

Article

Multi-Objective Optimization of Studs in Steel–Concrete Composite Beams

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Abstract

The arrangement of shear studs in steel–concrete composite beams (SCCBs) significantly influences both mechanical performance and economic efficiency. However, existing optimization studies have predominantly focused on cross-sectional dimensions and material grades, with systematic optimization of the mechanical parameters and spatial layout of shear connectors remaining largely unexplored. This study proposes a framework that couples machine learning surrogate models with the NSGA-II algorithm to address this gap. For a continuous SCCB, stud spacing, shear stiffness, and pull-out stiffness are adopted as optimization variables. The surrogate-assisted NSGA-II is employed to generate the Pareto front, and the analytic hierarchy process (AHP) combined with the technique for order preference by similarity to ideal solution (TOPSIS) is subsequently applied to identify the global optimal solution. The results demonstrate that the multilayer perceptron (MLP) delivers the best overall predictive accuracy. Feature importance analysis reveals that the shear stiffness of the studs over the pier, denoted KS-P, dominates the axial force response of the deck slab, contributing 48% of the total importance. After optimization, the deflection increases by 3.9%, whereas the axial force in the concrete slab decreases by 11.7% and the stud consumption is reduced by 88%, confirming the effectiveness and engineering practicality of the proposed method. The proposed methodology provides a theoretical basis and technical support for the refined design of shear connectors in SCCBs.

Keywords: steel–concrete composite beam; stud; machine learning; multi-objective optimization; SHAP analysis



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1. Introduction

Steel–concrete composite beams, which effectively combine the high tensile strength of steel with the superior compressive performance of concrete, achieve synergistic interaction between the two materials through shear connectors. Furthermore, these structures offer distinct advantages such as high construction efficiency, environmental friendliness, and controllable quality, thereby gaining increasingly widespread application in modern bridges and buildings [1–3]. Shear connectors, functioning as the critical components that ensure the cooperative work between steel and concrete, directly govern the overall structural safety and service life [4–7].

For a long period, headed shear studs have served as the most commonly employed shear connectors, owing to their ease of installation and reliable mechanical properties [8,9]. Extensive investigations have systematically examined the static behavior, fatigue performance, and ultimate capacity of studs through push-out tests [10,11]. With respect to large-diameter studs, Shim et al. [8] conducted push-out tests on studs with diameters of 25 mm, 27 mm, and 30 mm, revealing that existing design codes deliver conservative predictions of their capacity while simultaneously confirming adequate ductility. Ollgaard et al. [9] proposed a classic equation for the shear strength of studs based on 48 push-out tests, a formulation that was subsequently adopted by the AISC specification; nevertheless, subsequent investigations have indicated that this equation exhibits limited applicability to lightweight aggregate concrete. Research concerning studs embedded in ultra-high-performance concrete (UHPC) has demonstrated that, owing to the high toughness and dense microstructure of UHPC, substantially higher shear strength can be mobilized [12,13]. Moreover, investigations into the group stud effect have disclosed that, when the stud spacing becomes excessively small, the concrete damage zones surrounding adjacent studs overlap, leading to a pronounced reduction in load-carrying capacity [14,15]. In addition to conventional welded studs, demountable bolted connectors have attracted considerable attention because they facilitate disassembly and reuse, aligning with the principles of a circular economy [16,17]. Fahmy et al. [18] reported that the shear behavior of bolted connectors is significantly influenced by the bolt geometry, grout strength, preload, and material properties.

Beyond the mechanical performance of shear connectors, a number of studies have also addressed the optimization of composite beam design. Given that the design of composite beams involves multiple conflicting objectives, including load capacity, cost, carbon emissions, and construction duration, conventional single-objective optimization methods struggle to yield synergistically optimal solutions. Consequently, multi-objective optimization approaches have been extensively adopted in composite structural design in recent years. Silva et al. [19] employed a multi-objective particle swarm optimization (MOPSO) algorithm to optimize composite slabs, aiming to minimize CO₂ emissions and cost while maximizing load capacity; the results demonstrated that the proposed method significantly enhances load capacity while reducing both environmental and economic costs. Liu et al. [20] developed an intelligent finite element modeling approach for continuous composite girder bridges, integrating differential evolution and other algorithms, which resulted in material cost savings and substantial reductions in modeling and optimization time. Korouzhdeh et al. [21] optimized the cost and safety of composite beams using code-based formulations, and their sensitivity analysis revealed that concrete strength exerted a greater influence on cost than on safety, whereas the type of shear connector had a relatively minor impact. Deligia et al. [22] applied a genetic algorithm to optimize the variable cross-sectional shape of self-supporting steel truss–concrete composite beams, effectively reducing the beam section dimensions. Han et al. [23] proposed an improved multimodal multi-objective differential evolution algorithm and coupled it with the OpenSees platform for seismic optimization of composite frame structures, generating diverse Pareto solution sets that offer designers multiple viable cost–displacement trade-off schemes. In recent years, surrogate-assisted multi-objective optimization methods have gained increasing attention in civil engineering. Liu et al. [24] proposed a Pareto-guided active learning framework using Gaussian process surrogate to accelerate NSGA-II for arch dam shape optimization, achieving 70% computational cost savings while reducing both dam volume and tensile stress region. Fang et al. [25] developed a general framework integrating machine learning surrogate models with genetic algorithms for hybrid braced structures, enabling collaborative optimization under multiple seismic response indices. Sun et al. [26]

applied support vector regression combined with particle swarm optimization to optimize cable-stayed bridge damper parameters. Wang et al. [27] established a response-surface-based multi-objective optimization model for an upper-stiffened double-deck steel truss girder bridge using an improved AdaDelta algorithm, reducing the superstructure weight by 4.11%.

With the advancement of artificial intelligence, machine learning techniques have exhibited considerable potential in structural performance prediction and design optimization [28,29]. In the domain of shear connector capacity prediction, Saleh et al. [30] compared eight models based on 146 datasets and identified XGBoost as the most accurate predictor of the shear capacity of demountable bolts, achieving an R^2 of 0.996, with bolt diameter and reinforcement yield strength emerging as the key features. Ferreira et al. [31], focusing on the shear resistance of cellular composite beams, found that the CatBoost model, with an R^2 of 0.982, outperformed other algorithms and further derived a new predictive equation through gene expression programming. Wakjira et al. [32] predicted the flexural capacity of FRCM-strengthened beams using XGBoost, attaining an R^2 of 99.3%, and SHAP analysis indicated that the tensile reinforcement area and FRCM area were the most influential factors. Bakouregui et al. [33] applied XGBoost to forecast the axial compressive capacity of FRP-reinforced concrete columns, obtaining an R^2 of 0.987, and identified eccentricity, gross cross-sectional area, and concrete strength as the critical parameters. Hosseinpour et al. [34] investigated bolted connections in cold-formed steel composite beams and found that the ANN model provided superior accuracy compared with stepwise regression, with 98% of errors falling below 10%, and that steel plate thickness exerted the greatest influence. Furthermore, artificial intelligence has also been applied to the optimization of composite beams [35]. Deng et al. [36] developed a GANN-SVR stacked surrogate model based on a database of 1000 cases, which was constructed through experiments and finite element analysis for bolted connections in modular steel buildings, and coupled it with NSGA-II for multi-objective optimization of yield load, ultimate load, and steel consumption. Liu et al. [37] focused on ECC–concrete composite beams, established two databases for material mix proportions and structural performance, identified XGBoost and CatBoost as the optimal prediction models, and applied SHAP analysis to discern the critical design parameters, thereby enabling the automatic generation of structural schemes based on target bearing capacity and cost-efficient optimization of ECC mix proportions.

Traditional response surface methodology (RSM), despite its simplicity and interpretability, suffers from inherent limitations when applied to complex structural systems: poor scalability to high-dimensional problems due to exponential sample growth, and inadequacy in capturing highly nonlinear coupling effects among design variables. To address these issues, machine learning-based surrogate models, including Gaussian process regression, neural networks, and support vector regression, have been introduced. Compared with RSM, these methods offer three key advantages. First, they can efficiently handle high-dimensional design spaces without exponential sample growth. Second, they possess strong nonlinear mapping capabilities for accurate characterization of complex variable-response relationships. Third, they enable near-instantaneous prediction after training, substantially reducing reliance on time-consuming finite element analyses and cutting computational cost from hundreds of iterations to an acceptable level.

Notwithstanding the extensive research efforts that have been separately devoted to the mechanical behavior of shear connectors and the multi-objective optimization of composite beams, the following research gaps persist: (1) Existing optimization studies predominantly concentrate on the geometric dimensions and material parameters of composite beams, whereas systematic multi-objective optimization that specifically addresses the mechanical parameters and arrangement of shear connectors remains scarce;

(2) Interpretability analyses of the mechanical parameters and layout of shear connectors are still insufficient, making it difficult to elucidate the influencing mechanisms of key design parameters.

