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INVESTIGATION INTO AI-ASSISTED OPTIMIZATION OF THIN-WALLED CROSS-SECTIONS

ДОСЛІДЖЕННЯ ОПТИМІЗАЦІЇ ТОНКОСТІННИХ ПОПЕРЕЧНИХ ПЕРЕРІЗІВ ЗА ДОПОМОГОЮ ШТУЧНОГО ІНТЕЛЕКТУ

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Abstract *Cross-section selection determines the optimal geometry and material of beams, columns, trusses, and slabs to satisfy strength, stiffness, serviceability, and code requirements. Traditional methods analytical formulas, empirical code provisions, finite element analysis, and the finite strip method are reliable but often time-consuming and conservative. Artificial intelligence (AI) offers rapid design-space exploration, identification of non-intuitive solutions, and accelerated workflows that augment rather than replace engineer expertise.*

A variety of AI methodologies have been applied to cross-section design. Supervised learning models artificial neural networks, support vector machines, Gaussian process regression, and ensemble trees train on paired input–output data to predict performance metrics such as critical buckling loads, ultimate strength, and deflections in milliseconds, while uncertainty estimates guide risk-informed decisions. Reinforcement learning frames section assignment as a sequential decision process, with graph-based and multi-agent architectures achieving faster convergence and greater weight reductions than classical optimizers. Evolutionary algorithms, particle swarm optimizers, and generative adversarial networks explore mixed continuous and discrete variables to deliver flexible, multi-objective solutions. Hybrid physics-informed models embed equilibrium and stability equations into training pipelines or leverage derived features slenderness ratios and section moduli to enhance robustness, interpretability, and regulatory acceptance.

In conventional structural systems planar and three-dimensional frames, trusses, and shear walls AI-driven workflows yield measurable benefits. Graph-based reinforcement learning has reduced total steel weight by up to 12 percent compared to particle swarm or simulated annealing, while surrogate-based pipelines use neural networks or Gaussian process models to propose near-optimal member sizes in milliseconds, bypassing hours of finite element analysis. Integrated design-co-pilot platforms combine generative algorithms with automated code compliance checks to generate member-sizing proposals over ten times faster than manual methods, with deviations below 20 percent.

Thin-walled elements present additional complexity due to interacting buckling modes and nonlinear behavior. AI surrogates trained on finite-strip or finite-element datasets achieve R^2 values above 0.98 for buckling-load prediction and classify failure modes with over 95 percent accuracy. Gaussian processes and ensemble methods furnish predictive variances that support confidence-weighted decisions. Inverse-design frameworks coupling surrogates with genetic or swarm optimizers generate optimized profiles within 5 percent of validation targets. Symbolic regression yields explicit design equations suitable for incorporation into codes.

Permanent formwork systems which serve as both construction support and structural elements pose a multifaceted optimization challenge that spans structural support, thermal insulation, acoustic attenuation, fire resistance, and constructability. AI-augmented surrogates, inverse-learning loops, and generative networks can rapidly evaluate thousands of candidate profiles. Hybrid AI-FEA workflows shortlist top candidates for detailed simulation, apply AI-based validation checks to detect input inconsistencies, and iteratively refine surrogate accuracy through closed-loop retraining.

Despite these advances, critical gaps remain comprehensive case studies in active infrastructure, alignment with existing codes, transparent reporting of failure modes, long-term durability data, unified uncertainty quantification, and resilience under extreme loads. Addressing these gaps through interdisciplinary collaboration among structural engineers, AI researchers, software developers, and regulatory bodies will be essential to establish AI-driven cross-section optimization as a reliable, industry-standard practice in modern structural engineering.

Keywords: *Artificial intelligence, Machine learning, Permanent formwork, Cross-section optimization, Surrogate modeling, Generative Design, Physics-informed neural networks, multi-fidelity data integration, Structural health monitoring, Hybrid AI-FEA workflows.*

Introduction

Cross-section selection, which involves choosing the size, shape, and material of structural members such as beams, columns, trusses, and slabs, constitutes a fundamental task in structural engineering design. An optimal selection ensures safe and economical load-carrying capacity, compliance with serviceability requirements, and adherence to relevant codes. Traditional practice relies on analytical formulas, empirical provisions from standards such as Eurocode, AISC, and ACI, alongside iterative numerical techniques including finite element analysis and the finite strip method. Although these methods are well established, they often demand extensive computational time, expert judgment to address complex stability issues such as local, distortional, and global buckling, and tend toward conservatism to guarantee safety.

Recent advances in artificial intelligence, particularly in machine learning, reinforcement learning, evolutionary algorithms, and generative design, have introduced powerful decision-support tools that augment but do not replace the engineer's expertise. These AI-based approaches rapidly explore expansive design spaces, uncover non-intuitive solutions, and accelerate iterative workflows. For instance, graph-based reinforcement learning agents have been shown to assign standard steel sections in frame structures with reduced total weight and computational expense relative to particle swarm or simulated annealing optimizers [2]. Multi-agent systems further extend these benefits to three-dimensional building frames, achieving faster convergence toward minimum-volume configurations than classical metaheuristics, while industry applications report material savings of 18-25 percent without compromising code compliance [4].

Surrogate models based on supervised learning, such as artificial neural networks trained on harmony-search-optimized datasets, can predict near-optimal member dimensions in fractions of a second compared to the hours or days required by traditional methods. Fully automated “design co-pilot” platforms integrate generative AI directly into structural workflows, producing complete sizing proposals for reinforced-concrete shear walls over ten times faster than manual design, with deviations from expert solutions typically below 20 percent [8].

Thin-walled elements pose additional challenges due to their sensitivity to complex buckling interactions, including local flange buckling, distortional web-flange modes, and global flexural-torsional instabilities. Data-driven models trained on finite strip or high-fidelity finite element datasets have demonstrated excellent predictive accuracy: artificial neural networks forecasting critical buckling loads of cold-formed steel channels achieve coefficients of determination up to 0.98, and deep belief networks surpass traditional web-crippling equations, enabling the derivation of refined design formulas [18].

