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

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Abstract. *This research reviews the integration of artificial intelligence in structural cross-section selection, highlighting supervised learning, reinforcement learning, evolutionary algorithms, and physics-informed models as complementary methodologies. Supervised surrogates achieve millisecond-scale predictions of buckling and strength with* R^2 *up to 0.98, while reinforcement learning agents navigate discrete section catalogs under code-compliance constraints to reduce weight by 8–12%. Evolutionary and generative frameworks yield novel geometries and human-readable design formulas via symbolic regression. Hybrid physics-informed approaches embed equilibrium and buckling laws into neural networks, enhancing out-of-sample fidelity and uncertainty quantification through Bayesian methods. Case studies demonstrate 18-25% material savings and order-of-magnitude time reductions in both academic benchmarks and industry tools. The review identifies key challenges data scarcity, interpretability, regulatory alignment, and workflow integration and proposes future research directions including multi-fidelity learning, closed-loop AI-FEA pipelines, standardized benchmarking, and real-time model updating via structural health monitoring. Finally, the potential of AI-augmented design for permanent formwork systems is explored, advocating high-fidelity datasets and pilot implementations for multi-physics optimization.*

Key words: *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 underpins the safe, economical, and code-compliant design of beams, columns, trusses, and slabs. Traditional approaches analytical formulas, empirical code provisions (Eurocode, AISC, ACI), and iterative numerical techniques such as finite element analysis (FEA) or the finite strip method are well established but resource-intensive, rely heavily on expert judgment for stability issues (local, distortional, global buckling), and often include conservative safety margins. Recent advances in artificial intelligence (AI) offer a means to augment engineering expertise, accelerate design iterations, and explore non-intuitive solutions across expansive design spaces, without supplanting professional judgment.

AI Methodologies for Cross-Section Design

AI-based approaches to cross-section selection fall into four principal categories, each addressing distinct facets of the design challenge:

Supervised Learning leverages labeled datasets of geometric, material, and loading parameters paired with performance outcomes. Artificial neural networks (ANNs), support vector machines (SVMs), Gaussian process regressors (GPRs), and ensemble methods (random forests, gradient boosting) provide millisecond-scale predictions of buckling loads and ultimate strengths, achieving R^2 up to 0.98 for cold-formed steel channels and accurately classifying failure modes without repeated eigenvalue solves [12]. Bayesian extensions and SHAP-based interpretability mitigate "black-box" concerns, while limitations persist when extrapolating beyond the training distribution [1, 10, 11, 19].

Reinforcement Learning (RL) formulates section selection as a sequential decision problem. Graph-based agents, treating structural layouts as node-edge graphs, assign standard profiles with reward functions that integrate weight minimization and code compliance constraints. In planar frames, RL achieved lighter designs faster than particle swarm optimizers (PSO) [2]; multi-agent extensions to three-dimensional frames further accelerated convergence to minimum-volume configurations [3]. The principal trade-off is computational cost during training and policy interpretability.

Evolutionary and Generative Algorithms include genetic algorithms (GAs), PSO, simulated annealing, and generative adversarial networks (GANs). Hybrid GA-ANN workflows have optimized lipped channel sections for web-crippling loads, producing superior designs to code recommendations [20]. GAN-based frameworks propose novel perforated or nonstandard profiles, while gene expression programming and multi-gene symbolic regression yield human-readable equations suitable for code integration [14]. These algorithms flexibly handle mixed variables and multi-objective criteria but require careful tuning and substantial computational resources for high-dimensional searches.

Hybrid Physics-Informed Models integrate analytical mechanics directly into learning pipelines. Physics-informed neural networks (PINNs) embed equilibrium and buckling equations into loss functions, ensuring out-of-sample fidelity. Multi-fidelity training pipelines combine low-cost analytical or coarse FEA data with high-fidelity simulations, and online transfer learning adapts models via structural health monitoring (SHM) streams. Bayesian neural networks and Monte Carlo dropout furnish predictive distributions with confidence intervals. Implementations demonstrate surrogate predictions that replace thousands of FEA runs with millisecond-scale inferences, although loss weighting and multi-fidelity retraining introduce complexity.

Performance, Cost, and Time Efficiency

AI-driven methods yield substantial material savings, cost reductions, and time efficiencies in conventional structures.

In academic benchmarks, graph-based RL achieved an 8% steel weight reduction and halved computational time compared to PSO in a two-bay, two-story planar frame [2], while multi-agent RL in 3D frames delivered a 12% volume reduction compared to simulated annealing [3].

Industry trials report 18–25% material procurement reductions, attributable to fine-tuned cross-section dimensions beyond manual heuristics. A Pennsylvania bridge block optimized via generative design realized a 20% material saving and correspondingly lower procurement and transportation costs.

Supervised surrogates, trained on harmony-search-optimized datasets, furnish near-optimal member sizes in milliseconds versus hours of conventional analysis [7]. Fully automated “design co-pilot” platforms, such as Tsinghua’s structure-Copilot, propose reinforced-concrete shear-wall sizing over ten times faster than human engineers, with weight deviations within 20% [8].

Constraint-aware optimization ensures safety: RL reward penalties for code violations, Gaussian process regressions outpacing Eurocode and AISC for stainless-steel tubular columns, and deep learning of web-crippling strengths all foster lean yet reliable designs [16, 19, 21].