The present study proposes a multi-objective optimization methodology for stud connectors in SCCBs, integrating a machine learning surrogate model with the NSGA-II algorithm. First, a hybrid sampling method combining Box–Behnken design and Latin hypercube sampling was employed to construct the sample set, and mechanical responses such as deflection, crack resistance, and steel beam stress were obtained through finite element analysis. Second, the optimal machine learning algorithm was selected to develop a surrogate model, and importance and interaction analyses of the optimization parameters were performed. Then, the surrogate model was coupled with the NSGA-II algorithm to derive the Pareto optimal solution set, with composite beam deflection, crack resistance, and stud quantity serving as the optimization objectives. Finally, the optimal parameters of the studs were determined via AHP combined with TOPSIS, and the reliability of the proposed optimization method was verified.

2. Methodology

2.1. Machine Learning Models

2.1.1. Random Forest

Random Forest (RF) [38,39] constitutes an ensemble learning algorithm based on the Bagging strategy, composed of a large number of diversified decision trees, and is widely employed for both classification and regression prediction tasks. The algorithm achieves more robust and accurate predictions by aggregating the outputs of multiple weak learners. The core characteristic of RF lies in the introduction of a dual randomization mechanism. First, each decision tree is trained on a distinct bootstrap sample drawn from the original training set. Second, at each node split during the tree construction, the optimal partitioning attribute is sought exclusively from a randomly selected subset of features. Through this randomization procedure, the correlation among individual decision trees is substantially reduced, and by averaging the regression outputs of all trees, the variance of the model is drastically compressed. Consequently, the overfitting tendency that a single decision tree is prone to is effectively suppressed. The model prediction can be expressed as Equation (1).

$$f(x) = \frac{1}{T} \sum_{t=1}^T h_t(x) \quad (1)$$

where T is the number of decision trees, which is determined through hyperparameter optimization; and $h_t(\cdot)$ denotes the prediction output of the t -th decision tree.

As a bagging-type ensemble learning model, RF reduces the risk of overfitting by averaging the predictions of multiple decision trees, thereby exhibiting strong robustness. The principal advantages of the algorithm lie in its fast training speed and minimal data preprocessing requirements, as operations such as feature normalization are unnecessary. Moreover, RF is capable of outputting feature importance rankings, which are commonly computed either by the mean decrease in impurity (i.e., Gini importance) or by permutation importance, with the latter being more reliable when features are correlated. The Gini importance is one of the available methods that can be used to evaluate how input parameters influence the outputs. Additionally, the model remains insensitive to outliers and missing values, rendering it particularly well-suited for engineering problems in which the data quality is relatively poor.

2.1.2. Extreme Gradient Boosting

Extreme gradient boosting (XGBoost) [40,41] is an efficient ensemble learning algorithm implemented within the gradient boosting framework. It sequentially adds weak learners to progressively reduce the model bias and is widely used for regression and classification tasks on structured data. Compared with traditional gradient boosting methods, XGBoost explicitly incorporates both L1 and L2 regularization terms related to leaf node weights into the objective function and utilizes a second-order Taylor expansion of the loss function to construct a more accurate approximation of the objective. This approach accelerates convergence while effectively controlling model complexity. Furthermore, the algorithm implements weighted quantile sketch, sparsity-aware split finding, and cache-aware computational optimizations, enabling excellent computational efficiency and prediction accuracy when handling medium- to large-scale datasets. Specifically, XGBoost is an additive model composed of k decision trees.

Consider a given dataset consisting of n samples and m features $D = \{(x_i, y_i)\}$ ($|D| = n, x_i \in \mathbb{R}^m, y_i \in \mathbb{R}$), the prediction of the XGBoost model is given by Equation (2):

$$\hat{y}_i^{(t)} = \sum_{k=1}^t f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i), f_k \in \mathcal{F} \quad (2)$$

Let $\hat{y}_i^{(t)}$ denote the prediction of the i -th sample at the t -th iteration, with the objective of minimizing the regularized loss function. The objective function of XGBoost can then be expressed as:

$$\begin{aligned} \mathcal{L}^{(t)} &= \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \\ \Omega(f_k) &= \gamma T_k + \frac{1}{2} \lambda \|w_k\|^2 \end{aligned} \quad (3)$$

where $l(\cdot)$ denotes the training loss function that measures the discrepancy between the true value y_i and the predicted value $\hat{y}_i^{(t)}$, and $\Omega(f_k)$ is the regularization term for the k -th tree, with T_k being the number of leaves and w_k being the leaf weights. The parameter γ penalizes the number of leaves, while λ is the L2 regularization coefficient on the leaf weights. In addition, XGBoost also supports an L1 regularization term $\alpha \|w_k\|_1$ on the leaf weights, which further encourages sparsity.

As a representative boosting-type ensemble learning method, XGBoost progressively enhances model accuracy by iteratively optimizing residuals and demonstrates superior performance. Its principal advantage resides in its capacity to precisely capture the complex nonlinear relationships and high-order feature interactions between input parameters and mechanical responses, thereby endowing the model with strong generalization capability. Furthermore, the algorithm maintains consistently stable prediction accuracy across both low and high response intervals, while exhibiting a certain degree of robustness against the minor measurement noise commonly encountered in engineering practice.

2.1.3. Multi-Layer Perceptron

The MLP [42,43], also widely designated as an Artificial Neural Network (ANN), constitutes a classical feedforward neural network that has been extensively applied to classification and regression tasks by learning the underlying mapping relationships between inputs and outputs to resolve complex nonlinear problems. Distinguishing itself by multiple neuron layers, the MLP represents a specific type of ANN composed of numerous neurons and typically comprises an input layer, one or more hidden layers, and an output layer. Each node in the input layer corresponds to one dimension of the input features, with the number of nodes being equal to the dimensionality of the input. The hidden layers, of which there can be one or more, are referred to as a deep neural network when two or

more such layers are present, and the number of nodes in the output layer is configured according to the requirements of the specific task. In general, forward propagation in an MLP model is accomplished through the composition of affine transformations and nonlinear activation functions performed layer by layer, and the model can be expressed as Equation (4).

$$y_k = \phi \left(\sum_{i=1}^n \omega_{ki} x_i + b_k \right) \quad (4)$$

where y_k represents the output value of the output layer, specifically the predicted uplift capacity; ϕ denotes the activation function; ω_{ki} signifies the weight; n indicates the number of hidden layers; x_i corresponds to the input value from the input layer; and b_k represents the bias term. Commonly employed activation functions include the rectified linear unit, the hyperbolic tangent function, and the Sigmoid function. The parameters of the entire network are typically trained in an end-to-end manner through the backpropagation algorithm coupled with a gradient-based optimizer. As a classical neural network model, the MLP accomplishes complex mappings via multiple layers of nonlinear transformations, and its core advantages reside in its powerful capacity for fitting nonlinear problems, which permits adaptation to problems of varying complexity by adjusting the number of layers and neurons. Furthermore, once the training process is completed, the MLP offers a notably fast prediction speed, yielding results almost instantaneously.

2.2. NSGA-II Multi-Objective Optimization

NSGA-II, developed by Deb et al. [44] upon the foundation of the fast non-dominated sorting genetic algorithm, constitutes an elitist multi-objective evolutionary algorithm. By incorporating fast non-dominated sorting, crowding distance evaluation, and an elite preservation strategy, the algorithm effectively overcomes the shortcomings of early multi-objective genetic algorithms, namely high computational complexity, the requirement for specifying sharing parameters, and the susceptibility to losing elite solutions. Rather than relying on pre-defined weights or priority orders among objective functions, NSGA-II directly yields a set of uniformly distributed Pareto optimal solutions through the evolutionary process, thereby providing designers with a global view of trade-off alternatives in the objective space and supporting multi-criteria decision-making.

The fundamental algorithmic procedure can be summarized as follows:

- (1) An initial parent population of size N is randomly generated within the design space spanned by the decision variables, and the mechanical performance of each individual in terms of shear connector behavior is evaluated to obtain the response values for all objective functions.
- (2) Non-dominated sorting is performed on the parent population, partitioning the population into several fronts according to dominance relationships. The first non-dominated front consists of all individuals that are not dominated by any other individual in the current population. For individuals within the same front, the crowding distance is computed in each objective direction to quantify the density of solution distribution in their neighborhood, ensuring that the selection operation simultaneously drives convergence toward the Pareto front and maintains solution diversity.
- (3) Following the completion of sorting and crowding evaluation, a binary tournament selection operator is applied to select individuals from the parent population for crossover and mutation. The comparison criterion is as follows: individuals with a lower non-dominated front rank are preferentially selected; if two individuals belong to the same front, the one with a larger crowding distance is chosen. The selected individuals subsequently undergo simulated binary crossover and polynomial mutation.

with pre-specified crossover and mutation probabilities, respectively, generating an offspring population of size N .

