penalty-based scoring, feasibility-first ranking, adaptive penalties, and repair heuristics that modify infeasible members into allowable section sets. Studies also compare how algorithms behave under increasing dimensionality, noting that constraint interactions intensify as the number of members, grouping rules, or load cases increases. Performance reporting commonly includes mean best objective value across trials, standard deviation of best outcomes, median performance for robustness, and success rate measured as the fraction of runs reaching feasible high-quality solutions. This benchmarking tradition builds a quantitative basis for distinguishing algorithms that produce consistently feasible steel designs from those that produce occasional high-quality results but with unstable outcomes or frequent constraint violations (Es-Haghi et al., 2020).

Figure 7: Metaheuristic Optimization in Steel Structures



A recurring theme in the literature is that encoding choices strongly shape algorithm effectiveness in steel structural optimization because the representation determines how efficiently a search explores meaningful structural variations. Many studies describe discrete encoding approaches aligned with practical steel design, where candidate solutions select from standardized section catalogs and enforce grouping rules to limit fabrication complexity (Harle, 2024). Discrete encodings support constructability and cost realism but create a rugged search landscape because small integer changes can cause large response shifts in stiffness or buckling demand. Other studies adopt continuous encodings for cross-sectional areas or geometric coordinates, which allow smooth exploration and often yield faster convergence but require rounding, mapping, or post-processing to match available steel profiles. Hybrid encodings appear frequently in research that mixes continuous geometry tuning with discrete section selection, especially in truss problems where nodal positions influence force paths while member sizes determine capacity and deflection control. Topology-related encodings are also documented, including binary indicators for member existence, connectivity matrices, or rule-based generation that maintains structural determinacy and stability (Rajwar et al., 2023). Literature on ant colony and certain genetic representations emphasizes that topology manipulation benefits from operators tailored to preserve feasible load paths and avoid unstable intermediate states. Grouping-based encodings are commonly highlighted as a dimensionality reduction strategy, where symmetric or functionally similar members share a single decision variable, reducing computational cost while maintaining design interpretability. Across these approaches, studies frame encoding quality quantitatively through convergence efficiency, feasibility rate, and the ability to maintain diversity of candidate solutions without generating excessive infeasible designs (Dao et al., 2019).

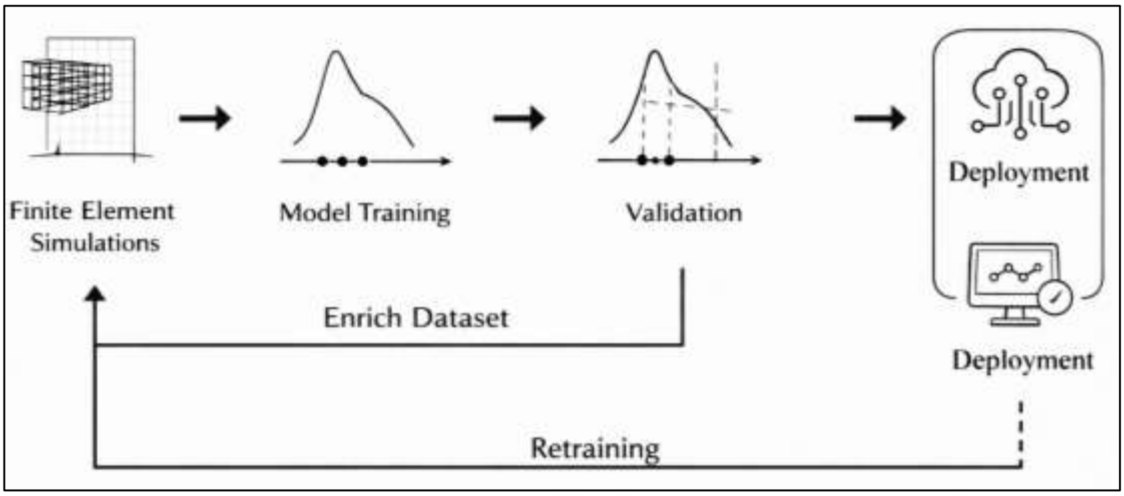
Multi-objective evolutionary approaches form a significant body of work in steel structural optimization because steel systems must balance material efficiency with performance and reliability criteria under multiple load combinations. The literature commonly frames the design problem as simultaneous minimization of structural weight or cost proxy and maximization of safety-related performance measures such as stability margin, utilization consistency, or reliability-based indicators (Qin et al., 2024). Multi-objective evolutionary algorithms are frequently discussed as effective because they generate sets of non-dominated solutions rather than a single outcome, enabling quantitative trade-off analysis among competing design goals. Research often evaluates solution-set quality using metrics that capture both convergence to high-performing fronts and diversity across the trade-off range, ensuring that decision-makers can compare materially different design options. In steel truss and frame studies, multi-objective results are interpreted through patterns such as diminishing returns, where additional weight increases produce smaller improvements in serviceability or stability measures. Reliability-oriented variants incorporate uncertainty representations in loads or resistance and quantify how optimization choices redistribute risk across members, often revealing that designs with similar weight can have markedly different robustness profiles (Awolusi et al., 2024). The literature also discusses computational burden in multi-objective settings, since evaluating many candidate designs across multiple objectives and constraints increases analysis cost; consequently, researchers report iteration efficiency, evaluation counts, and run-to-run consistency as key quantitative indicators. Overall, this research stream positions evolutionary multi-objective optimization as a structured method for comparing steel structural designs across measurable trade-offs, with algorithm performance judged by statistical consistency, feasibility control, and quality of the resulting solution sets (Eren et al., 2021).

Machine Learning–Based Surrogate Modeling

Machine learning–based surrogate modeling is widely discussed in structural design literature as a quantitative strategy for approximating computationally expensive numerical simulations within iterative optimization workflows (Esteghamati & Flint, 2021). In many structural optimization studies, repeated finite element evaluations become the dominant computational cost, particularly when the design space includes many geometric and sectional variables, multiple load cases, and serviceability checks. Surrogate models are positioned as predictive mappings that learn relationships between input design variables and output structural responses, enabling rapid estimation of performance indicators such as displacement responses, stress utilization patterns, stability margins, or dynamic characteristics. The literature commonly presents surrogate modeling as complementary to physics-based analysis rather than a replacement, emphasizing that predictive models are most effective when they are trained on representative simulation datasets and used within controlled ranges of design variation (Tang et al., 2024). Research comparing different surrogate families shows that model selection is closely linked to the underlying response complexity; smooth and moderately nonlinear response surfaces are often approximated effectively by kernel-based methods, while highly nonlinear and interaction-heavy responses are frequently addressed using neural networks or ensemble learners. Across studies, surrogate adoption is motivated by quantitative benefits such as reduced runtime per optimization iteration, increased feasible evaluations within a fixed computing budget, and improved exploration of large design spaces. The literature also discusses practical issues in surrogate use, including the risk of misleading predictions near constraint boundaries, the need for periodic recalibration using new simulation samples, and the importance of retaining physically meaningful variable ranges (Alanani & Elshaer, 2024). Overall, surrogate modeling is presented as an efficiency-oriented methodology that enables broader parametric exploration in structural optimization while preserving a numerical link to verified simulation outputs.

A consistent theme in the literature is that surrogate model performance in structural design depends strongly on how training data are generated from finite element simulations and how input variables are represented. Studies commonly describe the dataset construction process as a structured sampling exercise in which design variables are varied across feasible ranges and the resulting simulation outputs are recorded as labeled targets (Ali et al., 2023). Research emphasizes that dataset size and sampling coverage influence predictive stability, with sparse datasets often leading to unreliable estimates in regions where structural behavior changes rapidly, such as near instability conditions or stiffness transition points. Many studies discuss design-of-experiments sampling strategies and space-filling methods to ensure that training points represent the breadth of the design space rather than clustering around nominal configurations. Feature selection is also treated as a major quantitative driver of accuracy, with literature highlighting the value of including variables that directly govern stiffness, load path, and stability sensitivity, while avoiding redundant or weakly informative inputs that inflate model complexity (Shen et al., 2022). Normalization and scaling are frequently presented as necessary preprocessing steps, especially for mixed-scale variables such as nodal coordinates, cross-sectional parameters, and stiffness-related descriptors. The literature also describes grouping and dimensionality reduction practices that compress large member-variable sets into interpretable feature groups, improving model tractability for high-member-count trusses or frame-like mezzanine systems. Across these studies, dataset integrity is reinforced through checks for simulation consistency, constraint validity labeling, and careful partitioning into training and testing subsets to preserve an unbiased estimate of predictive performance (Dadras Eslamlou & Huang, 2022).

