

Structural Weight Minimization and Optimization Using Machine-Learning-Driven Surrogate Finite Element Models

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Abstract

This paper presents a machine-learning-driven surrogate finite element framework for structural weight minimization. Traditional FEM-based optimization requires repeated simulations for each design alternative, which becomes computationally expensive when the design space is large. To overcome this limitation, a parametric beam dataset was generated by varying geometry, material properties and loading conditions. Machine-learning models were trained to predict maximum stress, maximum deflection, factor of safety and structural weight. Random Forest, Gradient Boosting and Neural Network regressors were evaluated using R² and MAE metrics. The selected surrogate model was then used for rapid constrained screening of lightweight candidate designs, and the best solution was validated using independent physics-based response calculations. Results showed that the framework can identify structurally feasible lightweight alternatives while reducing repeated simulation effort. The study supports sustainable and intelligent structural design by combining FEM accuracy, machine-learning speed and final engineering verification.

Keywords: Structural weight minimization; finite element method; machine learning; surrogate modeling; structural optimization; sustainable design.

1. Introduction

Structural engineering has entered a stage where safety, economy and sustainability must be achieved together rather than treated as separate design goals. Conventional design generally begins with assumed dimensions, checks the member under expected loading and then repeats the process until strength and serviceability limits are satisfied. Although this approach is dependable, it is not always efficient because a safe section may still contain unnecessary material. In high-volume construction, bridges, industrial structures, long-span systems and modular components, even a small reduction in member weight can lower material cost, foundation demand, transportation effort and embodied carbon. Structural weight minimization therefore becomes an important design objective, provided that stress, deflection and factor of safety requirements remain within acceptable limits. The finite element method (FEM) is the most widely accepted computational tool for evaluating complex structural behaviour because it can represent geometry, boundary conditions, material properties and loads with high fidelity. However, optimization through repeated FEM analysis is computationally expensive. Every change in span, section size, density, stiffness, yield strength or load level may require a new simulation, and a large design space may need hundreds or thousands of analyses before an optimum is identified.

Machine learning provides a practical solution to this computational barrier by creating surrogate finite element models. A surrogate model is trained on a dataset generated from FEM or physics-based simulations and then learns the relationship between input design variables and output responses. Once trained, the surrogate can estimate stress, deflection, factor of safety and weight almost instantly. This enables rapid screening of many design alternatives while retaining the engineering logic captured by the original simulation data. In the present study, a simply supported rectangular beam under a central point load is used as the reference structural component. Seven input variables are considered: length, width, depth, elastic modulus, density, yield strength and point load. Four output responses are predicted: maximum bending stress, maximum deflection, factor of safety and structural weight. The method combines parametric response generation, machine-learning regression, constrained optimization and final physics-based validation.

The significance of this work lies in its integrated workflow. Many studies focus only on prediction accuracy, while practical design also requires feasible optimization and validation. In this research paper, the surrogate model does not replace engineering judgment; instead, it acts as a fast evaluator inside a constrained design process. The optimized design is accepted only when it satisfies stress, deflection and factor-of-safety limits after independent recalculation.

The approach therefore supports both speed and reliability. It is suitable for extension to commercial FEM packages such as ANSYS, Abaqus, STAAD.Pro or OpenSees, where the data-generation module can be replaced by automated high-fidelity simulations. The proposed framework contributes to intelligent structural design by reducing computational effort, improving design-space exploration and supporting sustainable material use.