- (4) The parent and offspring populations are merged to form a combined population of size $2N$, which is again subjected to non-dominated sorting and crowding distance calculation. Through the elite preservation strategy, N individuals are selected from the combined population to constitute the new parent population. The above evolutionary operations are repeated iteratively until the pre-specified maximum number of generations is reached or the convergence metrics of the Pareto front stabilize.

2.3. Multi-Objective Optimization Based on Hybrid Optimization Algorithm

The prerequisite for optimizing the objective functions lies in the necessity of establishing an explicit mapping relationship between the optimization objectives and the optimization parameters. For the stud arrangement optimization of the SCCB addressed in the present study, the relationships between the optimization parameters and the optimization objectives can be obtained through finite element model computations; however, the finite element model constitutes a typical implicit function, and a single analysis is considerably time-consuming. Moreover, the entire optimization process requires hundreds or even thousands of finite element model evaluations, consequently resulting in prohibitively low optimization efficiency. Given these considerations, a hybrid optimization framework that integrates ML and NSGA-II is proposed for the optimization problem of SCCB. The overall computational framework is illustrated in Figure 1, and the specific steps are outlined as follows:

- (1) Construction of training and testing sample sets based on the finite element model.

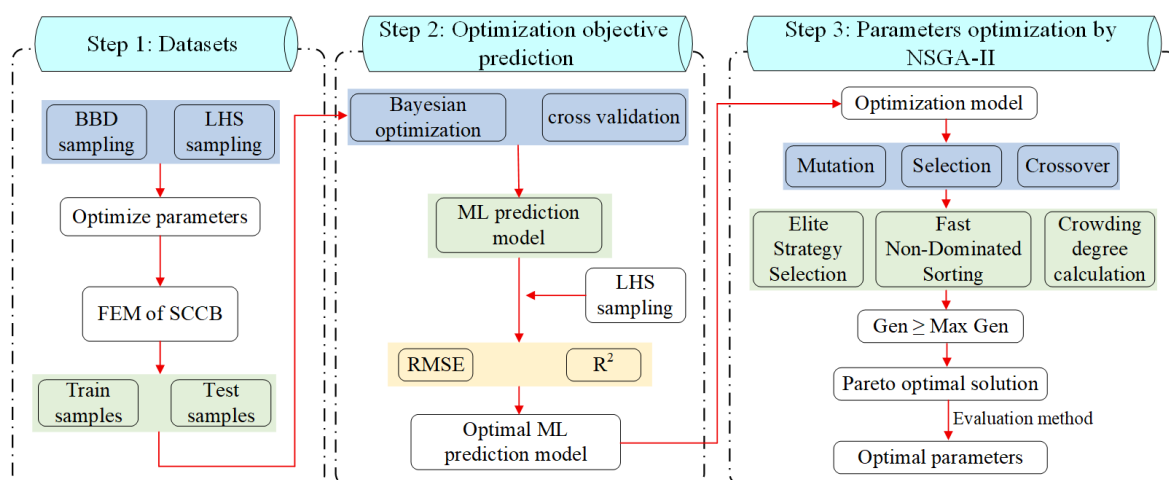


Figure 1. Flowchart of the hybrid optimization algorithm.

A certain number of sample sets for the optimization parameters are first obtained and divided into training samples and testing samples. These samples are subsequently input into the finite element model, yielding the corresponding training and testing sample sets.

- (2) Development of ML-based prediction models for the composite beam optimization objectives.

Different ML methods are employed to train prediction models for the SCCB optimization objectives using the training samples. The models are then evaluated by means of the mean squared error (RMSE) and the coefficient of determination (R^2) obtained from the testing samples, and the optimal ML prediction model is selected to ensure that a predictive model suitable for subsequent optimization is secured.

- (3) Optimization of the stud parameters through the integration of ML and the NSGA-II algorithm.

In accordance with the practical conditions of the project, a rational multi-objective optimization function is formulated. Building upon step (2), the NSGA-II algorithm is adopted to optimize the stud parameters.

3. The Development of the Database

3.1. Finite Element Model

The present study adopts a three-span steel–concrete composite continuous girder beam with span arrangements of 30 m, 53 m, and 30 m. The deck width measures 6.4 m, the steel girder height at the intermediate supports equals 2.4 m, whereas that at the end supports equals 1.3 m, and the deck slab thickness is 0.3 m. The steel girders employ Q345-grade steel, while C60 concrete is used for the deck slab. The finite element model was constructed using the QiaoTong finite element software (V26.1.111+1022). The model is discretised into 454 nodes and 452 beam elements. The beam elements are modelled as 2-node Timoshenko beam elements to reasonably account for shear deformation effects, with a uniform element length of 0.5 m. Since the bridge is a three-span continuous girder system, the boundary conditions are represented by three roller supports and one pinned support, which constrain the corresponding translational degrees of freedom to realistically simulate the actual support restraints. To account for the interfacial slip between the concrete deck and the steel girders, the deck slab and the steel girders were discretized independently using beam elements, and the connection between the two materials was realized through spring elements. The finite element model is illustrated in Figure 2.

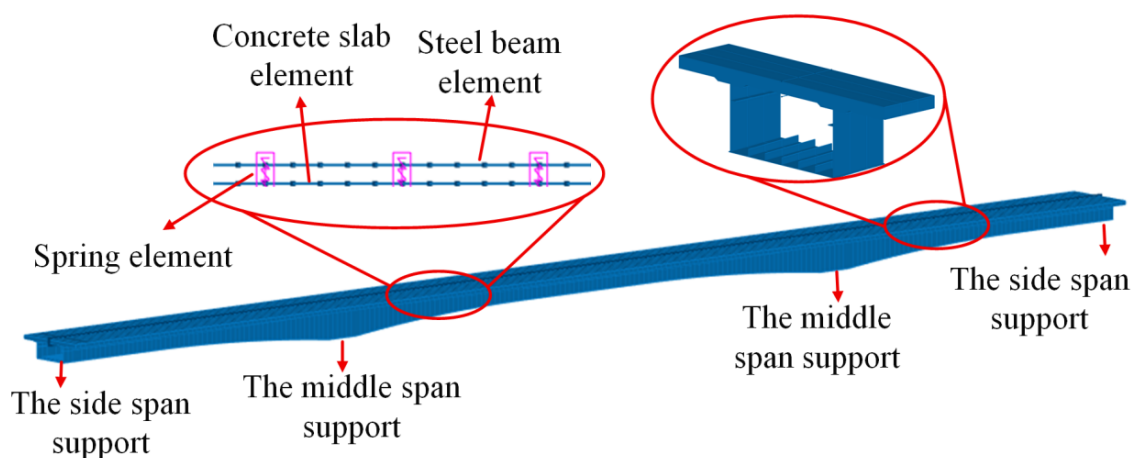


Figure 2. Finite element model of continuous beam.

To verify the validity of the modelling approach adopted in this study, a steel–concrete composite beam reported in the literature [45] was selected as a benchmark. The composite beam was modelled using the QiaoTong software, and the finite element model is shown in Figure 3. It should be noted that the original reference did not specify the exact elastic modulus of the concrete; moreover, this parameter varies considerably with different concrete grades. Therefore, based on the concrete strength grade described in that reference, the mid-span deflection of the composite beam was computed for a range of concrete elastic moduli from 2.5×10^4 MPa to 3.53×10^4 MPa. The computed results were then compared with those reported in the literature, and the comparison is summarized in Table 1. It can be seen from the table that the computational method adopted in this paper achieves satisfactory accuracy and can be reliably used for the following finite element analyses.

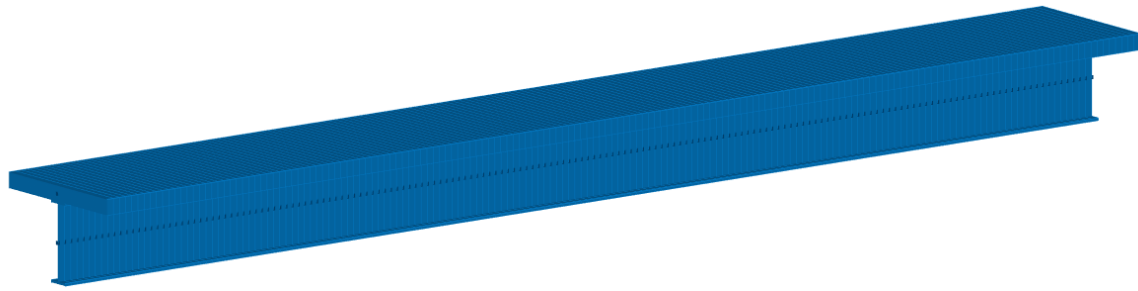


Figure 3. Finite element model of Reference [45].