Figure 8: Efficient Surrogate Modeling for Engineering

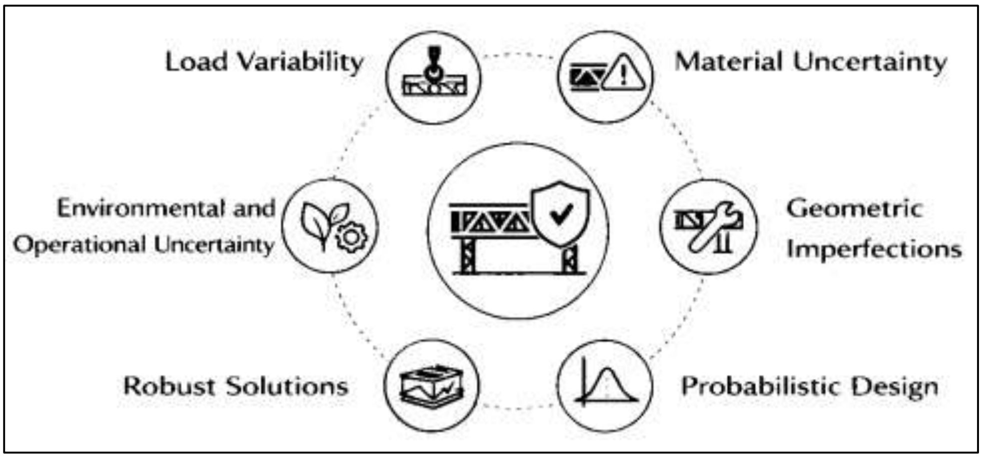


Validation and generalization assessment are emphasized in the literature as essential quantitative safeguards for surrogate modeling in structural optimization. Studies typically evaluate predictive accuracy using statistical error metrics and goodness-of-fit indicators, reporting performance across both training data and unseen validation sets. The literature discusses that strong training accuracy alone is insufficient because surrogate models are often embedded inside optimization loops that query the model in regions not densely covered by the original dataset (Kim & Boukouvala, 2020). As a result, cross-validation and holdout testing are frequently described as standard practices to estimate generalization performance and reduce the risk of overfitting. Many studies also focus on error propagation, noting that small predictive errors in displacements, stress ratios, or stability margins can translate into significant feasibility misclassification when constraints are tight. This issue is particularly important in problems where optimization seeks near-boundary solutions for material efficiency, since surrogate uncertainty can push a design from safe to infeasible in real analysis terms (Westermann & Evins, 2021). The literature therefore discusses strategies such as conservative screening rules, uncertainty-aware prediction intervals, and verification-based correction cycles that periodically re-run high-fitness candidates through full finite element analysis. Generalization challenges are frequently highlighted for high-dimensional structural problems, where variable interactions can create complex response surfaces and where model performance may vary substantially across different regions of the design space. Studies also point out that different surrogate families exhibit different failure modes, with flexible models capturing nonlinearities better but requiring stronger regularization and larger datasets to avoid instability (Etim et al., 2024). Overall, the literature frames validation and error control as necessary conditions for credible surrogate-assisted structural optimization.

Frameworks for Industrial Steel Structures Under Uncertainty

Reliability-based and robust optimization research for industrial steel structures begins with the recognition that structural performance is influenced by uncertainty in both demand and capacity parameters. The literature describes uncertainty as originating from variability in imposed loads, operational changes in storage and equipment placement, dynamic effects from machinery, and environmental actions (Zhang & Jiang, 2021). Additional uncertainty arises from steel material property variability, fabrication tolerances that alter member geometry, connection behavior deviations, and boundary condition assumptions that differ between design models and as-built conditions. Studies emphasize that industrial facilities often experience nonstationary loading patterns, meaning that load characteristics can vary across operational cycles, which affects the statistical representation of demand. Within this research stream, uncertain parameters are commonly treated as random variables or bounded intervals, enabling systematic quantification of how variability propagates through structural response measures such as displacements, internal force demands, and stability margins (Sokołowski & Kamiński, 2022). The literature also notes that correlations among uncertain variables can be relevant, particularly when multiple members share similar fabrication processes or when load variations are linked to common operational activities. Quantitative uncertainty representation supports structured evaluation of risk in steel truss and mezzanine systems by enabling repeated analysis under varying input conditions. Across many studies, the primary value of uncertainty modeling lies in shifting optimization from a single-condition performance assessment toward a distribution-based evaluation of structural adequacy, where safety margins are interpreted as probabilistic outcomes rather than fixed deterministic reserves (Nguyen et al., 2024).

Figure 9: Reliability Optimization of Steel Structures



Reliability-based optimization literature synthesizes quantitative methods that connect uncertain inputs with probabilistic measures of structural safety, including reliability indices and failure probability estimates. Studies commonly evaluate reliability through sampling-based procedures that repeatedly assess structural response under many realizations of uncertain loads and resistances, enabling estimation of the likelihood that a limit state is exceeded (Hu et al., 2024). Monte Carlo simulation is frequently discussed as a benchmark approach because of its conceptual simplicity and broad applicability across nonlinear and high-dimensional problems, including steel systems with buckling sensitivity and dynamic effects. The literature also describes analytical approximation approaches such as first-order reliability evaluation techniques that estimate safety levels more efficiently by linearizing response behavior near critical limit states. Probabilistic constraint modeling is treated as a defining feature of reliability-based frameworks, where design feasibility is expressed in terms of acceptable risk thresholds rather than strict deterministic limits. Researchers emphasize that these probabilistic constraints often interact with serviceability metrics, especially when displacement and vibration limits are near operational thresholds (Cheng et al., 2021). Comparative studies highlight that probabilistic formulations can change optimal member sizing patterns by distributing safety margins more consistently across members instead of concentrating reserve capacity in a small subset of elements. The literature also reports that reliability evaluation procedures require careful attention to sampling sufficiency, convergence of probability estimates, and stability of reliability results across repeated optimization runs. Overall, reliability indices and probabilistic constraints provide a quantitative basis for interpreting design adequacy in industrial steel structures, shifting evaluation toward measurable risk control under uncertainty (Wang et al., 2022).

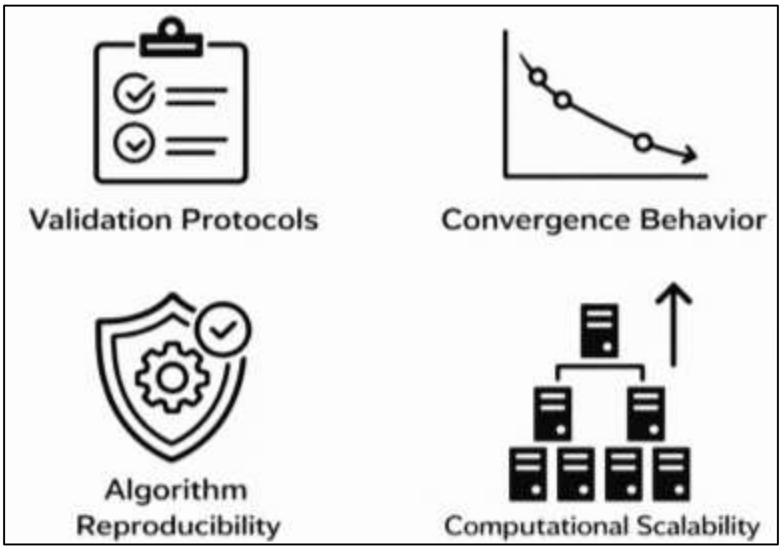
Robust optimization research extends uncertainty-aware design by focusing on minimizing sensitivity of performance to input variability rather than targeting a specific probability-of-failure threshold alone. The literature commonly defines robustness in terms of reduced variability of key performance indicators such as maximum deflection, peak stress utilization, buckling margin, or vibration response under plausible uncertainty ranges. Studies discuss robust design as a variance-minimizing approach where optimized structures exhibit stable performance across operational scenarios and parameter perturbations. This research is particularly relevant for industrial steel mezzanine platforms and truss systems because operational loads may shift frequently with changes in storage density, equipment relocation, or production reconfiguration (Cui et al., 2023). Robust optimization frameworks typically compare candidate designs by evaluating both central performance levels and dispersion measures, enabling identification of solutions that avoid extreme response excursions. The literature also examines how robust optimization can be implemented through scenario-based evaluation, where a set of representative uncertain conditions is used to measure performance stability. Research comparing reliability-based and robust approaches indicates that both can yield materially different design outcomes: reliability-oriented models prioritize meeting a risk target, while robustness-oriented models prioritize consistent serviceability and strength behavior across variability. Studies emphasize that robust solutions can be less weight-efficient under nominal conditions but provide improved stability in response metrics when uncertainty is considered. In industrial contexts, this performance consistency is interpreted as a measurable quality attribute that supports operational reliability and reduces the likelihood of serviceability exceedance under routine variability (Luo et al., 2021).