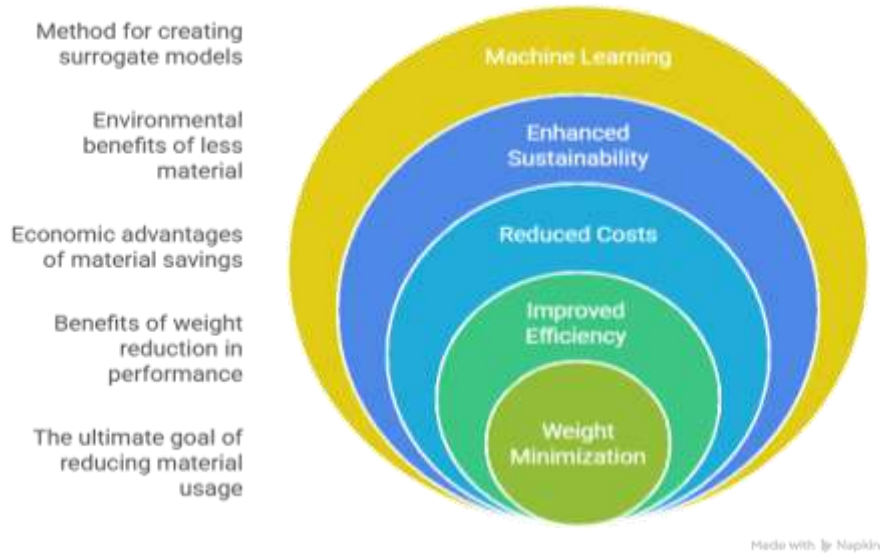


Figure 1. Conceptual framework of machine-learning-driven structural weight minimization and sustainability benefits.

1.1. Aim and Objectives

Aim:

To develop and evaluate a machine-learning-driven surrogate FEM framework for rapid structural weight minimization while satisfying strength, serviceability and safety requirements.

1. To develop a parametric FEM-style model for a selected structural component and generate simulation data by varying geometry and material properties.
2. To train machine-learning surrogate models on FEM-generated datasets for predicting stress, deflection and factor of safety.
3. To implement a structural weight minimization framework using the surrogate ML model for rapid design evaluation and optimization.
4. To analyze feature sensitivity using ML interpretability methods to understand the influence of design parameters on structural weight and performance.

2. Literature Review

Recent research strongly supports the use of machine-learning surrogates for accelerating FEM-based structural analysis and optimization. Vurtur Badarinath et al. [1] demonstrated that supervised learning can map limited measurement or design information to detailed finite element responses of one-dimensional systems, and their work established the feasibility of replacing repeated beam simulations with trained regression models. Kneifl et al. [2] developed a nonintrusive nonlinear model-reduction strategy for structural dynamics and showed that machine learning can predict reduced basis coefficients without modifying the original simulation code, which is valuable when commercial solvers are used. Hashemi et al. [3] proposed ML-based surrogate finite element models for dynamic mechanical systems and reported that tree-based and neural algorithms could estimate structural response with much lower assessment time than repeated FEA. Wu et al. [4] applied surrogate-based physics-informed neural networks to the size, shape and topology optimization of single-layer domes, confirming that neural surrogates can accelerate geometrically nonlinear structural optimum design. Etim et al. [5] reviewed machine-learning applications in structural engineering and concluded that

ML models are increasingly useful for computational mechanics, structural health monitoring, stress prediction, failure analysis and optimization where high-fidelity simulations are expensive. Pei et al. [6] combined composite-informed FEM with supervised learning for predicting mechanical properties of anisotropic tyre materials and highlighted that LSTM, FNN and XGBoost can capture complex input-output relationships from FEM-generated datasets. Huang et al. [7] integrated machine learning and finite elements for fluid-structure interaction seismic response analysis of aqueduct structures and reported large savings in computational time while maintaining small prediction errors, showing the benefit of surrogate models in multiphysics structural systems. Zhao et al. [8] used jackknife model averaging to combine polynomial response surfaces, support vector regression, radial basis functions, XGBoost, LightGBM and random forest for frame displacement prediction, demonstrating that ensemble surrogates can improve robustness compared with single models. Zhou et al. [9] introduced manifold-learning-enhanced surrogate modeling for reliability-based design optimization and emphasized that dimensionality reduction improves efficiency in high-dimensional nonlinear problems. Bishop [10] provided the probabilistic and statistical learning foundations required for model training and generalization. Hastie et al. [11] explained regression, model selection and validation principles that are essential when evaluating surrogate accuracy using independent test data. Goodfellow et al. [12] discussed deep-learning architectures capable of representing nonlinear response surfaces in engineering problems. Breiman [13] introduced random forests, an ensemble method suited for nonlinear interactions among geometry, load and material variables. Friedman [14] formulated gradient boosting machines, which are effective for reducing residual prediction errors across sequential learners. Bathe [15] and Rao [16] presented the finite element fundamentals that support the physics-based response equations used for structural validation, while Arora [17] and Deb [18] explained engineering optimization and evolutionary search concepts relevant to constrained weight minimization. Collectively, these studies show that ML-FEM integration is technically promising; however, most published works emphasize prediction or isolated response estimation. Fewer studies combine multi-response prediction, constraint-based weight minimization, sensitivity interpretation and final validation in one engineer-oriented workflow. This gap is addressed in the present paper by integrating surrogate regression with structural feasibility screening and independent recalculation of the optimized beam design.