Table 1. Comparison of results of numerical and various analytical models [45].

Model	Full Interaction		Full Shear Connection		0.5 Shear Connection Degree	
	Mid-Span Deflection (mm)	Percentage Difference Qiaotong Model (%)	Mid-Span Deflection (mm)	Percentage Difference Qiaotong Model (%)	Mid-Span Deflection (mm)	Percentage Difference Qiaotong Model (%)
QiaoTong model	[20.26, 21.56]	-	[22.70, 23.85]	-	[25.77, 26.74]	-
Study [45]	20.61	[1.73, 4.41]	23.62	[4.05, 0.96]	26	[0.89, 2.77]
Jasim's	19.84	[2.07, 7.98]	22.88	[0.79, 4.07]	25.34	[1.67, 5.24]
Nie's	19.84	[2.07, 7.98]	22.46	[1.06, 5.83]	24.58	[4.62, 8.08]
Girhammar's	19.84	[2.07, 7.98]	22.88	[0.79, 4.07]	25.34	[1.67, 5.24]
AISC	19.84	[2.07, 7.98]	19.84	[12.6, 16.81]	24.07	[6.60, 9.99]
Eurocode	19.84	[2.07, 7.98]	19.84	[12.6, 16.81]	24.31	[5.67, 9.09]

3.2. A Hybrid Sampling Method Combining Box–Behnken and Latin Hypercube

The Box–Behnken Design (BBD) [46] constitutes a class of three-level, second-order experimental design methodology specifically developed for efficiently estimating the main effects, interaction effects, and quadratic effects in quadratic polynomial response surface models, while eliminating the requirement for axial points at extreme levels. In contrast to the central composite design, the BBD avoids axial samples that extend beyond the predefined factor ranges, thereby constraining all experimental points to lie within or on the boundaries of the multidimensional cube defined by the upper and lower bounds of each variable. The design points of a BBD are composed of the midpoints of each edge of the cube together with the center point, and the number of experimental runs, denoted NBBD, depends solely on the number of decision variables k , which can be expressed as Equation (5):

$$N_{\text{BBD}} = 2k(k-1) + n_c \quad (5)$$

where n_c denotes the number of replicates runs at the center point, which serve to provide a pure error estimate and to enhance the predictive stability of the design in the central region. Given that the number of experimental runs required by the BBD is substantially smaller than those demanded by a full factorial design or a central composite design of comparable precision, while still maintaining favorable rotatability or near-rotatability, this design methodology has been extensively employed in the domain of structural engineering for parameter sensitivity analysis and predictive model development tasks that necessitate the fitting of second-order response surfaces.

Latin Hypercube Sampling (LHS) [47] constitutes a multidimensional uniform sampling method founded on a stratification principle. The core concept involves partitioning the value interval of each input variable into N non-overlapping subintervals of equal probability and randomly drawing one representative value from each subinterval. Subsequently, the single-sample results for all variables are randomly permuted and combined to form N multidimensional sample points. This mechanism ensures that the marginal distribution of any single dimension strictly covers the entire interval, thereby achieving a more uniformly space-filling distribution than simple random sampling under a limited sample size. In contrast to the structured layout of the BBD, the sample distribution gener-

ated by LHS does not depend on any pre-specified polynomial model form, offering the flexibility of a distribution-free assumption. Consequently, LHS is particularly well-suited for scenarios in which black-box models, such as tree ensembles and deep neural networks, serve as the predictive models, as it can effectively explore multiple local optimal regions that may exist within the design space.

Based on the preceding considerations, the structured samples supplied by the BBD can significantly reduce the estimation variance of the prediction model in regions where the response surface curvature is large and can endow the model with the capability to identify main effects and low-order interaction terms. Meanwhile, the randomly uniform samples provided by LHS compensate for the insufficient spatial coverage breadth of the BBD, effectively constraining the extrapolation bias of the model in unsampled regions. Therefore, the samples obtained from the BBD and LHS are combined in the present study to form the overall sample set used for training and validating the machine learning prediction models. This hybrid sampling strategy aims to maximize the predictive robustness of the ML models across the entire feasible design domain without incurring a significant increase in the computational cost of finite element analyses.

3.3. Collected Datasets

The optimization parameters considered in the present study primarily focus on the stud arrangement, encompassing the shear stiffness (KT), pull-out stiffness (KS), and spacing (D) of the studs. To optimize the stud parameters within different girder segments, the continuous girder is longitudinally divided into five zones, wherein the two end zones, each with a length of 21.5 m, constitute the non-optimized segments, whereas the three intermediate zones, with lengths of 20 m, 30 m, and 20 m in sequence, serve as the optimized segments, as illustrated in Figure 4.

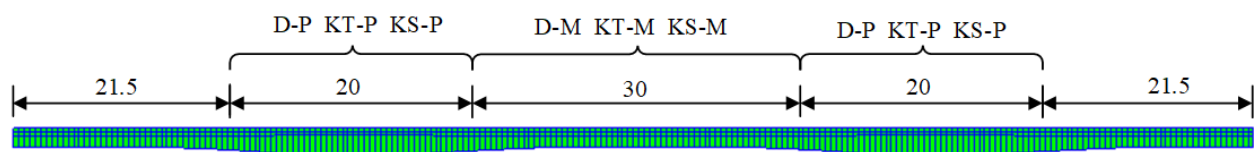


Figure 4. Schematic diagram of the partitioning of stud parameters (m).

According to Refs. [48,49], the stud spacing ranges from 0.5 to 6 m, the pull-out stiffness varies between 30 and 1100 kN/mm, and the shear stiffness ranges from 1 to 5815 kN/mm. The training sample set comprises 49 samples obtained through the BBD and 180 samples generated via LHS, whereas the testing sample set consists of 20 samples drawn by LHS. The corresponding finite element models were subsequently constructed. The value ranges of all parameters are summarized in Table 2.

Table 2. Optimization parameters and their value ranges.

Optimize Parameters	Range of Values
Stud space D-M, D-P (m)	0.5~6
Stud shear stiffness KT-M, KT-P (kN/mm)	30~1100
Stud Pull-out stiffness KS-M, KS-P (kN/mm)	1~5815

To evaluate the performance of three sampling strategies, namely LHS, BBD, and LHS + BBD, two quantitative uniformity metrics are adopted: Maximin distance [50] and discrepancy [51]. Maximin distance is used to quantify local uniformity, with larger values signifying superior spatial coverage, while discrepancy is employed to assess global

uniformity, where smaller values are desirable. The resulting values for the three methods are summarized in Table 3.

Table 3. Minimax distance and discrepancy of samples.

Indicator	LHS	BBD	LHS + BBD
Maximin distance	0.033	0.192	0.036
discrepancy	0.014	0.669	0.014

Given that the primary objective is to construct a global surrogate model, global representativeness of the design space is of foremost importance. Among the strategies that achieve the optimal global uniformity (i.e., LHS and LHS + BBD), the LHS + BBD approach exhibits superior local coverage. Although it does not outperform LHS in terms of global discrepancy, the LHS + BBD combination offers a more favourable trade-off by enhancing local filling characteristics while preserving the best attainable global uniformity. This balanced performance justifies our selection of the LHS + BBD hybrid as the final sampling strategy.

In the design of SCCBs, the primary considerations encompass the deflection, the crack resistance of the deck slab, the stresses in the steel girder, and the construction cost, where deflection and crack resistance represent serviceability performance, steel girder stresses reflect the load-carrying capacity, and cost indicates economic efficiency. The limiting values for the deflection, crack resistance, and steel girder stresses can be found in Refs. [49,52]. The deflection is evaluated under the moving load case (CS-0), the crack resistance is assessed under the frequent load combination (CS-1 to CS-5), and the steel girder stresses are checked under the fundamental load combination (CS-6 to CS-15), with both the frequent and fundamental combinations each comprising five load cases, as summarized in Table 4.

Table 4. Composition of loading cases.