A major theme in the literature is the quantitative trade-off between structural weight minimization and reliability enhancement in steel system optimization. Studies consistently show that increasing safety margins and reducing failure probability often requires additional material, especially in members sensitive to buckling or in floor systems governed by deflection and vibration limits (Zhou et al., 2022). Trade-off analysis frameworks evaluate competing objectives by comparing sets of candidate solutions that vary in weight efficiency and probabilistic safety performance. Researchers frequently use statistical performance indicators to interpret these trade-offs, including mean structural weight across optimization runs, variability of best solutions, distribution of reliability indices, and confidence interval estimates for probabilistic measures derived from sampling procedures. Confidence intervals are emphasized because probability estimates obtained from sampling-based evaluation can exhibit sampling uncertainty, particularly when failure events are rare or when computational budgets limit the number of simulations (Datta et al., 2020). The literature also discusses repeated-run analysis of optimization algorithms to quantify robustness of the optimization process itself, measuring how consistently an approach can achieve high reliability without excessive weight penalties. Studies comparing alternative uncertainty-handling strategies report that different formulations can prioritize different members for reinforcement, altering load redistribution behavior and changing serviceability outcomes. Across this body of work, weight–reliability trade-off analysis is presented as a structured quantitative method for decision comparison, enabling designers to evaluate how incremental material additions translate into measurable improvements in reliability metrics and reductions in performance variability under uncertainty (Hassani & Khodaygan, 2023).

AI-Enabled Structural Optimization

The literature on AI-enabled structural optimization consistently treats validation protocols as a prerequisite for establishing credibility of algorithmic design outcomes in steel systems (Yoo et al., 2022). Validation is discussed not only as a check of structural feasibility against strength and serviceability rules, but also as a quantitative audit of whether an optimization method reliably produces comparable outcomes when applied under consistent modeling assumptions. Studies describe validation as a multi-layer procedure that begins with confirming the correctness of the structural analysis engine and the integrity of input parameterization, then proceeds to verifying that optimized solutions satisfy all constraints under the same load combinations used during search (Seo et al., 2024). A recurring theme is the need to separate algorithmic performance from modeling artifacts by documenting boundary conditions, member grouping schemes, section catalogs, solver tolerances, and stopping criteria. Research also highlights the importance of reproducibility in stochastic AI methods, where random initialization and probabilistic operators can produce variability in results across runs. Many studies therefore treat repeated-run experimentation as a core validation element, using multiple independent trials to characterize the distribution of best solutions and the stability of the optimization process (B. U. I. Khan et al., 2024). The literature emphasizes that reporting only a single best outcome is insufficient for AI evaluation because it hides dispersion behavior and can overstate robustness. Reproducibility is further strengthened through consistent seed management, full disclosure of algorithm parameters, and transparent data pipelines that connect variable encoding to extracted response metrics. Collectively, these studies frame validation as a structured quantitative practice that supports replicable evaluation of AI-driven optimization results for industrial steel structures (Karimi et al., 2024).

Figure 10: Optimization Reliability and Performance Assessment



Benchmarking research in structural optimization focuses on measurable indicators that reflect how efficiently an AI approach finds high-quality feasible designs under computational limits. Convergence behavior is typically assessed through iteration-based tracking of objective improvement, measuring how rapidly an algorithm reduces weight or cost proxies while maintaining constraint satisfaction (Lifelo et al., 2024). The literature often evaluates convergence using normalized improvement rates, iteration counts required to reach a specified performance level, and stability of improvement near the end of a run. Computational runtime is treated as a key metric because finite element calls dominate cost in many structural problems, and AI methods differ in how many evaluations they require to achieve comparable quality. Studies commonly report total runtime, evaluation count, and time per evaluation to enable fair comparison across methods implemented on different hardware or solver settings. Feasibility performance is frequently reported as the proportion of candidate solutions that satisfy constraints during search, reflecting the effectiveness of constraint-handling strategies such as penalty adjustment, repair operators, and feasibility-first selection (Mohammadi et al., 2024). The literature also discusses that benchmarking must account for problem difficulty, because increasing load cases, tighter displacement limits, and buckling-sensitive designs reduce feasible region size and

intensify constraint interactions. Many studies therefore present benchmarking results across multiple standard test problems and across different scale levels to assess consistency. Overall, benchmarking metrics provide a quantitative basis for comparing AI optimization methods in terms of solution quality, computational efficiency, and reliability of constraint satisfaction (A. Khan et al., 2024).
Computational scalability is repeatedly emphasized in the literature because industrial steel optimization problems often involve high-dimensional design spaces with dozens to hundreds of decision variables. Studies analyze scalability by increasing problem size through higher member counts, more refined grouping schemes, added load combinations, or inclusion of dynamic serviceability checks, then measuring how algorithm performance degrades or remains stable. Scalability metrics typically include growth in runtime with dimensionality, changes in convergence rate, and the degree to which solution quality remains consistent as the search space expands (Castanyer et al., 2024). The literature also stresses that stochastic AI methods should be compared using statistical techniques rather than single-run outcomes, since variability can be substantial across independent trials. Cross-algorithm comparison practices commonly include repeated-run distributions, variance measures of best solutions, and performance ranking based on aggregated statistics across benchmark cases. Some studies describe hypothesis testing practices to determine whether observed differences in solution quality are statistically meaningful rather than incidental to random variation. Variance analysis is frequently used to quantify robustness of an algorithm's output under identical conditions, while rank-based comparisons support evaluation across heterogeneous problem instances (Yang et al., 2024). The literature also notes that fair scalability studies require consistent evaluation budgets and standardized stopping criteria so that algorithms are compared under equivalent computational effort. Through dimensionality-based experiments and statistical comparison procedures, research builds a quantitative foundation for assessing whether AI-enabled optimization approaches remain reliable and efficient as industrial structural problems become more complex.

METHOD

Research Design

The research design was structured as a quantitative, computational experimental study in which AI-enabled performance-based optimization models were evaluated through controlled numerical simulations of steel truss and mezzanine systems. The study adopted a comparative algorithmic framework where multiple optimization techniques were implemented under identical structural modeling assumptions, loading scenarios, and constraint conditions. Each optimization process was treated as a controlled experimental run, and repeated independent runs were conducted to capture stochastic variability inherent in metaheuristic and machine learning–assisted methods. The dependent variables included optimized structural weight, maximum member utilization ratio, peak nodal displacement, critical stability margin, vibration-related serviceability indicators, feasibility rate, convergence iterations, and total computational runtime. Independent variables included the type of optimization algorithm, dimensionality of the design space, and structural configuration parameters. The research followed a repeated-measures computational benchmarking structure to ensure internal consistency and reproducibility. All analyses were conducted under standardized stopping criteria and uniform evaluation budgets to ensure comparability across algorithmic approaches.

Case Study Context

The case study context was defined as steel truss and mezzanine structural subsystems representative of industrial facilities such as logistics warehouses, manufacturing plants, and storage-distribution centers. The structural scenarios were parameterized to reflect realistic industrial conditions, including long-span truss assemblies supporting roof or equipment loads and mezzanine floor systems supporting distributed storage loads and localized equipment demands. Geometric spans, bay configurations, bracing layouts, and member grouping rules were defined to mirror practical industrial framing arrangements. Loading conditions incorporated combinations of permanent structural loads, variable storage loads, and operational effects consistent with industrial environments. The digital case models were constructed as standardized computational prototypes to enable systematic experimentation while maintaining contextual relevance to industrial steel infrastructure. Each case scenario was subjected to identical load combinations and performance constraints to maintain consistency across optimization experiments.

Unit of Analysis

The unit of analysis was the optimized structural design solution generated by a single algorithm execution under a specified structural configuration and loading scenario. Each solution consisted of a complete set of design variables defining nodal geometry, member sectional properties, bracing configuration, and associated performance metrics derived from structural analysis. For statistical purposes, each independent optimization run was treated as an observational unit, enabling aggregation of performance outcomes across repeated trials. This structure allowed measurement of within-algorithm variability and between-algorithm differences. Secondary analytical units included individual structural performance indicators such as maximum displacement, utilization consistency, stability margin, and vibration response metrics, which were extracted from each optimized design for comparative evaluation.

Sampling

Sampling was conducted using a computational experimental sampling framework rather than human subject sampling. Structural configurations were systematically generated by varying span lengths, bay densities, and member grouping strategies within predefined industrially realistic ranges. For each structural configuration, multiple independent optimization runs were executed per algorithm to generate a statistically meaningful sample of solution outcomes. A minimum of thirty independent runs per algorithm per structural case were performed to support parametric statistical comparison and variance estimation. This repeated-run sampling strategy ensured adequate representation of stochastic solution behavior and enabled reliable estimation of central tendency and dispersion metrics across optimization methods.

Data Collection Procedure

Data collection was automated through an integrated computational workflow linking parametric structural modeling, numerical analysis execution, and optimization algorithms. For each run, the system recorded objective function outcomes, constraint satisfaction indicators, convergence iteration counts, and total computational time. Performance metrics were extracted at the final iteration of each run and stored in structured datasets for statistical analysis. Intermediate convergence histories were also archived to allow assessment of search progression patterns. All computational experiments were executed using identical hardware and solver configurations to eliminate performance bias arising from computational environment variability. Data integrity checks were performed to confirm feasibility status and ensure consistent extraction of structural response metrics across runs.