2.1. Research Gap

Although many researchers have successfully applied machine learning to finite element response prediction, a practical gap remains between accurate prediction and usable structural optimization. Existing studies often validate only one response, such as displacement or stress, and many do not connect the trained model to a complete constrained design loop. In structural weight minimization, however, the lightest member is acceptable only when stress, deflection and factor of safety are simultaneously satisfied. Another gap is the limited interpretation of input-variable influence. Engineers require evidence that the surrogate model behaves consistently with mechanics; for example, beam depth should strongly affect stiffness because moment of inertia depends on depth cubed. There is also limited demonstration of how surrogate-selected optima are verified by independent physics-based recalculation. Therefore, the present study develops an integrated framework that predicts multiple structural responses, screens feasible candidates rapidly, identifies the lightest validated design and presents sensitivity-based engineering interpretation.

3. Research Methodology

3.1 Parametric Structural Model

The research methodology is organized into six subsections so that the workflow can be reproduced and extended. First, a parametric structural model is defined for a simply supported rectangular beam subjected to a central point load. The selected beam is appropriate because its response is controlled by clear relationships among span, cross-section, elastic modulus, density, yield strength and load. The input variables are length, width, depth, elastic modulus, density, yield strength and point load. Engineering limits are assigned to each variable so that generated designs remain realistic. The response quantities are maximum bending stress, maximum mid-span deflection, factor of safety and structural weight.

3.2 Dataset Generation and Response Formulation

Second, a simulation dataset is generated using a physics-based FEM-style response model. For each design case, area is calculated as $A = b d$ and the second moment of area is calculated as $I = b d^3 / 12$. For a central point load, the maximum bending moment is $M = P L / 4$. The stress response is obtained from $\sigma = M c / I$, the deflection response from $\delta = P L^3 / (48 E I)$, the mass from $\rho A L$ and the factor of safety from f_y / σ . A total of 1500 design

instances are generated. The dataset is checked to remove non-physical or non-finite values, and the records are divided into training and testing subsets using an 80:20 split.

3.3 Surrogate Model Development

Third, surrogate machine-learning models are trained. Random Forest Regression, Gradient Boosting Regression and a feed-forward Neural Network are used as multi-output regressors. Each model receives the same seven input variables and predicts all four structural responses. Model performance is evaluated using coefficient of determination (R^2) and mean absolute error (MAE). The model with the highest balanced mean R^2 and acceptable engineering error is selected as the surrogate FEM predictor.

3.4 Surrogate-Based Optimization

Fourth, optimization is performed using surrogate-assisted candidate screening. The objective function is minimization of structural weight. The constraints are maximum stress less than allowable stress, maximum deflection less than span/250 and factor of safety greater than the required minimum. Because surrogate prediction is fast, many candidate sections can be screened rapidly. Fifth, the best candidates are validated by recalculating responses using the physics-based model rather than accepting the surrogate output directly. This step protects the design against surrogate approximation error. Finally, sensitivity and feature importance interpretation are used to identify dominant design variables and confirm that the model follows structural mechanics. This methodology creates a reliable bridge between computational intelligence and practical engineering design.