Inverse design frameworks coupling trained surrogates with genetic algorithms or particle swarm optimizers allow engineers to specify target performance criteria, such as a desired buckling capacity, and obtain optimized geometric parameters that agree within 5 percent of FEA validation. Moreover, gene expression programming and multi-gene symbolic regression produce interpretable equations suitable for incorporation into design codes [14].

Despite these promising developments, barriers to widespread AI adoption persist. High-quality training data are often proprietary or narrowly scoped, limiting model generalization to novel geometries and loading conditions. The opacity of many machine learning models raises concerns regarding interpretability and regulatory acceptance, while professional liability and code compliance demand design outputs that are both accurate and verifiable through conventional calculations or experimental testing. Integrating AI tools into established workflows encompassing BIM platforms, FEA packages, and project management systems also requires intuitive interfaces and robust data interoperability.

This review synthesizes the body of work on AI-assisted cross-section selection in civil and structural engineering, surveying methods applied to conventional beam-column and frame systems as well as thin-walled members. It highlights performance gains in material efficiency, design speed, and safety compliance, and critically examines challenges related to model interpretability, data quality, and workflow integration. To advance the field, we advocate embedding physics-informed constraints directly into learning pipelines, integrating multi-fidelity datasets that combine analytical models with high-resolution simulations, implementing dynamic model updating through real-time structural monitoring, and incorporating uncertainty quantification techniques such as Bayesian neural networks and Monte Carlo dropout to accompany predictions with confidence intervals.

Finally, we explore the potential of AI-FEA hybrid workflows for permanent formwork systems, which function both as construction formwork and as finished structural elements. By optimizing cross-sectional profiles for structural performance, thermal insulation, fire resistance, and constructability and by leveraging predictive models for long-term durability AI-augmented design promises to establish new standards in next-generation structural engineering practice.

AI Methodologies for Cross-Section Design and Analysis

The application of artificial intelligence to structural cross-section design and analysis leverages a diverse set of algorithmic approaches. Four principal methodological categories have emerged supervised learning, reinforcement learning, evolutionary and generative algorithms, and hybrid physics-informed models each offering distinct advantages for predicting performance metrics, automating decision processes, exploring vast design spaces, or embedding fundamental physical laws. The following section summarizes the core principles, representative implementations, and comparative strengths and limitations of these approaches, with pointers to the original research where appropriate.

Supervised Learning. Supervised learning methods train predictive models on paired examples of section geometry, material properties, loading conditions, and corresponding performance outcomes. Once trained, these models deliver near-instantaneous predictions of metrics such as critical buckling loads or ultimate strength. Typical implementations include multi-layer perceptron neural networks, support vector machines, Gaussian process regressors, and ensemble methods such as random forests or gradient boosting. For example, feed-forward neural networks trained on finite-strip analyses of cold-formed steel channels achieved coefficients of determination around 0.98 in predicting buckling loads and correctly classified local, distortional, and global failure modes without iterative eigenvalue solves [12]. Similarly, an ANN trained on 2 800 experimental and simulated compression and impact tests of thin-walled tubes demonstrated $R^2 \approx 0.86$ on unseen profiles, confirming its generalizability [11]. In fire scenarios, ANN, SVM, and random forest models outperformed Eurocode equations for slender I-beams by accurately capturing temperature–buckling interactions [10]. A Gaussian process surrogate trained on 280 finite-element simulations of cold-formed tubular columns delivered higher capacity-prediction accuracy than conventional formulas [1, 19]. The primary strengths of supervised learning lie in its inference speed and high fidelity when ample, high-quality training data are available, along with the ability to quantify uncertainty via Bayesian extensions. Limitations include reliance on dataset diversity which may restrict applicability to novel geometries or load cases and the “black-box” opacity of deep networks, although interpretability techniques such as SHAP are increasingly applied to mitigate this issue.

Reinforcement Learning. Reinforcement learning frames cross-section selection as a sequential decision problem in which an agent explores actions such as choosing or resizing members in a simulated structural environment, and receives rewards based on objectives like weight minimization or compliance with code provisions. Graph-based RL agents treat structural layouts as graphs with joints as nodes and members as edges, enabling the agent to respect connectivity and load paths naturally. Multi-agent architectures further accelerate convergence by assigning distinct roles one agent may select which member to modify while another chooses the section profile. In planar steel frames, a graph-based agent reduced final weight and computational cost compared to particle swarm optimization [2]. Extension to three-dimensional frames via a two-agent system produced minimum-volume designs more rapidly than simulated annealing or local search [3]. Reward functions in these studies explicitly integrated buckling and code compliance constraints, ensuring safety alongside material efficiency. Reinforcement learning excels when optimizing from discrete catalogs of standard profiles and can incorporate complex performance metrics directly into its objective, but its training phase can be computationally intensive, and the resulting policies often remain difficult to interpret without supplementary analyses.

Evolutionary and Generative Algorithms. Evolutionary and generative methods draw inspiration from natural processes, biological evolution, swarm behavior, or thermal annealing to search continuous and discrete design spaces. Genetic algorithms evolve populations of candidate cross sections through selection, crossover, and mutation; particle swarm optimization moves design vectors according to individual and collective best positions; simulated annealing accepts probabilistic perturbations to escape local minimum; and generative adversarial networks learn to produce novel geometries by pitting two neural networks against each other. Comparative benchmarks indicate that reinforcement learning can outperform PSO in weight reduction and convergence speed, yet PSO remains an effective baseline optimizer. Hybrid frameworks that couple GA with ANN surrogates have optimized lipped channel sections for web-crippling loads, yielding designs superior to standard code recommendations [20]. Emerging GAN-based workflows propose unconventional perforated or nonstandard profiles that satisfy structural criteria while expanding the design vocabulary. Symbolic regression via gene expression programming has also generated explicit formulas for GFRP hollow-section web-crippling capacity, providing interpretable equations grounded in numerical data [14]. These algorithms offer flexibility in handling mixed variable types and multi-objective problems, and symbolic approaches enhance interpretability; their drawbacks include significant computational demands for high-dimensional searches and sensitivity to parameter tuning.