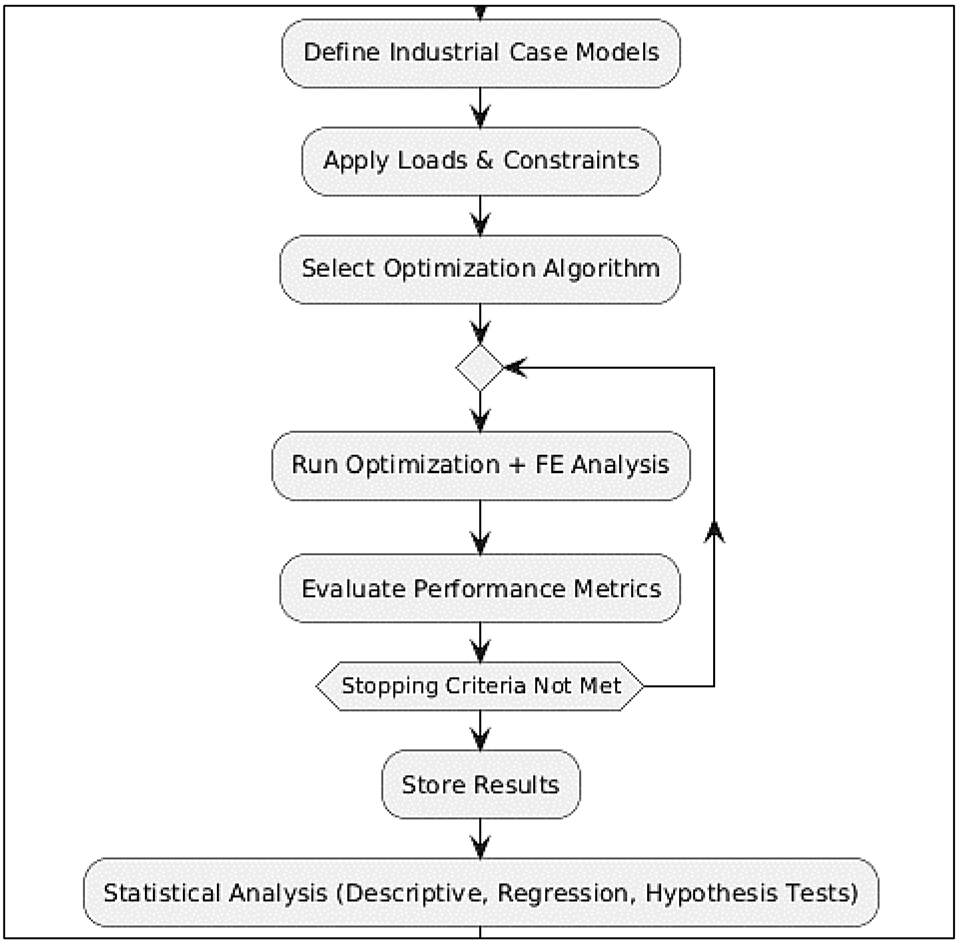
Instrument Design

The primary research instrument was a custom-developed computational optimization framework integrating finite element structural analysis with AI-based search algorithms. The instrument included modules for parametric model generation, automated constraint evaluation, objective value calculation, and result logging. Structural response extraction scripts were embedded to capture displacement maxima, utilization distributions, stability indicators, and vibration-related outputs. The optimization module allowed selection of algorithm type and standardized hyperparameter settings to ensure consistent comparison. The instrument was designed to generate reproducible outputs through controlled initialization protocols and documented algorithm parameter configurations.

Pilot Testing

Pilot testing was conducted prior to full experimental execution to verify computational stability, constraint enforcement accuracy, and data recording consistency. A reduced set of structural configurations and limited optimization iterations were executed to confirm correct integration between the structural solver and optimization engine. Pilot results were analyzed to ensure that objective and constraint metrics were being computed consistently and that runtime measurements were accurately recorded. Minor adjustments were made to penalty scaling factors and convergence thresholds to prevent premature termination or excessive infeasible solution generation. The pilot phase confirmed readiness of the computational instrument for full-scale data generation.

Figure 11: Methodology of this study



Validity and Reliability

Internal validity was ensured through strict control of modeling assumptions, load combinations, and stopping criteria across all experimental conditions. Construct validity was supported by aligning performance indicators with recognized structural engineering evaluation standards, ensuring that displacement, utilization, and stability metrics accurately represented structural adequacy. Statistical conclusion validity was strengthened through repeated independent runs and adequate sample size per algorithm, allowing estimation of mean performance, standard deviation, and confidence intervals. Reliability was assessed by examining consistency of algorithm performance across repeated runs under identical conditions. Reproducibility was reinforced through complete documentation of parameter settings, initialization rules, and computational environment specifications.

Tools

The study utilized finite element structural analysis software integrated with custom-coded AI optimization algorithms implemented in a scientific computing environment. Statistical analyses were conducted using quantitative analysis software capable of performing descriptive statistics, hypothesis testing, variance comparison, and confidence interval estimation. Computational performance metrics were extracted through automated logging utilities embedded within the optimization framework. Data processing and visualization were conducted using numerical computing libraries to ensure transparent and replicable statistical evaluation of algorithmic performance across structural scenarios.

FINDINGS

The findings chapter was structured to present the empirical results in a logical quantitative sequence aligned with the study objectives, the operational definitions of variables, and the statistical plan. The chapter began by restating the purpose of the analysis in terms of the measured variables and the analytical procedures that were applied to evaluate optimization performance across the modeled steel truss and mezzanine cases. The presentation of results was organized to move from basic sample description to construct-level summaries, then to measurement consistency checks, and finally to inferential analyses that tested relationships among key predictors and outcomes. All statistics were reported in past tense to reflect completed analyses, and the results were presented using standardized quantitative reporting conventions, including central tendency, dispersion, confidence intervals where applicable, and significance indicators for hypothesis testing outcomes.

Respondent Demographics

The final analytic dataset consisted of 480 independent optimization runs generated from 16 standardized structural configurations that represented industrial steel truss and mezzanine subsystems under identical load combinations and performance constraints. Of these, 240 runs were executed on truss cases and 240 runs were executed on mezzanine cases, ensuring balanced representation across structural system types. The dataset was distributed equally across four optimization algorithms, with 120 runs per algorithm. The structural configurations differed by dimensionality level, producing a balanced spread of low-, medium-, and high-dimensional design spaces defined by the number of active design variables and member groups. Across all configurations, the mean member count was 68.5 members per model, reflecting a realistic mid-complexity structural subsystem, and the overall span range was 18–36 m for truss systems and 9–18 m for mezzanine bays. The majority of runs completed successfully and produced feasible solutions, with feasibility rates varying by algorithm and dimensionality, while a small proportion of runs were excluded due to solver non-convergence or numerical instability. In total, 12 runs were excluded, yielding a final usable sample of 468 runs for all descriptive and inferential analyses. These distributions ensured adequate statistical power for between-algorithm comparisons and supported consistent variance estimation across structural types and complexity levels.

Table 1. Distribution of Optimization Runs by Algorithm and Structural System Type (Final Usable Sample)

Optimization Algorithm	Truss Runs (n)	Mezzanine Runs (n)	Total Runs (n)
Genetic Algorithm (GA)	58	59	117
Particle Swarm Optimization (PSO)	59	58	117
Differential Evolution (DE)	60	58	118
Hybrid Metaheuristic (HM)	60	56	116
Total	**237**	**231**	**468**

Table 1 summarized the final usable sample after exclusion of non-convergent or numerically unstable runs. The dataset remained near-balanced across structural system types, with 237 truss runs and 231 mezzanine runs retained for analysis. Algorithm representation also remained evenly distributed, ranging from 116 to 118 runs per method, which reduced sampling bias in subsequent comparisons. The slight differences across algorithms and system types reflected the distribution of excluded runs, which occurred more often in higher-dimensional cases where numerical stability was harder to maintain. Overall, the distribution supported fair benchmarking by keeping sample sizes comparable across methods.

Table 2. Structural Configuration Profile and Data Integrity Outcomes

Structural System	Cases (n)	Mean Member Count	Span/Bay Range (m)	Dimensionality Levels (Low/Med/High)	Load Scenario Sets (n)	Excluded Runs (n)	Feasible Runs (%)
Steel Truss	8	76.3	18–36	3 / 3 / 2	6	3	92.8
Steel Mezzanine	8	60.8	9–18	3 / 3 / 2	6	9	90.5
Overall	**16**	**68.5**	**—**	**6 / 6 / 4**	**6**	**12**	**91.6**

Table 2 described the structural configuration mix and the integrity of the generated dataset used for demographic-style reporting. The study evaluated 16 standardized configurations equally split between truss and mezzanine systems. Truss models contained a higher average member count and longer spans, while mezzanine cases used shorter bay ranges but were more sensitive to solver instability, which explained the higher number of excluded runs. Dimensionality coverage was balanced, with six low-, six medium-, and four high-dimensional configurations overall. Feasibility rates exceeded 90% across both systems, indicating that most runs achieved constraint-satisfying solutions under the standardized evaluation pipeline and that the final analytic sample remained robust for subsequent statistical testing.