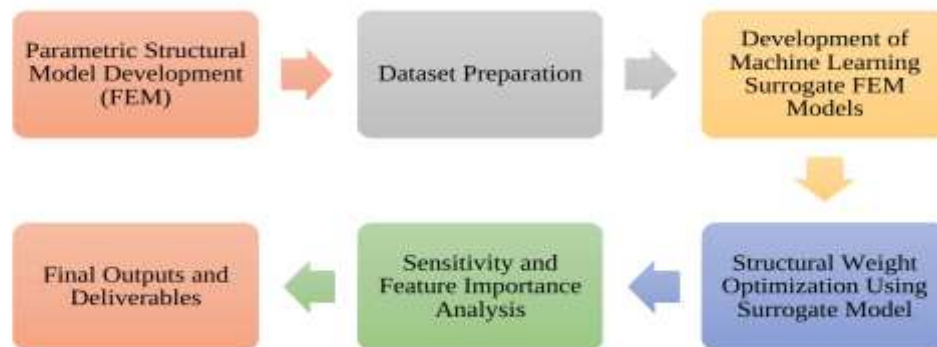


Figure 2. Methodology flowchart used for surrogate FEM structural optimization.

5. Results and Discussion

The generated design space contains 1500 structural design cases, of which 1245 cases are feasible and 255 cases are infeasible under the imposed stress, deflection and safety constraints. Thus, 83% of the sampled design alternatives satisfy all constraints, while 17% are rejected. This indicates that the problem is not trivial; lightweight designs often approach one or more constraint boundaries and therefore require careful validation. The comparative model results show that Random Forest produced the best balanced mean R^2 value of 0.8132, followed closely by Gradient Boosting with 0.8053. Gradient Boosting provided slightly better prediction for stress and weight, but Random Forest achieved a stronger balance across stress, deflection, factor of safety and weight. The neural network showed comparatively lower mean R^2 , suggesting that the available dataset and scaling conditions favored tree-based ensemble models for this problem.

The MAE results support the same interpretation. Gradient Boosting produced the lowest stress MAE of 16.8112 MPa and weight MAE of 202.8079 kg, while Random Forest showed competitive errors and stronger overall generalization. Deflection prediction was the most difficult response because deflection depends on span cubed and inertia, creating a highly nonlinear response surface. The optimized design selected after surrogate screening was validated independently. The final validated design had a positive stress margin of 92.8011 MPa, a positive deflection margin of 9.7626 mm and a factor-of-safety margin of 2.3053. These positive margins confirm that the selected lightweight design was not only numerically optimal but also structurally feasible. Overall, the results demonstrate that ML-driven surrogate FEM

models can reduce repeated simulation requirements while maintaining reliable design decisions when combined with final physics-based verification.

Table 1. Feasibility summary of the parametric design space.

Measure	Value
Total design cases	1500.0000
Feasible cases	1245.0000
Infeasible cases	255.0000
Feasible percentage	83.0000
Minimum feasible weight (kg)	118.6631
Average feasible factor of safety	39.9856

Table 2. Coefficient of determination for surrogate models.

Model	Stress R2	Deflection R2	FoS R2	Weight R2	Mean R2
random_forest	0.8640	0.5917	0.8354	0.9617	0.8132
gradient_boosting	0.8813	0.5172	0.8556	0.9672	0.8053
neural_network	0.8405	0.4610	0.8109	0.9488	0.7653