Hybrid and Physics-Informed Models. Hybrid methodologies integrate data-driven learning with physical principles to improve robustness, interpretability, and regulatory acceptance. Physics-informed neural networks enforce equilibrium and buckling differential equations within the training loss, guaranteeing that predictions obey fundamental laws even for out-of-sample geometries. Surrogate models enriched with engineered features such as section moduli or slenderness ratios leverage both raw inputs and analytically derived parameters. Symbolic regression techniques evolve human-readable design formulas that practitioners can adopt directly. To advance these approaches, researchers propose multi-fidelity integration of analytical approximations with high-fidelity simulations or experiments to balance training cost and accuracy, dynamic model updating using real-time structural monitoring data for lifecycle adaptation and embedding Bayesian neural networks or Monte Carlo dropout for uncertainty quantification alongside point estimates. Applications of physics-informed models include guaranteed-constraint buckling capacity prediction and surrogate-based optimization pipelines that replace thousands of finite-elements runs with millisecond-scale inferences. The main challenges involve the complexity of PINN implementations requiring careful weighting of physics versus data losses and the computational overhead of multi-fidelity training and frequent retraining.

Supervised learning delivers rapid, accurate predictions when comprehensive labeled data exist; reinforcement learning excels in discrete-catalog optimization under multifaceted constraints; evolutionary and generative algorithms offer flexible, multi-objective search capabilities; and hybrid physics-informed models marry data-driven inference with analytical rigor to enhance trust and generalization. Collectively, these methodologies constitute a complementary toolkit for AI-augmented cross-section design and analysis, charting a course toward more efficient, innovative, and verifiable structural engineering workflows.

Performance and Cost Optimization

Early demonstrations of AI's value in conventional structures focused on minimizing material usage while satisfying strength and serviceability requirements. In a landmark study [2] trained a graph-based reinforcement learning agent to assign standard steel sections to planar frame elements, achieving a lighter overall structure and faster convergence than a particle swarm optimizer, without compromising code compliance. Beyond academic benchmarks, AI-driven generative design platforms have been deployed on real infrastructure projects. For example, an AI-based generative algorithm optimized the geometry of a concrete bridge block in Pennsylvania, maintaining its load-bearing capacity while reducing material usage by 20%, which translated directly into lower procurement and transportation costs. Across multiple industry trials, firms have reported material procurement reductions of 18-25%, a benefit attributable to AI's ability to fine-tune cross-section shapes and dimensions more precisely than manual trial-and-error methods. Moreover, by integrating these tools early in the design phase, engineers can identify and eliminate unnecessary safety margins inherent in heuristic code provisions, yielding leaner sections that still satisfy ultimate strength, deflection limits, and vibration criteria. Multi-material optimization adjusting concrete strength, reinforcement ratios, or steel grades further balances performance and cost objectives, ensuring that AI-optimized solutions remain robust under both service loads and extreme events [9].

Design Efficiency and Time Savings. While material and cost gains are significant, AI integration also dramatically accelerates the design cycle. Traditional cross-section selection often involves numerous finite element or strip analyses, each iteration demanding hours of engineer time. Supervised-learning surrogates overcome much of this burden by learning from pre-computed, optimized designs. Bekdaş et al. [7] demonstrated that a neural network trained on harmony-search-optimized frame designs could ingest new geometry and loading conditions and output near-optimal member sizes in milliseconds, eliminating repeated optimization runs. Such surrogate models enable rapid "what-if" studies and real-time feedback during collaborative design sessions. Fully automated "design co-pilot" platforms represent the next evolution in workflow augmentation. For instance, AI structure-Copilot at Tsinghua University combines generative design with automated code compliance checks; in a 2024 case study of a reinforced-concrete shear-wall building, the system produced member sizing proposals over ten times faster than a human engineer, with only a 20% deviation in weight distribution. These productivity gains allow engineers to focus on higher-order tasks conceptual design, architectural integration, and resilience planning while routine sizing is automated, fostering innovation and reducing project lead times.

Safety and Reliability Enhancements. Ensuring that efficiency gains do not compromise safety is paramount. AI methods embed stability and strength constraints directly into their optimization routines. In reinforcement learning frameworks, configurations that violate global or local buckling limits incur penalties during training, guiding the agent toward safe yet efficient designs. Consequently, RL-optimized frames achieve both material savings and rigorous code compliance. Machine learning models also enhance predictive accuracy where empirical code formulas struggle. For cold-formed steel members, Xu et al. [16, 19] trained a Gaussian process regression surrogate on finite element simulations of stainless-steel tubular columns, achieving higher accuracy and lower variability in capacity predictions than Eurocode and AISC equations; this improved confidence allows engineers to reduce conservatism in section selection. Deep learning approaches similarly advance predictions of web-crippling strength in perforated sections, outperforming traditional empirical relationships and informing updated design guidelines. Beyond strength criteria, multi-objective AI optimizations incorporate deflection limits, vibration performance, and seismic response into a unified framework. Generative algorithms can simultaneously optimize section dimensions to satisfy drift restrictions under lateral loads and stiffness requirements for dynamic performance, ensuring both comfort and durability. By evaluating numerous load combinations in parallel gravity, wind, seismic AI models support comprehensive performance-based design, enhancing reliability without extending design timelines.

In conventional structural systems, AI methodologies have delivered measurable benefits across performance and cost optimization, design efficiency, and safety assurance. Reinforcement learning and generative design algorithms yield material-minimizing solutions that achieve 18-25% cost savings in practice. Supervised learning surrogates and design co-pilot platforms compress design cycles by an order of magnitude, enabling rapid exploration of alternatives and early-stage decision-making. Safety and reliability are strengthened through constraint-aware optimization and high-fidelity capacity prediction, resulting in lean, code-compliant cross-sections. These advances collectively pave the way for AI's adoption as a standard tool set in structural engineering practice.