Case	Load Combination	Remarks
CS-0	$1.0 \times LL$	Deflection
CS-1	$1.0 \times DL + 1.0 \times SC + 1.0 \times SS + 0.7 \times LL$	Axial force in concrete slab
CS-2	$1.0 \times DL + 1.0 \times SC + 1.0 \times UTR + 0.8 \times PTG + 1.0 \times SS + 0.7 \times LL$	
CS-3	$1.0 \times DL + 1.0 \times SC + 1.0 \times UTR + 0.8 \times NTG + 1.0 \times SS + 0.7 \times LL$	
CS-4	$1.0 \times DL + 1.0 \times SC + 1.0 \times UTD + 0.8 \times UTR + 1.0 \times SS + 0.7 \times LL$	
CS-5	$1.0 \times DL + 1.0 \times SC + 1.0 \times UTD + 0.8 \times NTG + 1.0 \times SS + 0.7 \times LL$	
CS-6	$1.2 \times DL + 1.0 \times SC + 0.5 \times SS + 1.4 \times LL$	Minimum/Maximum stress in steel girder
CS-7	$1.2 \times DL + 1.0 \times SC + 1.05 \times UTR + 1.05 \times PTG + 0.5 \times SS + 1.4 \times LL$	
CS-8	$1.2 \times DL + 1.0 \times SC + 1.05 \times UTR + 1.05 \times NTG + 0.5 \times SS + 1.4 \times LL$	
CS-9	$1.2 \times DL + 1.0 \times SC + 1.05 \times UTD + 1.05 \times PTG + 0.5 \times SS + 1.4 \times LL$	
CS-10	$1.2 \times DL + 1.0 \times SC + 1.05 \times UTD + 1.05 \times NTG + 0.5 \times SS + 1.4 \times LL$	

Note: DL: dead load, SC: Shrinkage and creep, UTD: uniform temperature drop, UTR: uniform temperature rise, PTG: positive thermal gradient, NTG: negative thermal gradient, SS: support settlement, LL: Lane load.

4. Results and Discussions

4.1. Optimization Model

In the present study, three optimization objectives and five constraints are formulated in accordance with the relevant code requirements. The three optimization objectives are defined as the maximum deflection of the composite beam under lane loading; the maximum crack width of the deck slab under load cases CS-1 to CS-5; and the stud consumption. The five constraints comprise the maximum deflection, the maximum crack width, the stud consumption, and the maximum and minimum stresses in the steel girder under load cases CS-6 to CS-10. It should be noted that, with respect to crack resistance, since a one-to-one correspondence exists between the axial force in the deck slab and the

crack width, the crack resistance optimization indicator is converted from crack width to the deck slab axial force. The deflection constraint is governed by the deflection limit of $L/500$ for flexural members prescribed in the code [49], yielding a limiting value of 0.106 m.

For the deck slab, the Chinese code [52] stipulates a maximum allowable crack width of 0.2 mm under serviceability limit states. To convert this crack-width limit into a corresponding axial force constraint, the crack width calculation formula provided in Equation (6.4.3) of the code is employed. By setting the crack width to 0.2 mm and substituting the actual geometric and material parameters of the deck slab (including reinforcement layout, cover thickness, and concrete strength grade), the corresponding tensile stress in the reinforcement is obtained from Equation (6.4.3). The axial force limit is then derived using Equation (6.4.4-1). Following this procedure, the crack-width limit is transformed into a maximum axial force limit of 14,850 kN, which is subsequently imposed as the constraint in the optimisation problem.

The allowable values for both the maximum and minimum stresses in the steel girder are set at 210 MPa according to the code, thereby ensuring that the stress levels at all critical sections do not exceed the design strength of steel. The stud consumption is restricted to a minimum of 200 to prevent an insufficient number of studs, which would otherwise result in excessive interface slip and inadequate shear transfer between the concrete slab and the steel girder. These five constraints delineate the feasible design space, confining the search process to rational solutions that simultaneously satisfy the requirements for strength, stiffness, crack control, and detailing, as expressed in Equation (6):

$$\begin{aligned}
 f_1 &= \text{DIS}_{\text{VL}} \\
 f_2 &= \max_{1 \leq i \leq 5} (N_{\text{CS-}i}) \\
 f_3 &= M_{\text{studs}} \\
 \text{s.t. } \text{DIS}_{\text{VL}} &< 0.106 \\
 \max_{1 \leq i \leq 5} (N_{\text{CS-}i}) &< 14850 \\
 \max_{6 \leq i \leq 10} (\sigma_{\text{CS-}i, \text{max}}) &< 210 \\
 \max_{6 \leq i \leq 10} (\text{abs}(\sigma_{\text{CS-}i, \text{min}})) &< 210 \\
 M_{\text{studs}} &> 200
 \end{aligned} \tag{6}$$

Here, f_1 and DIS_{VL} denotes the maximum deflection of the beam under lane loading; f_2 denotes the maximum axial force of the deck slab under load cases CS-1 to CS-5; $N_{\text{CS-}i}$ denotes the axial force of the concrete slab under load case CS- i , where i denotes the load case number; f_3 and M_{studs} denotes the stud consumption; and $\sigma_{\text{CS-}i, \text{max}}$ and $\sigma_{\text{CS-}i, \text{min}}$ denote the maximum and minimum stresses of the steel beam under load case CS- i .

4.2. Performance Analysis of Machine Learning Models

4.2.1. Performance Indicators

To quantitatively evaluate the predictive performance of the machine learning models, three typical regression metrics are adopted: the coefficient of determination (R^2), the root mean square error (RMSE) and the Mean Absolute Error (MAE), as defined in Equations (7)–(9):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - p_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - p_i)^2} \quad (8)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - p_i| \quad (9)$$

In the above expressions, y_i denotes the predicted value obtained from the machine learning model, p_i represents the actual value simulated by the finite element model, $\bar{y}$ indicates the mean of the finite element simulation results, and n stands for the total number of data points in the specified set.

The coefficient of determination (R^2) constitutes the most commonly employed evaluation metric in regression prediction, directly quantifying the degree of agreement between the model predictions and the actual values. Its value ranges from negative infinity to 1, with a value closer to 1 indicating a superior fitting performance. A smaller RMSE value signifies that the model predictions are more accurate.

4.2.2. Hyperparameter Tuning

This study employed three machine learning models, namely MLP, RF, and XGBoost, to predict the mechanical responses of SCCB. The hyperparameters of the three models were optimized via four-fold cross-validation combined with Bayesian optimization on the training samples, with the expected improvement (EI) serving as the acquisition function. The search space was defined based on preliminary trials, and the optimization was configured with 30 function calls, 10 random start points, a noise level of 0.01, and a fixed random seed of 1234. Apart from the aforementioned settings, all other parameters in the Bayesian optimization procedure were kept at their default values. The optimal hyperparameter ranges for all models, observed across the 16 load cases, are summarized in Table 5, while all other parameters were kept at their default values.

Table 5. Ranges of optimal hyperparameters for the three machine learning models.

MLP	XGBoost	RF
Activation = [relu, tanh]	n_estimators = [100, 200]	n_estimators = [20, 100]
hidden_layer_sizes = [3, 30]	learning_rate = [0.03, 0.05]	min_samples_split = [2, 8]
Solver = [lbfgs]	max_depth = [3, 10]	min_samples_leaf = [1, 1]
learning_rate = [adaptive, constant]	min_child_weight = [2, 6]	-
Alpha = [0.0001, 0.027]	reg_alpha = [0, 1]	-
-	reg_lambda = [0, 1]	-
-	colsample_bytree = [0.60, 1]	-
-	Subsample = [0.5, 1]	-

4.2.3. Comparison of Different Machine Learning Models

To systematically evaluate the applicability of three machine learning models, namely MLP, RF, and XGBoost, in predicting the mechanical responses of SCCB, the present study conducts a comparative investigation focusing on the predictive performance for three critical mechanical indicators: deflection, axial force in the concrete slab, and steel girder stresses. All models are trained with a uniform four-fold cross-validation splitting ratio, and their hyperparameters are determined through Bayesian optimization, thereby ensuring the fairness of the comparison and the reliability of the results.

Figures 5–7 present the prediction results obtained from the three models. From an overall assessment of prediction accuracy, all three models prove capable of effectively capturing the nonlinear relationships between the input parameters and the mechanical responses, with the predicted data points generally distributed along the ideal $y = x$ line and no systematic deviations observed. Nevertheless, notable differences emerge with respect to prediction accuracy, dispersion, and error distribution. In terms of deflection prediction,

all predicted values produced by the MLP model fall within an error band of $\pm 5\%$, whereas the XGBoost model yields three points with errors exceeding $\pm 5\%$ and one point exceeding $\pm 10\%$, and the RF model keeps all errors within $\pm 10\%$ although three points still exceed $\pm 5\%$. With regard to the axial force in the deck slab, the MLP predictions again all lie within $\pm 5\%$; the XGBoost predictions are all controlled within $\pm 10\%$, with one point exceeding $\pm 5\%$; and the RF predictions are all within $\pm 5\%$. Concerning steel girder stress prediction, the MLP model generates 12 points with errors surpassing $\pm 5\%$ and 2 points surpassing $\pm 10\%$, the XGBoost model produces 16 points exceeding $\pm 5\%$ and 3 points exceeding $\pm 10\%$, while the RF model maintains all errors within $\pm 10\%$ yet has 13 points exceeding $\pm 5\%$.