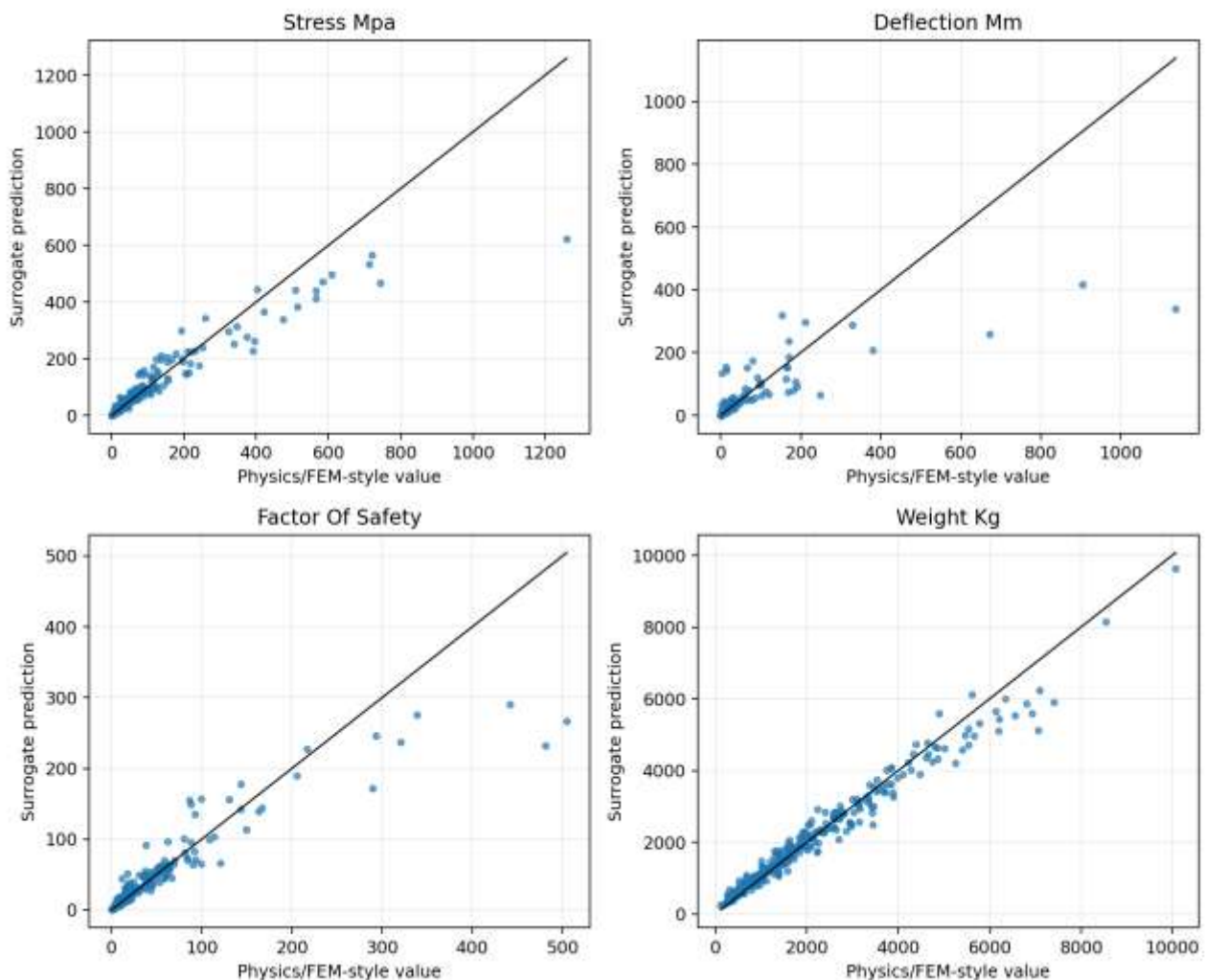


Figure 3. Surrogate prediction accuracy against physics-based response values.

Table 3. Mean absolute error for surrogate models.

Model	Stress MAE	Deflection MAE	FoS MAE	Weight MAE
random_forest	18.7959	15.2536	8.7074	218.9574
gradient_boosting	16.8112	18.2580	8.8532	202.8079
neural_network	22.6531	20.1067	11.9042	277.3491