AI in Thin-Walled Cross-Section Analysis and Optimization

Thin-walled structural members, including cold-formed steel channels, plate girders, and stainless-steel tubular columns, are valued for their high strength-to-weight ratios, yet their design involves intricate interactions among local, distortional, and global buckling modes that challenge both closed-form formulas and conventional numerical methods. Recent advances demonstrate that artificial intelligence techniques can accurately predict critical capacities, optimize cross-section geometry, and even derive novel design expressions for such members. This section considers four interrelated topics: machine learning–based prediction of buckling and strength, ultimate strength and fire-performance modeling, inverse design and optimization, and model performance with interpretability considerations [17].

Machine Learning-Based Prediction of Buckling and Strength. A central effort in recent research has been the development of supervised learning surrogates that map geometric and material descriptors directly to buckling loads and ultimate strengths, thereby replacing iterative eigenvalue analyses in finite-strip or finite-element frameworks. For example, feed-forward artificial neural networks trained on finite-strip data of cold-formed steel channels with inputs such as flange width, lip length, thickness, stiffener geometry, and effective length have achieved coefficients of determination around 0.98 on validation sets and correctly classified buckling modes with over 95 percent accuracy, effectively eliminating repeated eigenvalue solves [12]. Kernel methods and ensemble techniques have also proven effective: Gaussian process regression models trained on a few hundred finite-element simulations of tubular stainless-steel columns reduced mean absolute error by 30 percent compared to Eurocode 3 formulas, while providing predictive variances for confidence-weighted decisions. Decision-tree ensembles such as Random Forests and gradient boosting machines capture nonlinear interactions among slenderness ratios, section moduli, and imperfection sensitivity factors, and their feature-importance metrics reveal the most influential geometric parameters, guiding targeted stiffening strategies and rapid stability assessments.

Ultimate Strength and Fire-Performance Modeling. Predicting ultimate capacity under combined axial-bending loads and elevated temperatures introduces additional complexity due to temperature-dependent stiffness degradation and nonlinear failure modes. Machine learning models trained on extensive finite-element datasets have outperformed empirical code equations in such scenarios. In one study, multiple algorithms including neural networks, support vector machines, random forests, and polynomial regressions were benchmarked against Eurocode fire provisions for slender I-beams under lateral-torsional buckling, achieving a 40 percent reduction in predictive error and capturing intricate interactions between thermal softening and buckling behavior [10]. Deep belief networks applied to web-crippling of perforated channels have likewise surpassed traditional empirical formulas, enabling the formulation of improved capacity expressions. For combined axial–bending failure, ensemble models trained on both experimental and simulated beam-column tests achieved coefficients of variation near 0.07 far below the 0.22-0.23 values of Eurocode 3 and AISC specifications thereby permitting reduced conservatism in design without sacrificing reliability [21]. By integrating temperature-dependent material models and multiple limit states into unified learning frameworks, AI approaches now support streamlined, performance-based design workflows that address serviceability, strength, and fire requirements concurrently.

Inverse Design and Optimization. Beyond forward prediction, inverse-design methodologies leverage trained surrogates in combination with evolutionary or swarm-based optimizers to prescribe target performance criteria and automatically generate optimal cross-section geometries. For instance, coupling an artificial neural network surrogate with a genetic algorithm enabled engineers to specify a desired buckling capacity for rib-stiffened thin-wall structures and obtain geometric parameters that matched finite-element validation within 5 percent error, dramatically reducing the number of design iterations required. Hybrid metaheuristic frameworks that combine particle swarm optimization with neural-network surrogates have consistently outperformed code-based recommendations for cold-formed channels under web-crippling loads. Symbolic regression techniques, such as gene expression programming, further refine this process by evolving explicit mathematical formulas trained on extensive parametric datasets that relate geometry to capacity in a form immediately adoptable within design guidelines [14]. Together, these workflows accelerate the conceptual design phase by bridging performance targets and validated cross-section proposals without laborious manual sweeps.

Model Performance and Interpretability. High predictive accuracy alone does not guarantee engineering adoption; models must generalize to unseen geometries and provide transparency in their decision logic. Best practices include rigorous cross-validation, out-of-sample testing, and sensitivity analyses to ensure robust extrapolation. Transfer-learning strategies allow pre-trained networks to adapt efficiently to new section families, leveraging shared buckling physics to minimize additional data requirements. Explainable AI methods, such as SHapley Additive exPlanations, quantify the contribution of each input variable confirming, for example, that thickness and flange dimensions dominate buckling behavior while revealing subtle interactions among geometric parameters [12]. Embedding physically meaningful features such as slenderness ratios and section moduli into model inputs further enhances interpretability and reduces reliance on spurious correlations. Finally, uncertainty quantification techniques, including Bayesian neural networks and Monte Carlo dropout, produce prediction intervals that align with traditional reliability-based design frameworks, enabling engineers to apply informed safety margins alongside point estimates.

By uniting high-fidelity prediction, unified capacity modeling, inverse design workflows, and advanced interpretability, AI methods are redefining thin-walled cross-section design. As datasets expand and physics-informed approaches mature, these tools are poised to become indispensable in practice, complementing and extending the capabilities of classical finite-element and code-based methods.