AI in Thin-Walled Cross-Section Analysis

Thin-walled elements, with their sensitivity to local, distortional, and global buckling modes, benefit from data-driven surrogates and inverse design.

Buckling and Strength Prediction. Neural networks trained on finite-strip data for cold-formed channels achieved $R^2 \approx 0.98$ and >95% mode-classification accuracy [12]. GPR models on tubular column simulations reduced mean absolute error by 30% compared to Eurocode 3, while ensemble methods elucidate feature importance (e.g., thickness, flange width) to guide stiffening strategies.

Fire-Performance Modeling. ANNs, SVMs, random forests, and polynomial regressions benchmarked against Eurocode fire provisions for slender I-beams achieved a 40% reduction in predictive error, accurately capturing temperature–buckling interactions [10]. Deep belief networks further refine web-crippling capacity predictions under perforation.

Inverse Design. Coupling ANN surrogates with genetic or swarm optimizers yields cross-section geometries that match FEA validations within 5% error. Symbolic regression via gene expression programming generates closed-form formulas for design code adoption [14].

Interpretability and Uncertainty Quantification. Transfer learning adapts pre-trained networks to new section families with minimal data. Explainable AI techniques (SHAP, LIME) reveal input contributions, and Bayesian networks provide calibrated confidence intervals aligned with traditional reliability indices.

Case Studies and Translational Pathways

Controlled experiments and pilot implementations illustrate the practical impact of AI methods.

Academic Benchmarks. Harmony-search truss designs with neural surrogates, achieving >95% accuracy for 10-bar and 25-bar trusses in under a millisecond [7]. Qin et al.'s generative-design platform matched expert shear-wall proposals within a 20% weight deviation [8].

Commercial Tools. Autodesk's Revit and Robot modules report 10–15% material savings for steel and concrete sections; Tekla Structural Designer's automated steel-sizing routine reduces manual rework by up to 30%. Cloud services recommend steel connection details in seconds.

Workflow Integration. Symbolic regression yields explicit design equations adoptable in codes (e.g., Asghar et al.'s GFRP web-crippling formula within 3% error

[14]). Surrogate-augmented FEA pipelines reduce high-fidelity analyses by ~80%. BIM integrations enable direct import of loads and export of optimized section data.

Proposed Enhancements and Future Directions

To bridge the remaining gaps and foster widespread adoption, research should be pursued.

P*hysics-Informed and Multi-Fidelity Learning:* Embed shell stability and multi-physics constraints (thermal, acoustic, durability) into PINNs; combine analytical formulas, coarse and fine FEA data for cost-effective pretraining and targeted fine-tuning.

Dynamic Model Updating: Implement online learning from SHM data to adapt surrogates over a structure's service life; employ Bayesian and ensemble methods for real-time uncertainty quantification.

Benchmark Repositories and Regulatory Alignment: Establish open-access datasets of thin-walled profiles and frame assemblies; define standardized metrics (weight reduction, time savings, safety margins) and community challenges; engage code committees to draft AI tool validation protocols and safety-factor methodologies.

Extreme Load and Durability Modeling: Generate specialized datasets for seismic, blast, and fire scenarios; quantify long-term phenomena (creep, fatigue, corrosion); integrate life-cycle assessment and maintenance cost metrics into optimization objectives.

Human-Computer Interaction and Explainability: Develop engineer-friendly XAI plugins (SHAP, saliency mapping) in CAD/FEA platforms; conduct user-acceptance studies to refine interfaces and change-management strategies.

Closed-Loop AI-FEA Workflows: Combine surrogate screening with targeted FEA validation and iterative retraining; automate mesh-refinement guidance; embed classifiers for input-deck error detection.

Application to Permanent Formwork Systems

Permanent formwork precast panels, profiled decks, insulated concrete forms present a multi-physics optimization challenge (hydrostatic pressure, composite action, thermal insulation, acoustic attenuation, fire resistance, constructability). AI surrogates trained on composite FEA and experimental data enable millisecond predictions of structural, thermal, and acoustic performance. Inverse-design loops coupled with GAs or variational autoencoders generate novel profiles that satisfy multi-physics criteria. Hybrid AI-FEA workflows shortlist candidate sections and refine through detailed FEA, reducing simulation runs by an order of magnitude. Future work should expand high-fidelity datasets to include moisture transport, thermal diffusion, and corrosion mechanisms, and incorporate embodied carbon and maintenance metrics into objective functions. Real-world pilot projects instrumented with SHM systems are essential to close the design–operation feedback loop.

Summary and conclusions.

AI-augmented cross-section selection unifies supervised learning, reinforcement learning, evolutionary algorithms, and physics-informed models into a complementary toolkit that enhances material efficiency, accelerates design cycles, and preserves safety and code compliance. Benchmarks and pilot projects substantiate 8-25% material savings, order-of-magnitude time reductions, and high-fidelity predictive accuracy. To transition from research to routine practice, the community must address data scarcity, interpretability, regulatory frameworks, and workflow integration. Embedding AI within standardized benchmarks, explainable tools, SHM-driven adaptive learning, and cross-disciplinary collaboration will solidify AI-driven cross-section optimization as a cornerstone of modern structural engineering.

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