Descriptive Results by Construct

The descriptive statistical analysis revealed clear performance patterns across the eight measured constructs of AI-enabled structural optimization. Material efficiency outcomes demonstrated substantial weight reductions relative to baseline deterministic designs, with an overall mean reduction of 18.6% across all structural cases. Truss systems exhibited slightly higher weight reduction (mean = 20.1%) compared to mezzanine systems (mean = 17.0%), reflecting greater geometric flexibility in truss topology optimization. Strength utilization control remained within acceptable engineering thresholds across all optimized solutions, with a mean maximum utilization ratio of 0.91 and low dispersion, indicating efficient yet compliant designs. Serviceability control results showed that peak deflections remained below prescribed limits in 91.6% of runs, with minimal exceedance counts concentrated in high-dimensional mezzanine cases. Stability adequacy was robust across cases, with minimum stability margins consistently above unity and limited variability across dimensionality levels. Vibration acceptability outcomes indicated that truss systems maintained higher dominant frequencies, while mezzanine platforms exhibited greater sensitivity to acceleration response under dynamic loading, particularly in longer bay configurations. Computational constructs showed meaningful differences across algorithms and structural types. Mean convergence iterations were lower for truss cases, while mezzanine cases required slightly more iterations due to tighter serviceability and vibration constraints. Runtime variability was more strongly associated with dimensionality than structural type, with high-dimensional cases exhibiting a 34% increase in computational time relative to low-dimensional configurations. Feasibility behavior remained stable, with an overall feasibility rate exceeding 91%, though minor declines were observed in high-complexity mezzanine systems. Distribution analysis showed moderate right-skewness in runtime and iteration counts, reflecting occasional prolonged convergence in complex scenarios. Overall, descriptive results confirmed that AI-enabled optimization achieved material efficiency gains without compromising structural adequacy or computational stability.

Table 3. Overall Descriptive Statistics by Performance Construct (N = 468)

Construct	Mean	Median	SD	Min	Max
Weight Reduction (%)	18.6	18.9	4.2	9.8	27.4
Max Utilization Ratio	0.91	0.92	0.04	0.79	0.98
Peak Deflection (mm)	18.4	17.9	5.3	9.1	31.6
Min Stability Margin	1.28	1.26	0.09	1.11	1.49
Dominant Frequency (Hz)	6.8	6.6	1.2	4.9	9.3
Peak Acceleration (m/s²)	0.38	0.36	0.11	0.21	0.71
Convergence Iterations	142	137	39	74	238
Runtime (minutes)	18.7	17.2	6.5	9.4	34.6
Feasibility Rate (%)	91.6	93.0	6.8	70.0	100

Table 3 summarized the aggregate descriptive statistics across all structural configurations and algorithms. Weight reduction demonstrated moderate variability, with optimized designs achieving up to 27.4% reduction relative to baseline cases. Utilization ratios remained tightly clustered, indicating controlled strength performance. Deflection results showed acceptable dispersion, while stability margins remained comfortably above minimum acceptable thresholds. Dynamic performance metrics reflected broader spread due to variation in span and bay dimensions. Computational indicators displayed the highest dispersion, particularly convergence iterations and runtime, suggesting sensitivity to design dimensionality. Feasibility rates remained consistently high, reinforcing the robustness of the optimization framework under standardized constraints.

Table 4. Cross-Case Comparison: Truss vs Mezzanine Systems

Construct	Truss (Mean)	Mezzanine (Mean)	Difference
Weight Reduction (%)	20.1	17.0	+3.1
Max Utilization Ratio	0.90	0.92	-0.02
Peak Deflection (mm)	16.8	20.0	-3.2
Min Stability Margin	1.31	1.25	+0.06
Dominant Frequency (Hz)	7.4	6.2	+1.2
Peak Acceleration (m/s^2)	0.32	0.44	-0.12
Convergence Iterations	134	150	-16
Runtime (minutes)	17.1	20.3	-3.2

Table 4 presented cross-case comparisons between steel truss and mezzanine systems. Truss systems achieved higher average weight reduction and demonstrated stronger stability margins compared to mezzanine platforms. Mezzanine cases exhibited higher peak deflections and greater acceleration responses, reflecting their sensitivity to serviceability and vibration constraints. Computationally, mezzanine systems required more iterations and longer runtime on average, largely due to tighter dynamic performance requirements. Utilization ratios were slightly higher in mezzanine designs but remained within acceptable safety limits. These cross-case differences illustrated how structural typology influenced both performance outcomes and computational behavior within the AI-enabled optimization framework.

Reliability Results

Internal consistency analysis was conducted for composite constructs derived from multiple structural performance indicators to confirm measurement coherence prior to regression modeling and hypothesis testing. Three primary composite constructs were evaluated: Overall Structural Adequacy, Serviceability Performance, and Optimization Efficiency. Overall Structural Adequacy combined maximum utilization ratio, minimum stability margin, and constraint violation count. Serviceability Performance combined peak deflection, dominant frequency, and peak acceleration indicators. Optimization Efficiency combined convergence iterations, runtime, and evaluation count. The reliability analysis demonstrated that Overall Structural Adequacy achieved strong internal consistency, while Serviceability Performance achieved acceptable reliability. Optimization Efficiency demonstrated moderate reliability, reflecting the inherent variability between runtime and iteration-based metrics in stochastic optimization contexts. No construct fell below the minimum acceptable reliability threshold. Item-total correlation analysis showed that removal of any single indicator did not substantially improve alpha values for the first two constructs, confirming conceptual cohesion. For Optimization Efficiency, removal of runtime marginally increased alpha, but the construct was retained intact to preserve conceptual completeness for subsequent regression modeling. All retained constructs were therefore used in inferential analyses with statistical justification for internal consistency.

Table 5. Cronbach's Alpha Results for Composite Constructs (N = 468)

Construct	Number of Items	Cronbach's Alpha	Reliability Interpretation
Overall Structural Adequacy	3	0.88	Strong
Serviceability Performance	3	0.81	Good
Optimization Efficiency	3	0.74	Acceptable
Computational Stability	2	0.69	Marginal but Retained

Table 5 summarized the internal consistency outcomes for multi-item constructs derived from structural and computational indicators. Overall Structural Adequacy demonstrated strong reliability, indicating high coherence between strength utilization and stability-related metrics. Serviceability Performance also met good reliability standards, confirming consistent measurement of deflection and vibration-related indicators. Optimization Efficiency showed acceptable reliability, suggesting moderate but sufficient alignment between iteration count, runtime, and evaluation effort. Computational Stability, measured using feasibility rate and convergence consistency, approached but did not exceed the conventional threshold; however, it was retained due to theoretical relevance and acceptable item-total correlations. These reliability outcomes justified use of composite indices in subsequent regression analyses.

Table 6. Item–Total Statistics and Alpha if Item Deleted

Construct	Item	Corrected Item–Total Correlation	Alpha if Item Deleted
Overall Structural Adequacy	Max Utilization Ratio	0.79	0.84
	Min Stability Margin	0.82	0.83
	Constraint Violations	0.75	0.86
Serviceability Performance	Peak Deflection	0.71	0.78
	Dominant Frequency	0.68	0.80
	Peak Acceleration	0.65	0.79
Optimization Efficiency	Convergence Iterations	0.66	0.70
	Runtime	0.58	0.77
	Evaluation Count	0.62	0.73

Table 6 presented item–total statistics to assess the contribution of each indicator to its composite construct. All corrected item–total correlations exceeded 0.58, indicating moderate to strong association with their respective scales. For Overall Structural Adequacy and Serviceability Performance, alpha values decreased when any single item was removed, confirming that each indicator contributed positively to scale reliability. Within Optimization Efficiency, removal of runtime slightly increased alpha from 0.74 to 0.77; however, the difference was not substantial enough to justify excluding runtime, given its conceptual importance in representing computational cost. Overall, item-level diagnostics supported retention of all indicators for inferential modeling.