Case Studies and Practical Implementations

Academic Benchmarks. Academic research has established controlled benchmarks that validate AI-driven cross-section methods against traditional optimizers. In planar steel frames [2] applied a graph-based reinforcement-learning agent to a two-bay, two-story configuration and achieved an 8 percent reduction in total steel weight relative to a particle swarm optimizer while halving computational time. Takenaka et al. [3] extended this approach to three-dimensional building frames, using a multi-agent system that co-learned member selection and section assignment to deliver a 12 percent volume reduction compared to simulated annealing and local-search methods. Generative-design platforms such as AI structure-Copilot were benchmarked on reinforced-concrete shear walls by Qin et al. [8], who reported member sizing proposals meeting all code provisions with only a 20 percent deviation in weight from expert designs and an order-of-magnitude speedup. For cold-formed steel columns, Xu et al. [19] trained Gaussian process regressors on finite-element simulations of tubular stainless-steel members under axial load, producing coefficients of variation below 0.1 compared to 0.22–0.23 for Eurocode and AISC equations. Harmony-search-optimized truss designs have likewise been emulated by neural-network surrogates: Bekdaş et al. [7] achieved over 95 percent accuracy in predicting near-optimal member sizes for 10-bar and 25-bar trusses in under a millisecond, compared to minutes for iterative optimization. These studies confirm that AI methods can match or surpass classical approaches in both performance and computational efficiency, and they provide standardized models for reproducible algorithm comparisons.

Industry Tools and Pilot Projects. Commercial vendors and emerging start-ups are beginning to embed AI capabilities into structural analysis and design workflows. Autodesk's Robot Structural Analysis and Revit generative-design modules employ proprietary AI-inspired optimizers to suggest steel and concrete section sizes under load and deflection constraints, with reported material savings of 10–15 percent on typical building projects. Tekla Structural Designer incorporates an automated steel-sizing routine that iterates finite-element checks with code compliance verifications, reducing manual rework by up to 30 percent in mid-rise office structures. Pathw.ai offers specialized AI services for steel connection design, using data-driven rule extraction to recommend bolt patterns, plate thicknesses, and weld sizes in seconds. Cloud-based AI services deliver optimized member recommendations and design rationales via remote APIs, though adoption is still limited by concerns over data privacy and liability; pilot projects at European infrastructure firms have demonstrated feasibility. In research settings, open-source frameworks built on TensorFlow and PyTorch interface with FEA packages (OpenSees, Abaqus) via scripting, enabling rapid prototyping of surrogates and inverse-design loops that bridge academia and industry [5, 6, 15].

Translation to Practice. Bridging AI research outputs and routine engineering practice involves converting model predictions into familiar design formats and integrating surrogates into established workflows. Symbolic regression techniques produce explicit, code-style equations that practitioners can adopt directly. Asghar et al. [14] used gene expression programming to derive a closed-form web-crippling equation for pultruded GFRP hollow sections, achieving mean absolute errors within 3 percent of finite-element data. Nguyen et al. [22] applied multi-gene genetic programming to cold-formed steel channels, generating formulas that improve upon AISI provisions for local and distortional buckling and include parameter tables and safety factors aligned with standard formats. Surrogate-based FEA workflows use trained ANNs, GPRs, or ensembles to prescreen candidate sections, reducing the number of high-fidelity analyses by approximately 80 percent while preserving design quality. AI-guided mesh refinement models identify critical regions in plate-girder simulations, delivering two- to threefold speed-ups with error bounds below 5 percent. Closed-loop optimization prototypes combine surrogates and FEA validation in an iterative cycle until convergence, merging AI's speed with numerical fidelity. Early BIM integrations allow AI models to import loads and boundary conditions directly from the building model, perform surrogate evaluations, and export optimized section properties for documentation. These pathways demonstrate how AI can augment traditional processes automating routine tasks, expanding design exploration, and freeing engineers to concentrate on verification and innovation.

Rigorous academic benchmarks confirm that AI algorithms can rival or exceed classical optimizers in frames, trusses, and columns, delivering both material savings and computational efficiency. Industry tools from Autodesk and Tekla to specialized services like Pathw.ai are beginning to integrate AI into engineer workflows. Practical translation strategies, including AI-derived design equations and surrogate-based FEA pipelines, bridge the gap between research and practice. Continued collaboration among researchers, software vendors, and regulatory bodies will be essential to realize AI's full potential as a mainstream toolset in structural engineering.

Proposed Improvements and Future Research

Although AI-driven methods have demonstrated considerable promise in automating and optimizing cross-section design, key methodological gaps and industry barriers persist. We prioritize twelve enhancements and research directions, organized into four domains AI-based section selection, classical FEA integration, strategic real-world applicability, and regulatory and educational alignment each mapped to earlier recommendations.

AI-Based Section Selection Enhancements. Embedding structural mechanics directly into learning frameworks can improve model robustness beyond the training distribution. Physics-informed neural networks (PINNs) augment the loss function with equilibrium, compatibility, and buckling residuals, ensuring that predicted capacities satisfy governing equations by construction. For cold-formed steel channels, PINNs might penalize violations of shell stability conditions and Orr–Sommerfeld buckling criteria, markedly improving generalization to novel geometries and boundary conditions.

A multi-fidelity data pipeline further reduces data-generation costs and accelerates convergence. In such a scheme, a large corpus of low-fidelity data analytical buckling formulas, simplified beam-column interaction results, and coarse FEA outputs serves for initial pretraining. Subsequent transfer-learning fine-tuning on smaller, high-fidelity experimental or detailed simulation datasets refines predictions while retaining the physics-informed structure.

To accommodate evolving materials and practices, dynamic model updating introduces online or incremental learning from streaming structural health monitoring (SHM) data strains, displacements, accelerations and periodic new FEA results. This continuous-learning paradigm adjusts network weights without full retraining, producing adaptive surrogates whose fidelity improves over a structure's service life.

Finally, uncertainty quantification is essential for safety-critical decisions. Bayesian neural networks with weight distributions, Monte Carlo dropout at inference, and deep ensembles can deliver predictive distributions rather than point estimates. Calibrated confidence intervals (e.g., 90 % or 95 %) allow engineers to apply explicit safety factors and support regulatory risk assessments.

Integration with Classical FEA. AI-driven simplification of FEA models can drastically reduce runtimes in early design stages. Surrogate predictors of stress gradients and buckling zones can guide adaptive mesh refinement resolving flange–web junctions with fine shell elements while coarsening mid-span regions thereby cutting FEA runtimes by 30–50 % with negligible loss of accuracy.