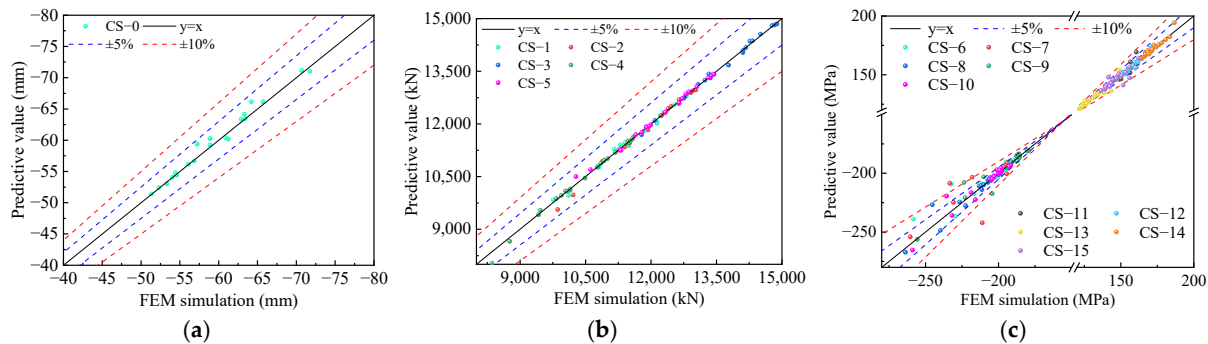


Figure 5. Prediction results of MLP: (a) Deflection. (b) Axial force in concrete slab. (c) Stress in steel girder.

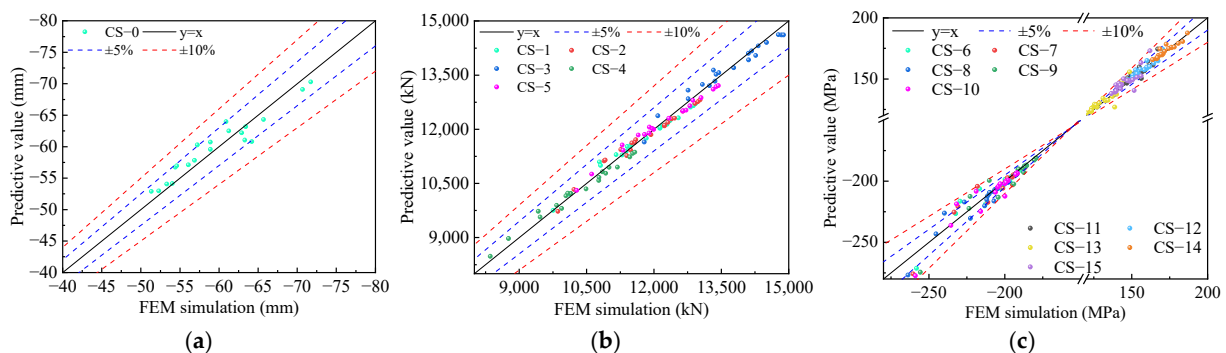


Figure 6. Prediction results of RF: (a) Deflection. (b) Axial force in concrete slab. (c) Stress in steel girder.

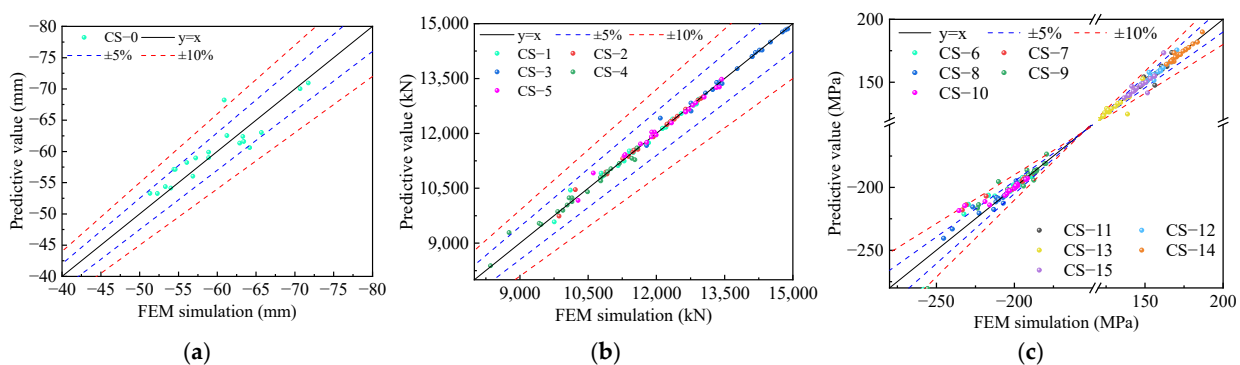


Figure 7. Prediction results of XGBoost: (a) Deflection. (b) Axial force in concrete slab. (c) Stress in steel girder.

The MLP model achieves the highest accuracy in predicting both the deflection and the deck slab axial force. For steel girder stress prediction, the MLP model outperforms

XGBoost, although it proves slightly inferior to RF. Therefore, a comprehensive comparison indicates that the MLP exhibits good performance across the 16 load cases.

Figures 8–10, along with Table 6, present the RMSE, MAE, and R^2 values obtained by the RF, XGBoost, and MLP models across 16 distinct load cases (CS-0 to CS-15). For comparability, the RMSE and MAE values have been normalised to the interval [0.5, 1]. The results clearly reveal pronounced performance hierarchies among the three models, as well as their divergent adaptability to specific loading cases.

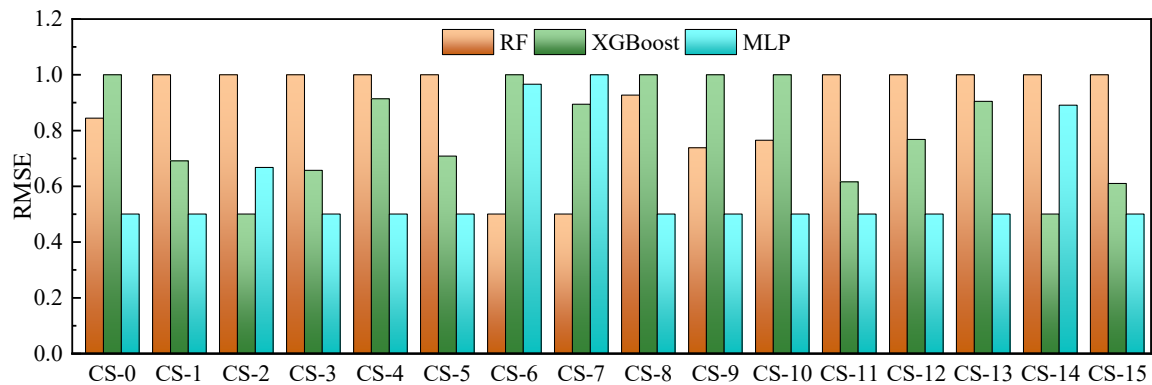


Figure 8. RMSE of different machine learning models.

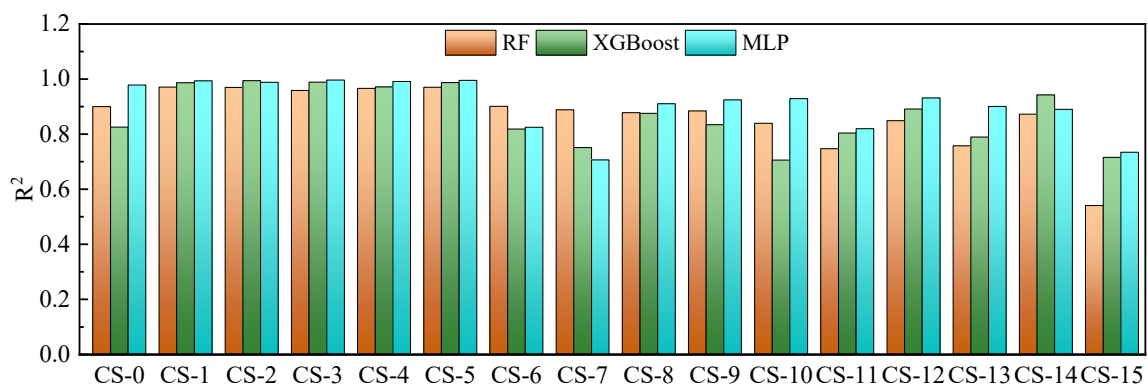


Figure 9. R^2 of different machine learning models.