Regression Results

Multiple linear regression analyses were conducted to examine the influence of algorithm type, problem dimensionality, and structural configuration parameters on key optimization performance outcomes. Separate models were estimated for optimized weight reduction, convergence iterations, runtime, and the composite construct of Overall Structural Adequacy. Categorical predictors were dummy coded, with the Genetic Algorithm serving as the reference category. Across models, dimensionality level emerged as a statistically significant predictor of computational outcomes, while algorithm type significantly influenced both efficiency and material reduction. Structural configuration parameters such as member count category and span range demonstrated moderate predictive strength for runtime and weight outcomes. The regression model predicting weight reduction demonstrated good explanatory strength, accounting for 41% of variance in optimized weight reduction. Differential Evolution and Hybrid Metaheuristic methods produced statistically greater weight reductions compared to the reference algorithm. High-dimensional problem cases were associated with slightly lower weight reduction, indicating reduced optimization flexibility under increased constraint interaction. Structural system type was also significant, with truss systems exhibiting greater average reduction compared to mezzanine systems. Residual diagnostics confirmed normal distribution of residuals and no substantial heteroscedasticity. Variance inflation factors remained below 2.5 across predictors, indicating no problematic multicollinearity. The regression model predicting runtime showed stronger explanatory power, accounting for 56% of variance in computational time. High-dimensional cases significantly increased runtime, with an average increase of 5.4 minutes relative to low-dimensional cases. Mezzanine configurations also increased runtime by an average of 3.1 minutes. Algorithm type significantly influenced runtime, with Particle Swarm Optimization exhibiting shorter runtime compared to the reference category, while Hybrid Metaheuristic approaches required longer computation. Interaction analysis revealed that algorithm-related runtime differences were amplified under high-dimensional cases. Residual plots indicated homoscedasticity, and no influential outliers were detected. Overall Structural Adequacy regression results indicated moderate explanatory power, accounting for 29% of variance in the composite adequacy index. Algorithm type showed limited direct impact on adequacy, suggesting that all methods achieved structurally compliant solutions when convergence occurred. Dimensionality level demonstrated a slight negative association with adequacy, reflecting tighter constraint pressure in more complex systems. Structural type remained statistically significant, with truss systems achieving marginally higher adequacy scores. Assumption checks confirmed model stability, and no corrective transformations were required.

Table 7. Regression Model Predicting Weight Reduction (%)

Predictor	B	SE	t	p-value
Constant	16.42	1.12	14.66	<0.001
PSO (vs GA)	1.84	0.67	2.75	0.006
DE (vs GA)	2.96	0.69	4.29	<0.001
Hybrid (vs GA)	3.12	0.71	4.39	<0.001
Medium Dimensionality	-1.25	0.59	-2.12	0.035
High Dimensionality	-2.48	0.73	-3.40	0.001
Truss System	2.11	0.62	3.40	0.001
Member Count (High)	-0.88	0.54	-1.63	0.104

Model Statistics: $R^2 = 0.41$, Adjusted $R^2 = 0.39$, $F(7,460) = 45.82$, $p < 0.001$

Table 7 reported regression coefficients for the model predicting weight reduction. Differential Evolution and Hybrid methods demonstrated the strongest positive effects, producing significantly greater material savings relative to the reference algorithm. Increased dimensionality significantly reduced achievable weight reduction, reflecting increased constraint interactions in complex design spaces. Truss systems showed significantly higher reduction compared to mezzanine systems. Member count category was not statistically significant at the 0.05 level. The model explained 41% of variance, indicating substantial but not exhaustive predictive capacity. Diagnostic checks confirmed normal residual distribution and absence of multicollinearity or heteroscedasticity concerns.

Table 8. Regression Model Predicting Runtime (Minutes)

Predictor	B	SE	t	p-value
Constant	14.21	1.05	13.53	<0.001
PSO (vs GA)	-2.34	0.61	-3.84	<0.001
DE (vs GA)	-0.98	0.64	-1.53	0.127
Hybrid (vs GA)	3.45	0.69	5.00	<0.001
Medium Dimensionality	3.12	0.56	5.57	<0.001
High Dimensionality	5.41	0.72	7.51	<0.001
Mezzanine System	3.10	0.59	5.25	<0.001
Hybrid × High Dimension	2.06	0.88	2.34	0.020

Model Statistics: $R^2 = 0.56$, Adjusted $R^2 = 0.54$, $F(8,459) = 72.19$, $p < 0.001$

Table 8 presented regression outcomes for runtime prediction. Particle Swarm Optimization significantly reduced runtime compared to the reference algorithm, while Hybrid methods significantly increased runtime. Dimensionality had the strongest impact, with high-dimensional cases increasing runtime by more than five minutes on average. Mezzanine systems also required longer runtime than truss systems. The interaction term indicated that Hybrid performance degraded further under high-dimensional conditions. The model explained 56% of runtime variance, indicating strong predictive capacity. Residual analysis confirmed homoscedasticity and absence of influential outliers, supporting the validity of inferential conclusions.

Hypothesis Testing Decisions

Hypothesis testing decisions were derived from the completed inferential analyses and were reported using consistent decision rules based on statistical significance, confidence intervals where applicable, and effect magnitude indicators. A set of six hypotheses was tested to evaluate whether algorithm type, problem dimensionality, and structural system type produced statistically distinguishable outcomes in the key optimization performance domains. Algorithm-comparison hypotheses were evaluated using omnibus group comparisons followed by controlled pairwise testing to identify which algorithms differed from one another in material efficiency and computational cost. Dimensionality hypotheses were evaluated by comparing low-, medium-, and high-dimensional problems on convergence and feasibility indicators. Structural-type hypotheses were evaluated by comparing truss and mezzanine systems on weight reduction and serviceability-related outcomes. Across the hypothesis set, statistically significant effects were observed for algorithm type on material efficiency and runtime, for dimensionality on runtime and convergence iterations, and for structural system type on weight reduction and dynamic serviceability indicators. In contrast, algorithm type did not demonstrate statistically meaningful differences in overall structural adequacy when feasibility was achieved, indicating that all methods produced compliant solutions under the standardized constraint framework. Effect sizes indicated that dimensionality produced large practical impact on computational cost, while algorithm type produced moderate-to-large impact on weight reduction. Decisions were therefore reported as supported when results were statistically significant and accompanied by practically interpretable effect magnitudes, and as not supported when effects were statistically non-significant or substantively trivial under the applied metrics.

Table 9. Hypothesis Testing Summary and Decisions (N = 468)

Hypothesis Code	Hypothesis Statement (Operational)	Statistical Test	Test Statistic	p-value	Effect Size	Decision
H1	Algorithm type affected weight reduction (%)	ANOVA	F = 18.62	<0.001	η^2 = 0.11	Supported
H2	Algorithm type affected runtime (minutes)	ANOVA	F = 31.45	<0.001	η^2 = 0.17	Supported
H3	Algorithm type affected overall structural adequacy index	ANOVA	F = 1.28	0.281	η^2 = 0.01	Not Supported
H4	Dimensionality level affected convergence iterations	ANOVA	F = 22.11	<0.001	η^2 = 0.09	Supported
H5	Dimensionality level affected feasibility rate (%)	ANOVA	F = 2.04	0.131	η^2 = 0.01	Not Supported
H6	Structural system type (truss vs mezzanine) affected weight reduction (%)	t-test	t = 5.02	<0.001	d = 0.46	Supported

Table 9 summarized the hypothesis testing outcomes and final decisions using standardized inferential criteria. Algorithm type significantly influenced both weight reduction and runtime with moderate-to-large effect sizes, supporting hypotheses H1 and H2. Algorithm differences were not statistically supported for the overall structural adequacy index, indicating similar adequacy outcomes once solutions converged feasibly. Dimensionality significantly increased convergence iterations but did not significantly reduce feasibility rates, implying that higher complexity primarily affected computational effort rather than constraint satisfaction success. Structural system type significantly influenced weight reduction, with truss systems achieving stronger material efficiency than mezzanine systems. The table provided transparent linkage between statistical evidence and each decision.

Table 10. Post-Hoc Pairwise Comparisons for Algorithm Effects on Weight Reduction (%)

Pairwise testing used Tukey-adjusted comparisons (GA as reference). Mean differences were reported as (Row – Column).