Automated validation classifiers, trained in historical FEA cases, can scan input decks for common setup errors unconstrained degrees of freedom, misapplied boundary conditions, inconsistent element formulations and flag them prior to simulation, reducing returns by up to 70 %.

AI-assisted exploration and visualization dashboards can present Pareto-optimal sets of cross sections balancing weight, cost, and safety indices in real time. By coupling rapid surrogate predictions with reduced-order FEA checks in a closed loop, engineers can interactively filter and compare hundreds of options within minutes, fostering innovation and avoiding locally confined choices.

Strategic and Real-World Applicability. The establishment of a standardized benchmarking framework including an open-access repository of thin-walled profiles, beam and frame assemblies, and high-fidelity FEA and experimental data will promote reproducibility and fair algorithm comparisons. Defined metrics such as percentage weight reduction, computational time, and safety margins should be included, with periodic community challenges to drive advancement and regulatory dialogue.

Integrating AI with structural health monitoring closes the loop between design and operation. By feeding in-service SHM data (strain, acceleration, temperature) into anomaly-detection and model-updating algorithms, emerging damage or performance drift can be identified early, prompting maintenance or design reassessments. This synergy enhances resilience and supports lifecycle optimization of structural systems.

Regulatory and Educational Alignment. To secure formal acceptance of AI in safety-critical design, joint working groups of standards bodies (AISC, Eurocode committees), academics, and software vendors must define validation protocols, documentation requirements, and certification pathways. Specifying minimum dataset sizes, interpretability criteria, and safety-factor methodologies will embed AI outputs into recognized design codes.

Engineer-friendly explainable AI (XAI) tools integrated as plugins in mainstream CAD and FEA software should provide interactive dashboards that employ SHAP, LIME, or saliency mapping to answer “why” questions about model recommendations, bridging the gap between black-box predictions and domain expertise.

Finally, tailored educational and training programs spanning university curricula modules, professional certification courses, and continuing-education workshops must cover AI fundamentals, surrogate modeling, PINNs, uncertainty quantification, and hands-on case studies. These initiatives will equip both future and practicing engineers with the skills required to deploy AI effectively in structural workflows.

By pursuing these enhancements from methodological advances and FEA integration to strategic benchmarks and professional development the structural engineering community can address data scarcity, interpretability, and regulatory alignment, fully harnessing AI to deliver safer, more economical, and innovative infrastructure solutions.

Research Gaps and Areas Needing Additional Attention

Despite significant advances in AI-augmented cross-section design, several critical gaps hinder full adoption and engineering confidence. First, most studies remain confined to academic benchmarks or small-scale pilot projects. Comprehensive case studies in active commercial developments such as bridges, high-rise buildings, and industrial facilities are urgently needed. These studies should trace AI-recommended cross-sections through construction, document material savings, cost impacts, fabrication tolerances, and field performance under service loads. Only by demonstrating reliability amid real-world variability can practitioners justify investments in new AI-driven workflows.

Second, current building codes and design standards were devised around empirical formulas and classical analysis, which often differ from AI-generated solutions. Rigorous investigations must map AI model inputs and outputs to existing code provisions (for example, Eurocode, AISC, ACI), establish acceptable tolerance ranges, and propose amendments or supplemental guidelines for AI-derived designs. Collaborative forums that bring together researchers, code committees, and industry stakeholders will be essential to draft validation protocols and certification criteria for AI tools.

Third, literature overwhelmingly emphasizes successes while underreporting method failures and limitations. Systematic documentation of AI failure modes whether due to sparse or biased data, extrapolation beyond training domains, or flawed model assumptions is vital. A shared repository of anonymized failure cases would enable collective learning, help define each method's domain of applicability and guide robust risk-mitigation strategies.

Fourth, AI-optimized cross-sections have proven effective in short-term load tests and simulations, yet their long-term behavior such as creep, fatigue, corrosion, and thermal cycling remains largely unquantified. Establishing longitudinal monitoring programs for AI-designed structures will generate crucial durability data. Integrating these observations into dynamic retraining pipelines will ensure that AI recommendations account for real-world degradation mechanisms, thereby safeguarding service-life performance.

Fifth, engineers depend on probabilistic frameworks and safety factors to manage uncertainty, but AI models typically produce deterministic outputs. Research must develop unified risk-management methodologies that quantify input uncertainties (for example, material properties and loading conditions), propagate them through AI models, and translate predictive distributions into design safety factors. Demonstrating alignment between AI-derived confidence intervals and code-prescribed reliability indices will be key to regulatory acceptance.

Sixth, most AI investigations address routine gravity, wind, or serviceability loads, yet structures must also resist extreme events such as seismic accelerations, blast loads, fire exposure, and impacts. Dedicated studies are required to generate appropriate training datasets via advanced finite-element simulations, physical testing, or multi-physics models; to evaluate AI extrapolation capabilities; and to embed physics-informed safeguards against unsafe predictions under novel or extreme conditions.

Seventh, while material savings and design-cycle reductions are often highlighted, the substantial upfront investment in data generation, model development, software integration, and personnel training are rarely quantified. A comprehensive cost-benefit framework should capture these initial and ongoing expenses, estimate payback periods across project scales, and compare traditional and AI-augmented workflows in terms of labor hours, licensing fees, and pipeline maintenance costs.

Eighth, even the most advanced AI models offer limited value if they fail to integrate smoothly with existing engineering tools and processes. Research is needed on human-computer interaction and workflow integration examining how AI modules interface with BIM platforms, finite-element software, and project-management systems. User-acceptance studies and pilot deployments across diverse engineering teams will identify cultural and organizational barriers, preferred interfaces, and effective change-management strategies.

Ninth, explainable AI techniques such as SHAP values, saliency maps, and symbolic regression promise to demystify model decisions, yet their practical effectiveness in supporting engineer judgment remains untested. Empirical evaluations should compare different XAI methods, assess their impact on review time and confidence levels, and establish standardized protocols tailored to structural design contexts.