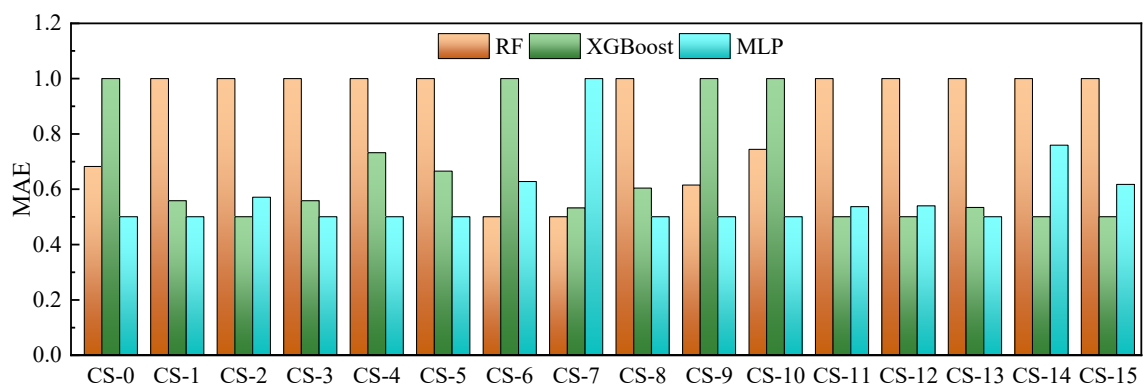


Figure 10. MAE of different machine learning models.

Table 6. Performance indicators of machine learning models.

Case	MLP			RF			XGBoost		
	R ²	RMSE	MAE	R ²	RMSE	MAE	R ²	RMSE	MAE
CS-0	0.98	0.00084	0.00059	0.90	0.00179	0.00154	0.83	0.00237	0.00179
CS-1	0.99	71,370	55,896	0.97	148,659	124,646	0.99	100,764	63,195
CS-2	0.99	94,596	57,040	0.97	151,591	142,477	0.99	65,871	38,058
CS-3	1.00	53,280	41,850	0.96	175,423	143,150	0.99	91,608	53,620
CS-4	0.99	80,520	40,244	0.97	159,925	144,324	0.97	146,193	86,721
CS-5	0.99	62,262	40,170	0.97	149,034	128,215	0.99	98,354	76,785
CS-6	0.82	7,194,939	3,893,250	0.90	5,409,737	3,796,700	0.82	7,323,575	4,172,250
CS-7	0.71	9,931,119	5,536,650	0.89	6,117,235	4,167,000	0.75	9,138,790	4,391,800
CS-8	0.91	4,955,276	2,804,500	0.88	5,785,939	3,919,050	0.88	5,837,963	3,393,150
CS-9	0.92	5,073,309	2,926,650	0.88	6,270,396	4,093,550	0.83	7,501,430	4,549,250
CS-10	0.93	4,421,293	2,566,250	0.84	6,656,638	4,083,450	0.71	9,004,211	4,236,400
CS-11	0.82	2,649,583	1,631,500	0.75	3,135,726	2,360,200	0.80	2,761,885	1,491,050
CS-12	0.93	1,583,194	1,163,300	0.85	2,349,662	1,836,500	0.89	1,992,953	1,080,800
CS-13	0.90	2,386,791	1,521,200	0.76	3,724,898	2,504,050	0.79	3,469,732	1,588,400
CS-14	0.89	2,012,591	1,197,200	0.87	2,170,833	1,421,000	0.94	1,463,028	863,950
CS-15	0.73	3,525,560	2,052,450	0.54	4,630,994	3,273,950	0.71	3,646,658	1,688,950

For the RMSE, the MLP model delivers the most accurate predictions for deflection; for the axial force in the deck slab, MLP achieves the lowest error in four cases, whereas XGBoost does so in one case; and for steel girder stress prediction, MLP ranks best in seven cases, XGBoost in one case, and RF in two cases. Regarding the R², MLP again yields the highest value for deflection; for deck slab axial force, all three models exhibit R² values uniformly close to unity, indicating nearly equivalent performance; and for steel girder stresses, MLP attains the highest R² in five cases, XGBoost in three cases, and RF in two cases. For the MAE, MLP yields the lowest value in nine cases, XGBoost outperforms the others in five cases, while RF is the best in only two cases. These findings indicate that MLP achieves the highest predictive accuracy, followed by XGBoost, whereas RF exhibits the poorest overall performance.

Tables 7–9 present the results of the Friedman test and post hoc Nemenyi test for the three performance metrics RMSE, R², and MAE. The Friedman *p*-values are below 0.05 for all three metrics, indicating that the differences in predictive performance among the three models are statistically significant. MLP achieves the lowest mean rank across all metrics. It significantly outperforms both XGBoost and RF in terms of RMSE and R² ($p < 0.05$), and significantly outperforms RF in terms of MAE ($p = 0.0075$), whereas its difference from XGBoost in MAE does not reach statistical significance ($p = 0.431$). Taken together across the three metrics, MLP exhibits significantly and robustly better predictive performance than RF, and it also significantly outperforms XGBoost on the majority of the metrics. Therefore, MLP can be regarded as the best choice among the three models.

Table 7. Statistical test of three models (RMSE).

Models	Friedman <i>p</i>	Mean Rank	Nemenyi <i>p</i>			Judgement Criterion of <i>p</i>
			MLP	RF	XGBoost	
MLP	0.0023	1.3125	1	0.0023	0.0356	0.05
RF	0.0023	2.5000	0.0023	1	0.6505	0.05
XGBoost	0.0023	2.1875	0.0356	0.6505	1	0.05

Table 8. Statistical test of three models (R^2).

Models	Friedman p	Mean Rank	Nemenyi p			Judgement Criterion of p
			MLP	RF	XGBoost	
MLP	0.0023	1.3125	1	0.0023	0.0356	0.05
RF	0.0023	2.5000	0.0023	1	0.6505	0.05
XGBoost	0.0023	2.1875	0.0356	0.6505	1	0.05

Table 9. Statistical test of three models (MAE).

Models	Friedman p	Mean Rank	Nemenyi p			Judgement Criterion of p
			MLP	RF	XGBoost	
MLP	0.0104	1.5000	1	0.0075	0.4310	0.05
RF	0.0104	2.5625	0.0075	1	0.1805	0.05
XGBoost	0.0104	1.9375	0.4310	0.1805	1	0.05

In terms of computational cost, the total training and testing time for one representative load case (CS-0) is approximately 124.3 s for MLP, compared to 15.5 s for XGBoost and 4.5 s for RF. Although MLP requires a longer training time, this remains an acceptable one-time offline cost. Moreover, the primary computational bottleneck in our framework lies in the finite element simulations and the cumulative time spent on the extensive model inferences required by the optimization algorithm, rather than in model training itself. Consequently, the moderate increase in training time is well justified by the significant gain in predictive accuracy.

Collectively, when all three metrics (RMSE, MAE, and R^2) are taken into account, the MLP model demonstrates the most favourable overall performance, while XGBoost and RF show slightly inferior performance.

4.3. Importance of Optimization Parameters

Poor interpretability remains a major obstacle hindering the application of machine learning (ML) algorithms in practical engineering. Understanding why a model produces a particular prediction based on specific feature values is essential to establishing trust in its outputs. Among the three models evaluated in this study, the MLP model achieves the best predictive accuracy; however, its multi-layer nonlinear transformations inherently render it a typical “black-box” model, making its prediction process difficult to interpret intuitively. Therefore, it is necessary to conduct interpretability analyses of the model predictions to reveal the underlying mechanisms through which each design parameter influences the structural responses.

The Shapley Additive Explanations (SHAP) method provides an effective avenue for interpreting machine learning models [53,54]. Grounded in the Shapley value from cooperative game theory, SHAP constructs an additive explanation model in which each input feature is treated as a contributor, and its marginal contribution to the prediction is quantified accordingly. The absolute value of the SHAP value reflects the importance of each input feature to the output parameter: the larger the SHAP value, the more significant the feature’s contribution to the prediction. In this study, the SHAP method is employed to conduct a global feature importance analysis of the six optimization variables, with the aim of quantifying the contribution of each design parameter to the mechanical responses of the SCCB.

Figure 11 presents the feature importance distributions of the six independent variables, namely D-P, D-M, KT-P, KT-M, KS-P, and KS-M, across the 16 load cases spanning

from CS-0 to CS-15, thereby reflecting the degree to which different parameters contribute to the predicted mechanical responses of the SCCB.