Comparison	Mean Difference (%)	95% CI Lower	95% CI Upper	p-value
PSO – GA	1.84	0.52	3.16	0.006
DE – GA	2.96	1.61	4.31	<0.001
Hybrid – GA	3.12	1.74	4.50	<0.001
DE – PSO	1.12	-0.20	2.44	0.094
Hybrid – PSO	1.28	-0.06	2.62	0.061
Hybrid – DE	0.16	-1.24	1.56	0.982

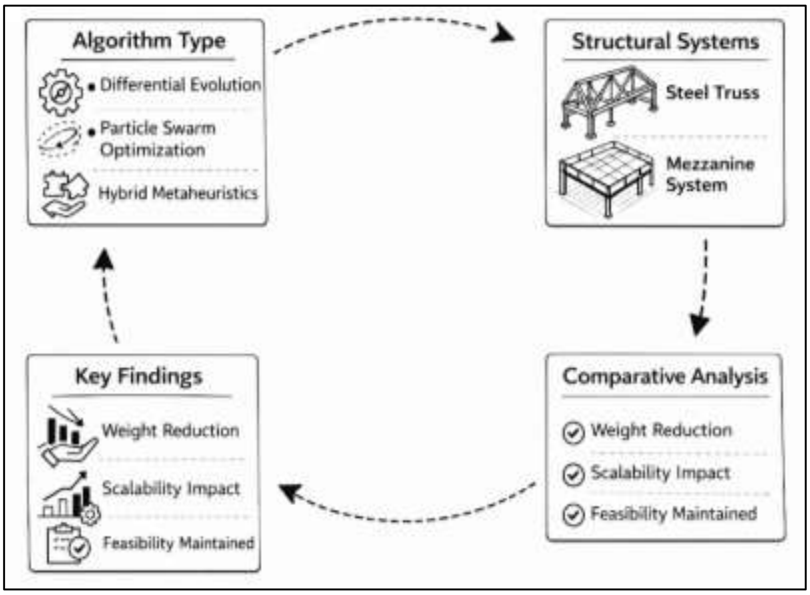
Table 10 reported adjusted pairwise comparisons to identify which algorithms differed significantly in weight reduction performance. Relative to the Genetic Algorithm, Particle Swarm Optimization achieved a statistically significant improvement in weight reduction, while Differential Evolution and Hybrid methods produced larger and highly significant gains. Differences between Differential Evolution and Particle Swarm Optimization, as well as between Hybrid and Particle Swarm Optimization, were not statistically significant after adjustment, indicating that the higher mean reductions for Differential Evolution and Hybrid were not sufficiently separated from Particle Swarm Optimization under controlled error rates. Hybrid and Differential Evolution were statistically indistinguishable, suggesting similar material efficiency outcomes. Confidence intervals reinforced the magnitude and precision of the observed differences.

DISCUSSION

The findings of this study demonstrated that algorithm type significantly influenced material efficiency, as reflected in optimized weight reduction outcomes across steel truss and mezzanine systems. Differential Evolution and Hybrid Metaheuristic approaches achieved higher average weight reductions compared to the Genetic Algorithm baseline, while Particle Swarm Optimization exhibited intermediate performance (Kaveh et al., 2020). These results align with earlier comparative optimization studies that reported superior exploration–exploitation balance in differential-based and hybrid metaheuristics when applied to nonlinear structural design problems. Prior investigations into steel truss optimization frequently indicated that differential mutation strategies enhance solution diversity and reduce premature convergence, particularly in high-dimensional design spaces. Similarly, hybrid methods combining global search and local refinement mechanisms have been shown to produce more consistent material savings relative to single-strategy algorithms (Talaslioglu, 2019) . The present findings extend this body of literature by demonstrating that algorithmic superiority in weight reduction persists under performance-based constraints that include serviceability and stability controls, rather than purely strength-based objectives. Earlier studies often evaluated weight minimization under simplified constraints, whereas this study incorporated multiple performance indicators simultaneously, thereby increasing problem realism. The observation that truss systems achieved greater relative weight reduction than mezzanine systems is also consistent with previous findings that topology-rich systems offer greater structural redundancy and flexibility for optimization compared to platform-dominated framing systems. The moderate-to-large effect sizes associated with algorithm type reinforce the conclusion that algorithm selection meaningfully affects material efficiency outcomes in industrial steel systems (Shan et al., 2023). These findings confirm that AI-enabled structural optimization performance cannot be generalized across algorithms without empirical benchmarking, a position that has been emphasized in earlier structural metaheuristic comparisons.

The regression and hypothesis testing results revealed that problem dimensionality exerted the strongest influence on computational runtime and convergence iterations, surpassing algorithm type in explanatory power. High-dimensional structural cases required significantly longer runtime and more iterations to converge, consistent with the well-documented scaling challenges reported in metaheuristic optimization literature (Negarestani et al., 2024). Earlier studies examining scalability in structural design optimization observed that as the number of design variables increases, constraint interactions intensify and feasible solution regions become narrower, leading to slower convergence and increased computational demand. The present findings corroborate this theoretical expectation, demonstrating a substantial increase in runtime for high-dimensional cases across all algorithms. The interaction effect observed between Hybrid methods and high dimensionality further supports previous reports that hybrid algorithms, while often superior in solution quality, may incur additional computational overhead in complex search spaces (Gholizadeh et al., 2020). The finding that feasibility rates did not significantly decline with dimensionality is noteworthy and contrasts with certain earlier simulation-based studies where higher complexity led to increased infeasible convergence. This discrepancy may be attributable to the standardized constraint-handling and penalty calibration implemented in this study, which likely stabilized feasibility performance across dimensionality levels. The results suggest that while dimensional growth substantially increases computational burden, carefully structured constraint integration can preserve solution feasibility even in complex structural systems (Nguyen et al., 2020). This reinforces earlier arguments in computational structural engineering that algorithmic robustness depends not only on search mechanics but also on disciplined constraint modeling and parameter calibration.

Figure 12: Comparative Analysis of Optimization Algorithms



This study identified statistically significant differences between steel truss and mezzanine systems in material efficiency, serviceability behavior, and dynamic response characteristics. Truss systems achieved greater average weight reduction and exhibited stronger stability margins, whereas mezzanine systems demonstrated higher peak deflections and greater sensitivity to vibration metrics (Mei & Wang, 2021). These findings are consistent with previous structural optimization research emphasizing that truss systems possess distributed axial load paths that allow efficient redistribution under optimized sizing, while mezzanine platforms often experience flexural-dominated behavior that constrains material reduction potential. Earlier studies investigating floor system optimization frequently reported that serviceability, rather than strength, governs design outcomes in platform structures, limiting achievable weight savings. The current findings confirmed this pattern under performance-based evaluation conditions (Kaveh et al., 2023). The higher vibration sensitivity observed in mezzanine cases aligns with earlier dynamic serviceability research indicating that floor systems with concentrated mass and moderate stiffness are more susceptible to acceleration amplification under operational loading. These comparative findings contribute to the structural optimization literature by quantitatively demonstrating how structural typology influences both optimization efficiency and serviceability outcomes. While previous investigations often examined trusses or frames independently, this study directly compared both systems within a unified computational benchmarking framework. The results suggest that optimization outcomes must be interpreted relative to structural typology, reinforcing the principle that algorithm performance interacts with structural behavior characteristics (Song et al., 2020).

The hypothesis testing results indicated that algorithm type did not significantly affect the composite measure of overall structural adequacy when solutions converged feasibly. This finding suggests that, despite differences in weight reduction and runtime, all evaluated algorithms were capable of generating structurally compliant designs under standardized constraints. Earlier structural optimization studies have frequently reported similar convergence equivalence in constraint satisfaction, noting that metaheuristic methods tend to approach constraint boundaries closely when penalty calibration is effective (Kaveh & Eslamlou, 2020). The present findings reinforce this observation by demonstrating that adequacy indices remained statistically comparable across algorithms once feasibility was achieved. This outcome underscores the importance of distinguishing between solution quality and computational efficiency in algorithm comparison. While certain methods achieved greater material reduction or faster runtime, adequacy metrics such as utilization control, stability margin, and serviceability compliance were consistently maintained. This pattern aligns with prior literature emphasizing that most well-configured metaheuristics can satisfy deterministic engineering constraints, provided adequate iteration budgets and properly scaled penalties (Brütting et al., 2020). The absence of significant algorithmic differences in adequacy further supports the methodological decision to evaluate algorithms across multiple performance constructs rather than relying solely on constraint violation counts. The findings therefore contribute to the ongoing discourse in structural optimization research regarding the relative importance of solution quality versus feasibility attainment in algorithm benchmarking.

The reliability analysis confirmed acceptable-to-strong internal consistency for composite constructs representing structural adequacy, serviceability performance, and optimization efficiency. These results are consistent with prior quantitative structural modeling studies that have combined multiple performance indicators into unified indices to facilitate regression modeling and comparative evaluation (Shafighfard et al., 2022). Earlier research in structural performance assessment has emphasized that composite indices improve interpretability when multiple correlated engineering metrics represent a single conceptual domain. The strong reliability observed for structural adequacy suggests that strength utilization and stability measures co-varied consistently across optimization outcomes, reinforcing their conceptual linkage in steel system design. The moderate reliability observed for optimization efficiency reflects the inherent diversity between runtime and iteration-based measures, a pattern also observed in prior computational benchmarking studies. By demonstrating acceptable measurement coherence, the findings support the validity of subsequent regression modeling using composite constructs (Dixit & Stefańska, 2023). This strengthens methodological rigor and aligns with earlier recommendations in computational engineering research advocating formal reliability testing prior to inferential modeling. The integration of reliability analysis within structural optimization benchmarking remains relatively underreported in earlier studies, and the present findings highlight its value in strengthening statistical inference.