Tenth, the ultimate promise of AI-augmented design lies in closed-loop systems that adapt based on in-service performance. However, few implementations demonstrate end-to-end workflows from AI-optimized cross-section selection to structural-health-monitoring feedback. Pilot projects embedding sensors in AI-designed members and retraining models with performance data will illustrate the feasibility of cyber-physical systems. Detailed case reports should describe system architectures, data-pipeline designs, retraining schedules, and retrofit decision criteria.

Addressing these gaps will require coordinated efforts among structural engineers, AI researchers, software developers, and regulatory authorities. By pursuing real-world validation, regulatory alignment, failure transparency, long-term monitoring, uncertainty quantification, extreme-event robustness, economic analysis, workflow integration, explainability, and SHM feedback loops, the community can elevate AI-driven cross-section design from a promising research frontier to an indispensable foundation of modern structural engineering practice.

Application for Permanent Formwork Section Calculation

Permanent formwork systems, including precast concrete panels, profiled steel decks, insulated concrete forms (ICFs), and stay-in-place composite elements, serve both as construction formwork and as structural components in the completed structure. Their design must satisfy a complex matrix of requirements, such as adequate strength, stiffness, fire resistance, long-term durability, thermal and acoustic performance, constructability, and cost constraints. The multifaceted demands of permanent formwork thus present an ideal opportunity for AI-augmented section calculation methods to deliver holistic optimization.

Overview and Multi-Functional Demands. Permanent formwork remains in place and contributes to the structural behavior of slabs, beams, or walls. During concrete placement, it resists hydrostatic pressures and construction loads; thereafter, it participates in composite load-carrying capacity under live and dead loads. In ICF systems, it provides thermal insulation that influences heat transfer and overall energy performance, while in partition walls it offers acoustic attenuation via integral damping layers. Formwork materials must also maintain integrity and load-bearing capacity during fire exposure. Moreover, features such as interlocking profiles or modular panels streamline on-site assembly and reduce labor costs. Balancing these competing objectives through manual trial-and-error or sequential design loops is time-consuming and prone to suboptimal trade-offs, whereas AI methods can consider all functional requirements concurrently and identify section geometries that satisfy multi-physics criteria.

Design Challenges in Structural, Durability, and Thermal Performance. Permanent formwork design involves intricate load paths: during concrete placement, formwork must accommodate dynamic pressures and construction weights, and after curing it must act compositely under life, dead, and environmental loads. Long-term durability challenges arise from corrosion susceptibility in steel decking interfaces with concrete, requiring predictive models of moisture ingress and chloride diffusion. Thermo-physical interactions in ICF systems affect both thermal gradients and bond behavior, influencing shrinkage and cracking risk. Fire-exposure scenarios demand that formwork prevent spalling and maintain structural integrity under elevated temperatures governed by performance-based criteria. Classical finite-element analyses that model contact interfaces, nonlinear material behavior, and thermal-mechanical coupling are accurate but computationally intensive when iterating multiple section profiles for multi-objective optimization.

AI-Driven Approaches for Rapid Evaluation and Inverse Design. Machine-learning surrogate models trained on extensive datasets of finite-element simulations and experimental results can predict structural capacities, deflections, thermal resistances, and acoustic performance in milliseconds, replacing full-physics analyses in preliminary screening. Inverse-design frameworks allow engineers to specify target criteria such as minimum load capacity, R-value thresholds, or acoustic transmission losses and yield optimal formwork dimensions and material configurations. These loops typically couple neural-network or Gaussian-process surrogates with genetic algorithms to converge rapidly on viable solutions. Generative adversarial networks and variational autoencoders propose novel section shapes such as variable-depth steel decking or thermally optimized rib patterns in ICFs that satisfy multi-physics constraints and reveal innovative designs beyond standard catalogs.

Hybrid AI-FEA Workflows for Speed and Fidelity. Combining AI predictions with targeted finite-element validations ensures both computational efficiency and model fidelity. Initial AI-guided screening can reduce thousands of candidate profiles to a shortlist of five to ten, on which engineers then perform detailed finite-element analyses, thereby cutting total simulation runs by an order of magnitude. Pre-analysis AI classifiers can automatically detect boundary-condition mismatches, material property errors, and meshing inconsistencies in finite-element input files, minimizing reruns and improving workflow reliability. Closed-loop optimization pipelines feed validated simulation results back into surrogate retraining, refining accuracy without full dataset retraining for each iteration.

Key Benefits and Directions for Future Research. AI-augmented permanent formwork design offers accelerated multi-objective optimization that concurrently addresses structural, thermal, durability, and constructability targets, yielding material and cost savings through precise geometric tuning. Constructability insights emerge from evaluating modular assembly within the optimization loop, while resilience can be enhanced by integrating structural health monitoring data to adapt designs over the service life. Future research should prioritize the development of standardized, high-fidelity datasets encompassing composite action, thermal-mechanical coupling, and corrosion mechanisms for robust surrogate training. Life-cycle assessment metrics including embodied carbon and maintenance costs must be incorporated into AI objective functions. Physics-informed constraints for moisture transport, thermal diffusion, and fire-induced spalling should be embedded within learning architectures. Finally, field validation through pilot projects instrumented with real-time monitoring systems will close the loop between AI design, construction realities, and in-service performance, establishing permanent formwork section calculation as a rigorous, data-driven practice.

Conclusions

This review has demonstrated that artificial intelligence offers a powerful, complementary toolkit for structural cross-section design, unifying supervised learning, reinforcement learning, evolutionary and generative algorithms, and hybrid physics-informed models. In conventional frames, trusses, and columns, AI methods have matched or exceeded the efficiency and material-savings of classical optimizers, while surrogate models and design co-pilot platforms have compressed design cycles by an order of magnitude. For thin-walled members, machine-learning and deep-learning surrogates accurately predict complex buckling and strength interactions, support inverse design workflows that achieve target capacities within narrow error bounds and yield interpretable formulas that can inform future code provisions.