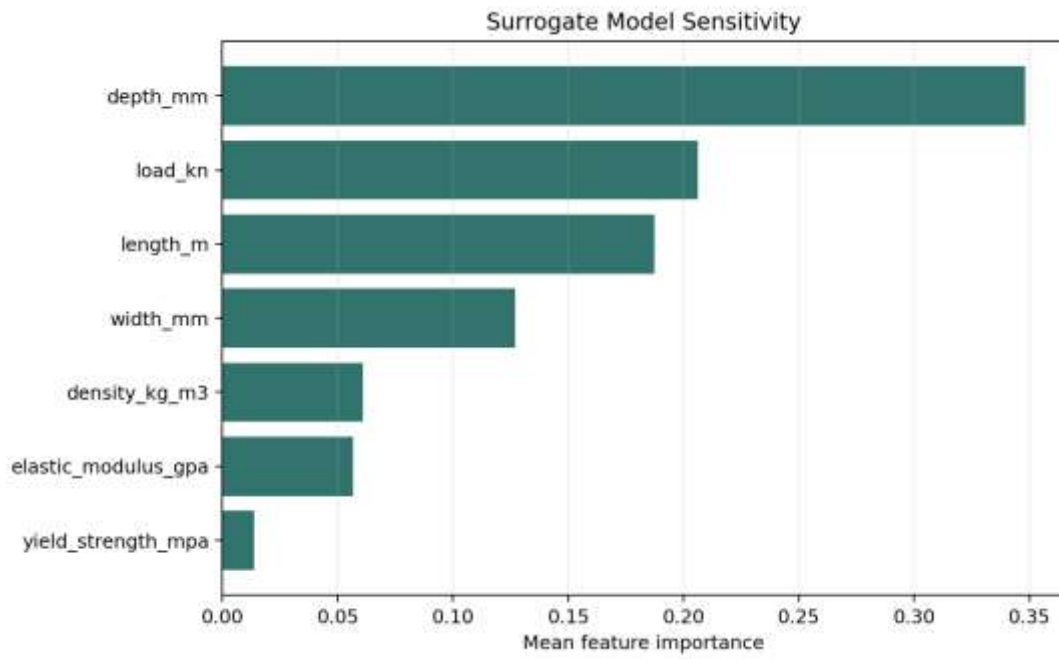


Figure 4. Feature importance and sensitivity of the selected surrogate model.

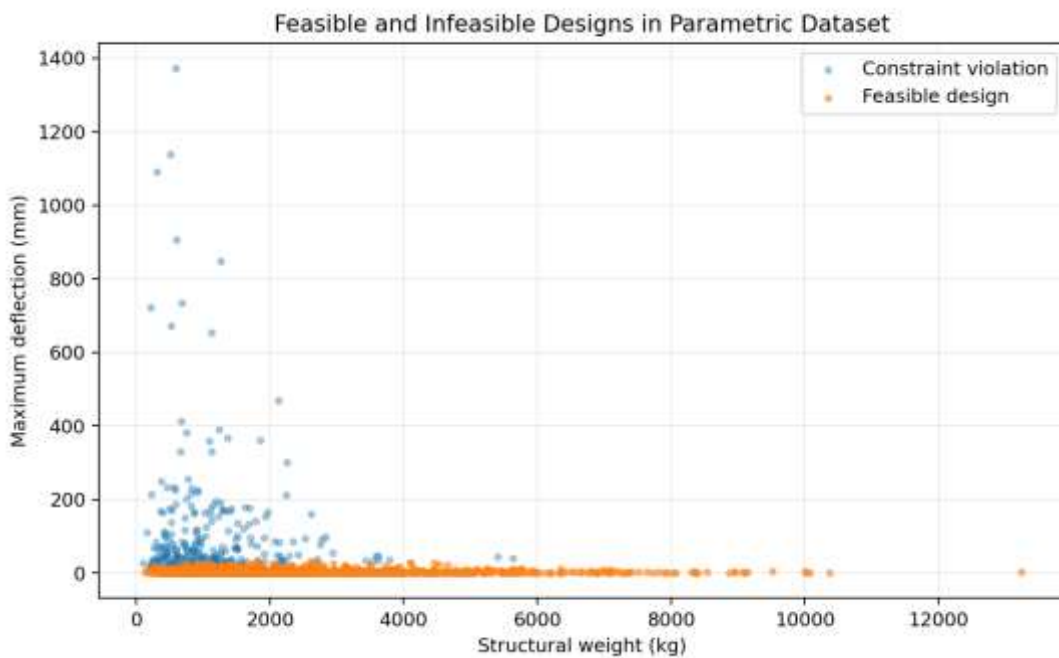


Figure 5. Feasible and infeasible design regions in the generated design space.

Table 4. Optimized design and validation results.

Quantity	Value
length_m	5.0000
width_mm	80.4657
depth_mm	250.8627
elastic_modulus_gpa	210.0000
density_kg_m3	2400.0000
yield_strength_mpa	500.0000
load_kn	100.0000
validated_weight_kg	242.3000
validated_stress_mpa	107.1989
validated_deflection_mm	10.2374
validated_factor_of_safety	4.3053
validated_feasible	True

Table 5. Validation margins of the optimized design.