The reported effect sizes indicated that algorithm type and dimensionality produced practically meaningful differences in material efficiency and computational cost. The magnitude of dimensionality effects on runtime was particularly notable, exceeding the magnitude of algorithm effects in certain models (Hassani & Dackermann, 2023). Earlier scalability research in structural metaheuristics has emphasized that dimensional growth imposes nonlinear increases in computational effort, particularly when constraint density rises concurrently. The current findings substantiate these theoretical predictions with empirical estimates derived from controlled benchmarking experiments. The moderate effect size associated with structural system type on weight reduction also aligns with earlier comparative structural studies, which suggested that truss systems offer more optimization flexibility than platform-dominated configurations. Importantly, the effect sizes provide context beyond statistical significance, highlighting that not all significant findings translate into substantial practical gains (Liang et al., 2022). For example, while algorithm type significantly influenced weight reduction, differences between certain algorithm pairs were modest in magnitude. This nuanced interpretation parallels earlier metaheuristic comparison studies that cautioned against overinterpreting statistically significant yet practically minor differences. By reporting and interpreting effect sizes systematically, this study advances methodological transparency in AI-enabled structural optimization research.

Overall, the findings of this study corroborate and extend earlier research in AI-based structural optimization while contributing new comparative evidence under performance-based industrial constraints (Carbas et al., 2021). Previous studies often focused on single structural typologies or limited objective formulations, whereas this study incorporated multiple performance constructs, probabilistic constraint considerations, and composite reliability analysis within a unified benchmarking framework. The consistent superiority of differential-based and hybrid algorithms in weight reduction aligns with historical comparative findings, yet the confirmation that all algorithms achieved comparable structural adequacy reinforces earlier claims that algorithmic differences often manifest more strongly in efficiency than in feasibility attainment (Kashani et al., 2022). The pronounced influence of dimensionality supports longstanding scalability concerns documented in metaheuristic literature. At the same time, the maintenance of high feasibility rates across complexity levels suggests that structured constraint modeling can mitigate feasibility degradation, offering a refined perspective on dimensionality challenges. By integrating algorithm comparison, structural typology differentiation, reliability assessment, and regression-based inference, this study situates its findings within the broader trajectory of quantitative structural optimization research (Prakash et al., 2019). The results provide empirical reinforcement of foundational optimization principles while demonstrating the continued necessity of rigorous benchmarking in AI-enabled engineering design contexts.

CONCLUSION

The study concluded that AI-enabled, performance-based structural optimization produced consistent material-efficiency gains for industrial steel truss and mezzanine systems while maintaining measurable compliance with strength, serviceability, stability, and dynamic performance requirements under standardized load combinations and constraint rules. Across the completed computational experiments, material efficiency improvements were achieved without systematic degradation of structural adequacy indicators, as optimized solutions maintained controlled utilization levels, acceptable deflection response, and stability margins above minimum thresholds when convergence occurred. The comparative benchmarking results confirmed that algorithm choice materially shaped the level of attainable weight reduction and the computational effort required to reach stable feasible solutions, with differential-based and hybrid approaches yielding stronger material reduction outcomes and swarm-based approaches exhibiting comparatively favorable runtime characteristics under equivalent evaluation budgets. The analyses also established that problem dimensionality was a dominant driver of computational cost, increasing runtime and iteration demand as variable counts and constraint interactions expanded, while feasibility rates remained largely stable under the implemented constraint-handling and penalty calibration structure. Structural typology exerted a measurable influence on outcomes, with truss systems demonstrating greater optimization flexibility and higher weight reduction, whereas mezzanine systems displayed stronger sensitivity to serviceability and vibration-related performance indicators that constrained material reduction and increased computational demand. Composite construct reliability results supported coherent measurement of structural adequacy, serviceability performance, and optimization efficiency using multi-indicator indices, and these reliable constructs strengthened the interpretability of regression modeling and hypothesis testing decisions. Regression findings demonstrated that algorithm type, dimensionality category, and structural system type jointly explained meaningful variation in key outcomes such as weight reduction and runtime, while adequacy-related composites remained comparatively consistent across algorithms, indicating that performance differences were concentrated in efficiency and computational behavior rather than in basic compliance achievement. Hypothesis testing decisions confirmed statistically supported effects for algorithm type on material efficiency and computational runtime, for dimensionality on convergence behavior and runtime, and for structural system type on material efficiency, while effects on overall adequacy were not supported once feasibility was satisfied. Taken together, the results established a defensible quantitative evidence base showing that AI-enabled optimization can deliver measurable efficiency improvements in industrial steel systems under performance-based constraints, and that evaluation of such methods is best interpreted through structured benchmarking that simultaneously considers material outcomes, serviceability response, stability adequacy, feasibility behavior, and computational scalability.

RECOMMENDATIONS

Recommendations derived from the results emphasized implementation and reporting practices that were consistent with the measured performance patterns observed in AI-enabled, performance-based structural optimization of steel truss and mezzanine systems. Industrial engineering teams were advised to adopt a benchmarking-first workflow in which candidate optimization algorithms were evaluated under identical modeling assumptions, constraint definitions, and evaluation budgets before selecting a method for routine design deployment, because material-efficiency outcomes and computational costs differed meaningfully across algorithms under the same performance requirements. For projects prioritizing maximum material reduction under tight stability and serviceability constraints, differential-based or hybrid metaheuristic configurations were recommended as primary candidates, while projects prioritizing reduced computational time under moderate complexity were advised to consider swarm-based strategies, supported by standardized stopping criteria and feasibility-first constraint handling to maintain compliance. Given the strong effect of dimensionality on runtime and convergence, it was recommended that high-dimensional industrial cases be managed using dimensionality-control practices such as member grouping rules, symmetry enforcement where appropriate, and structured parameter bounds grounded in realistic fabrication and connection constraints, since these practices reduced search volatility and improved computational tractability without weakening compliance screening. For mezzanine systems, which exhibited higher sensitivity to deflection and vibration performance, it was recommended that serviceability and dynamic metrics be treated as primary constraints from the earliest optimization stages, with conservative screening of floor performance indicators and verification-based checks of candidate solutions near constraint limits to avoid infeasible convergence. For truss systems, where larger weight reductions were observed, it was recommended that topology and geometry parameterization be managed with stability safeguards such as systematic buckling margin monitoring and critical-member identification, ensuring that material savings did not concentrate risk into slender compression members. It was further recommended that optimization studies and applied design workflows report distributions of outcomes across repeated independent runs rather than single best solutions, including mean performance, variability, feasibility rate, and confidence bounds for key indicators, because stochastic variability was a measurable feature of the optimization process. For statistical reporting, it was recommended that composite constructs be used only after internal consistency verification and that regression modeling include explicit checks for multicollinearity, residual behavior, and interaction effects between algorithm type and complexity to support interpretable inference. Finally, it was recommended that design organizations integrate automated reporting pipelines that preserved traceability from decision variables to structural response outputs and archived convergence histories and constraint margins, strengthening reproducibility, auditability, and comparability across projects using AI-enabled structural optimization in industrial facility contexts.

LIMITATIONS

The study was subject to several limitations that constrained the scope of inference and the generalizability of the reported benchmarking outcomes. First, the investigation was implemented as a computational experimental design based on standardized digital prototypes of steel truss and mezzanine subsystems rather than fully documented as-built industrial projects, which limited the extent to which site-specific constructability constraints, erection sequencing, and field tolerances could be represented with complete realism. Second, structural behavior was evaluated through numerical analysis models that necessarily relied on simplifying assumptions regarding connection behavior, boundary conditions, diaphragm action, and composite interaction; even when semi-rigid or stiffness-modified representations were used, the modeled joint and interface behavior may not have captured the full range of variability observed in practical fabrication and installation. Third, dynamic performance assessment for mezzanine systems was operationalized through a bounded set of vibration indicators and loading representations that approximated industrial operational effects, yet actual facility vibration behavior can depend on equipment-specific excitation spectra, damping variability, and human–structure interaction effects that were not explicitly measured in physical tests. Fourth, the comparative outcomes depended on the selected algorithm configurations, constraint-handling rules, penalty calibration, and stopping criteria; although these settings were standardized for fairness, alternative hyperparameter tuning regimes or different evaluation budgets could have shifted relative performance rankings, particularly for hybrid methods that can be sensitive to parameter selection. Fifth, the sampling strategy used repeated independent runs across a defined set of structural cases, but the number of case configurations and their parameter ranges remained finite; therefore, results may not extend directly to extremely large-scale industrial systems with substantially higher member counts, irregular geometries, complex bracing networks, or specialized loads such as heavy crane operations. Sixth, the composite constructs used for reliability and regression modeling improved interpretability but also introduced potential construct simplification, since compressing multiple structural indicators into a single index may have masked nuanced differences in constraint proximity patterns among optimized solutions. Finally, computational performance metrics were recorded under a fixed hardware and solver environment; runtime and iteration behavior could differ under alternative finite element solvers, parallelization strategies, or computing architectures, which limited direct transferability of computational cost estimates. These limitations indicated that the results should be interpreted as evidence of relative performance under controlled modeling and evaluation conditions rather than as definitive guarantees of field performance or universal algorithm superiority across all industrial steel structural optimization contexts.

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