Case studies in both academia and industry validate AI's potential: benchmark problems demonstrate reproducibility and performance gains; commercial tools embed generative and surrogate-based routines into mainstream software; and translation pathways through symbolic regression and surrogate-augmented FEA pipelines offer practical routes for adoption. Yet critical challenges remain, including the need for comprehensive real-world validations, regulatory alignment, systematic reporting of failure modes, long-term durability monitoring, unified uncertainty quantification, and resilience under extreme loads.

Focusing on permanent formwork systems, we have shown how AI-augmented surrogates, inverse-learning frameworks, and generative profiles can address the multi-physics demands of strength, stiffness, thermal insulation, acoustic performance, fire resistance, and constructability in a single optimization loop. Hybrid AI-FEA workflows and closed-loop retraining further balance computational speed with model fidelity, paving the way for high-throughput, multi-objective design.

Moving forward, realizing AI's full promise will require interdisciplinary collaboration among structural engineers, material scientists, AI researchers, software developers, and regulatory bodies. Standardized benchmark repositories, engineer-friendly explainable AI tools, and integrated structural health monitoring feedback loops will be essential to build trust and drive widespread deployment. By addressing data scarcity, interpretability, and code-compliance barriers, the community can transform AI-driven cross-section optimization from a research frontier into a reliable, industry-standard practice that delivers safer, more economical, and more resilient infrastructure.

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Анотація. *Вибір поперечних перерізів визначає оптимальну геометрію та матеріал балок, колон, ферм і плит з урахуванням вимог міцності, жорсткості, експлуатаційних характеристик і нормативних положень. Традиційні підходи – аналітичні формули, емпіричні положення нормативів, методи скінченних елементів і скінченої смуги є надійними, але часто потребують значного часу та закладають консервативні запаси безпеки. Штучний інтелект (ШІ) пропонує швидке дослідження простору проєктних рішень, виявлення нетривіальних варіантів і прискорені робочі процеси, які доповнюють, а не замінюють експертизу інженера.*

Різноманітні методи ШІ застосовуються до проєктування поперечних перерізів. Моделі з навчанням з учителем – штучні нейронні мережі, метод опорних векторів, гаусівська процесійна регресія та ансамблеві дерева навчаються на парах «вхід-вихід» для прогнозування таких метрик, як критичні навантаження при втраті стійкості, остаточна несуча здатність і прогини за мілісекунди, а оцінки невизначеності допомагають приймати рішення з урахуванням ризиків. Підкріплювальне навчання розглядає призначення перерізу як послідовний процес прийняття рішень; графові та мультиагентні архітектури забезпечують більш швидке збіжність і зменшення маси конструкції порівняно з класичними оптимізаторами. Еволюційні алгоритми, оптимізація рою частинок і генеративні змагальні мережі досліджують одночасно неперервні та дискретні змінні, пропонуючи гнучкі багатокритеріальні рішення. Гібридні фізично-інформовані моделі вбудовують рівняння рівноваги та стійкості в процес навчання або використовують похідні характеристики – коефіцієнти стінності та моменти опору для підвищення надійності, інтерпретованості та відповідності нормативам.

У звичних конструктивних системах – плоских і тривимірних рам, ферм і діафрагм жорсткості робочі процеси на основі ШІ приносять вимірні переваги. Графове підкріплювальне навчання зменшило загальну масу сталі до 12 % у порівнянні з оптимізаторами рою частинок або імітованого відпалу, а конвеєри з сурогатними моделями (нейронні мережі або гаусівські процеси) пропонують близько оптимальних розмірів елементів за мілісекунди, уникаючи годин аналізу методом скінченних елементів. Інтегровані платформи «асистент проєктування» з поєднанням генеративних алгоритмів та автоматизованих перевірок відповідності нормам генерують пропозиції щодо розмірів перерізів у понад десять разів швидше за ручні методи, з відхиленнями менше 20 %.

Тонкостінні елементи ускладнені взаємодією різних режимів втрати стійкості та нелінійною поведінкою. Сурогатні моделі, навчені на даних скінченних смуг або скінченних елементів, досягають коефіцієнтів детермінації R^2 вище 0,98 при прогнозуванні навантажень, що призводять до втрати стійкості, і з точністю класифікують режими відмови понад 95 %. Гаусівські процеси та ансамблеві методи дають оцінки дисперсії *прогнозів, що підтримують рішення з урахуванням довіри. Інверсні схеми проєктування, які поєднують сурогати з генетичними або ройовими оптимізаторами, генерують оптимальні профілі з похибкою до 5 % від перевірок. Символічна регресія дозволяє отримувати явні формули, придатні для включення до норм.*

Системи незнімної опалубки, що виконують роль і монтажної підтримки, і несучих елементів, ставлять багатофункціональне завдання – одночасно забезпечувати структурну міцність, теплову ізоляцію, звукоізоляцію, вогнестійкість і зручність монтажу. Сурогатні моделі, інверсні цикли та генеративні мережі на основі ШІ можуть оперативно оцінювати тисячі варіантів профілів. Гібридні робочі процеси ШІ-МКЕ відбирають кращі кандидати для детального моделювання, застосовують перевірки консистентності вхідних даних і поступово підвищують точність сурогатів за допомогою замкнутих циклів навчання.

Незважаючи на досягнення, залишаються значущі прогалини: комплексні дослідження на реальних об'єктах, узгодження з чинними нормативами, прозора документація невдач методів, дані про довгострокову довговічність, єдина методика кількісної оцінки невизначеності та стійкість в екстремальних умовах. Усунення цих прогалин через міждисциплінарну взаємодію інженерів, дослідників ШІ, розробників ПЗ і регуляторних органів вирішальне для впровадження оптимізації поперечних перерізів на основі ШІ як надійної практики у сучасному будівництві.

Ключові слова: *штучний інтелект, машинне навчання, незнімна опалубка, оптимізація поперечних перерізів, сурогатне моделювання, генеративне проєктування, фізично-інформовані нейронні мережі, інтеграція даних різної точності, моніторинг стану конструкцій, гібридні робочі процеси ШІ-МКЕ.*