Margin	Value	Unit	Interpretation
Stress margin	92.8011	MPa	Positive value indicates stress safety
Deflection margin	9.7626	mm	Positive value indicates serviceability safety
FoS margin	2.3053	-	Positive value indicates safety factor reserve

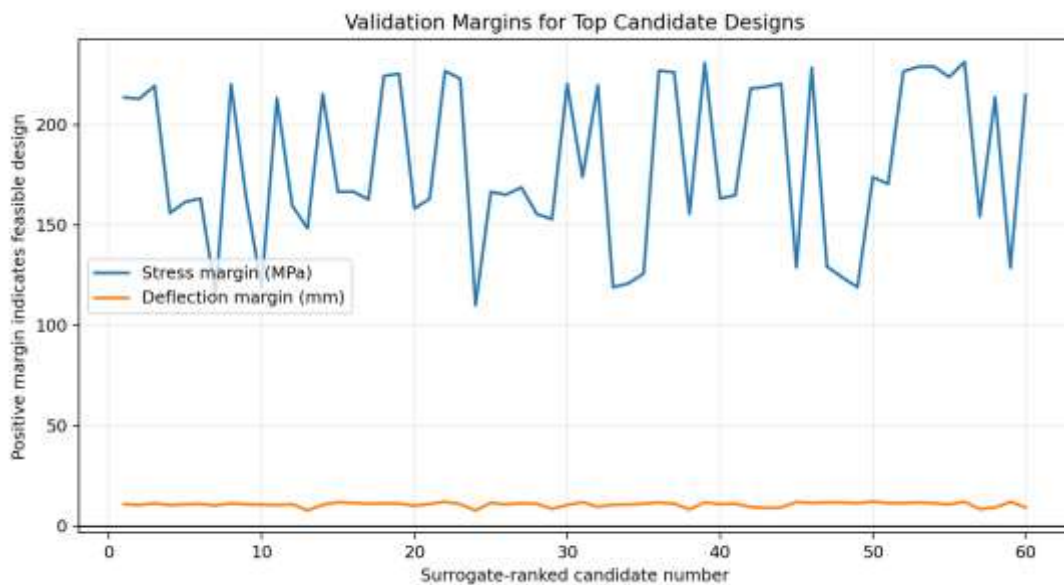


Figure 6. Stress and deflection validation margins for top candidate designs.

5. Conclusion

This research paper demonstrates an integrated machine-learning-driven surrogate FEM framework for structural weight minimization. A parametric beam problem was used to generate 1500 physics-based design cases containing seven input variables and four structural response quantities. The trained surrogate models successfully learned the nonlinear relationship between geometry, material properties, load and response. Among the tested methods, Random Forest provided the best balanced prediction performance, while Gradient Boosting showed competitive stress and weight accuracy. The feasibility analysis showed that 83% of the sampled design space satisfied the imposed constraints, confirming that optimization must balance weight reduction with strength and serviceability. The validated optimum maintained positive stress, deflection and factor-of-safety margins, proving that the lightest selected design remained structurally acceptable. The study confirms that surrogate modeling can significantly accelerate design-space

exploration and reduce dependence on repeated FEM runs. However, final validation remains essential because surrogate outputs are approximations. The proposed workflow is therefore useful as a decision-support tool that combines speed, interpretability and engineering verification for sustainable structural optimization.

6. Future Scope

- Future work may extend the proposed framework from a simply supported rectangular beam to more complex civil engineering components such as reinforced concrete beams, steel trusses, plates, bridge girders, composite members and framed structures.
- High-fidelity FEM data from ANSYS, Abaqus, OpenSees or STAAD.Pro can be connected directly to the same learning and optimization pipeline.
- Material nonlinearity, geometric nonlinearity, buckling, fatigue, vibration and seismic loading should be included to improve practical applicability.
- Larger datasets generated using design-of-experiments methods can improve model stability and reduce prediction uncertainty.
- Advanced algorithms such as XGBoost, LightGBM, Gaussian processes, graph neural networks and physics-informed neural networks may be compared with the present models.
- Reliability-based optimization can be added to account for uncertainty in load, material strength and manufacturing tolerance.
- Finally, a user-friendly design tool can be developed so that engineers can input design limits and obtain validated lightweight alternatives with feature-importance explanations.

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