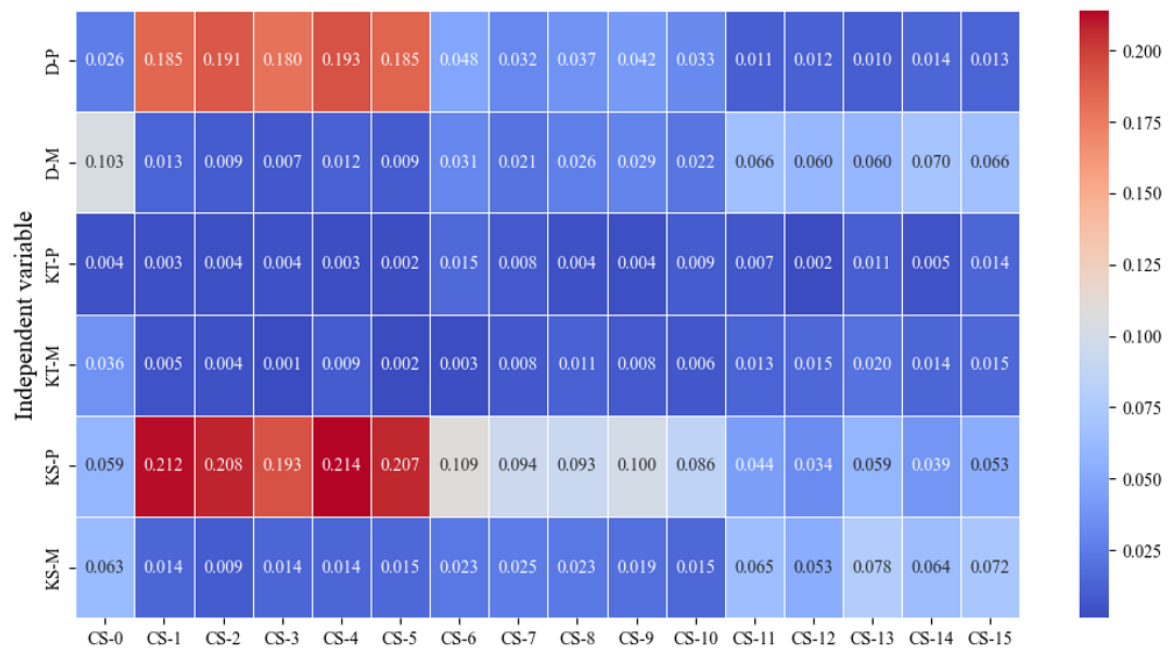


Figure 11. Heatmap of feature importance across 16 load cases.

From an overall perspective of the global Parameter importance distribution, the six independent variables can be categorized into four distinct tiers, exhibiting pronounced disparities in their contributions. Specifically, KS-P emerges as the absolutely dominant feature, maintaining a high importance level across all load cases and reaching a peak under load cases CS-1 to CS-5. D-P is identified as a locally important feature, displaying elevated importance exclusively within the CS-1 to CS-5 load cases. D-M and KS-M fall into the category of secondary features, with generally low overall importance and exerting a certain influence only under particular load cases. KT-P and KT-M are classified as negligible features, as their importance remains exceedingly low throughout all 16 load cases and contributes virtually no substantive influence on the model outputs. This observation indicates that the pull-out stiffness of the studs exerts a relatively minor effect on the mechanical responses of the SCCB.

With regard to deflection prediction, the importance ranking of the optimization parameters follows the order $D-M > KS-M > KS-P > KT-M > D-P > KT-P$, wherein D-M exerts the greatest influence, accounting for 35% of the total importance. This finding suggests that the stud spacing at the mid-span plays a critical role in controlling the deflection of the SCCB. Concerning the prediction of the deck slab axial force under CS-1 to CS-5, the importance ranking is $KS-P > D-P > KS-M > D-M > KT-M > KT-P$. KS-P contributes the highest proportion (48% on average across CS-1 to CS-5), followed by D-P (44% on average across CS-1 to CS-5). Given that the maximum tensile axial force in the deck slab typically occurs over the pier, it can be inferred that adjusting the shear stiffness and spacing of the studs over the pier represents the most effective strategy for mitigating this maximum axial force. In terms of steel girder stress prediction under CS-6 to CS-15, the importance ranking is $KS-P > D-M > KS-M > D-P > KT-M > KT-P$. KS-P accounts for the largest share (34% on average across CS-6 to CS-15), followed by D-M (22% on average across CS-6 to CS-15) and KS-M (21% on average across CS-6 to CS-15). This indicates that modifying the shear stiffness of the studs at both the pier and mid-span, together with

the mid-span stud spacing, constitutes the most effective approach for improving the steel girder stresses.

For the predictions of displacement, deck axial force, and steel girder stress, representative load cases CS-0, CS-1, and CS-6 were selected, the swarm plots of each feature are presented in Figure 12. In the displacement prediction model, feature D-M exerts the strongest influence and shows a negative correlation: high D-M values yield negative SHAP contributions, whereas low values yield positive ones, implying that an increase in D-M suppresses the predicted displacement. Meanwhile, KS-P and KS-M also have considerable impacts, though in opposite directions—high KS-P values tend to raise the displacement, while low KS-M values play a dominant negative role. For the deck axial force prediction model, KS-P emerges as the primary positively correlated feature; its high values significantly increase the predicted axial force, whereas D-P exhibits a negative correlation, with its high values concentrated in the negative SHAP region. In contrast, KS-M and D-M are weak, with their SHAP scatter points clustered around zero. In the steel beam stress prediction model, KS-P again remains the dominant positively correlated feature. The effect of D-P displays nonlinearity, but high values correspond to negative contributions; low KS-M values correspond to pronounced negative contributions that markedly reduce the predicted stress. The features D-M, KT-P, and KT-M have negligible effects. Overall, KS-P consistently acts as the core positive driving factor in both axial force and stress predictions, and should therefore be regarded as a key physical parameter for monitoring, whereas the primary driver for displacement prediction originates from D-M.

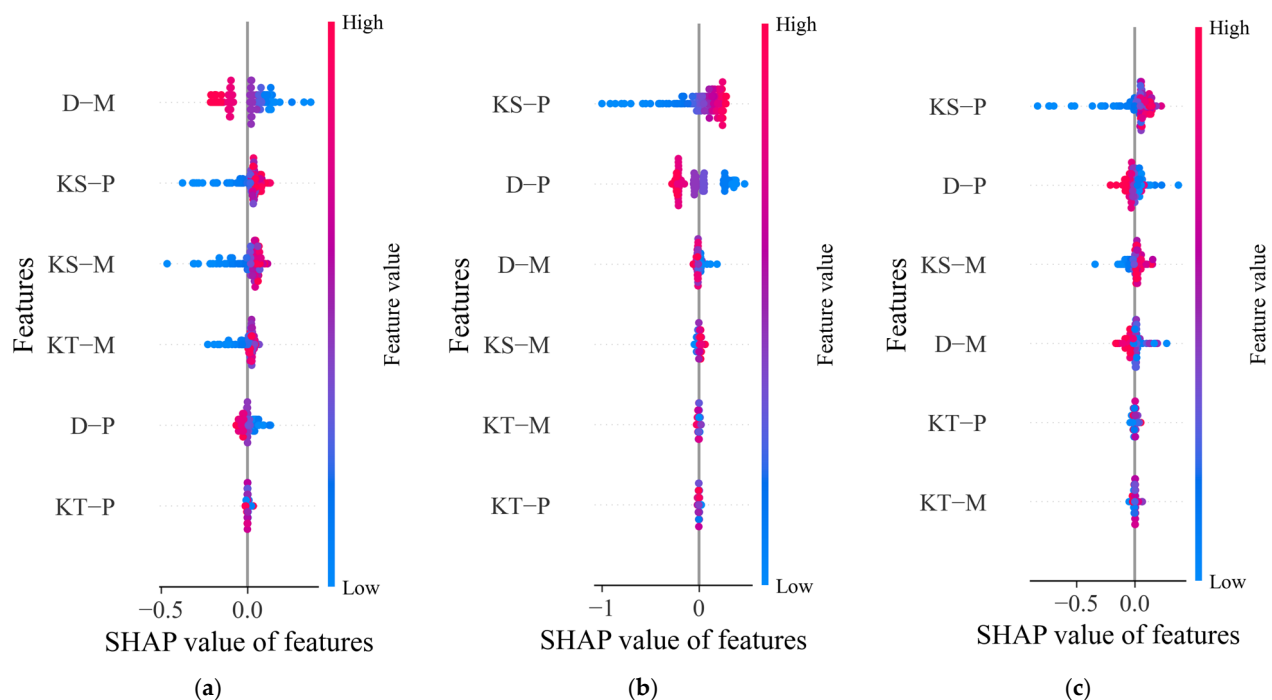


Figure 12. SHAP value analysis of features: (a) CS-0. (b) CS-1. (c) CS-6.

4.4. Analysis of Optimization Results

4.4.1. Analytic Hierarchy Process

The AHP, proposed by Saaty [55], constitutes a multi-criteria decision-making method that integrates qualitative judgment with quantitative analysis. Its fundamental principle lies in decomposing a complex decision problem layer by layer through a hierarchical structure, conducting pairwise comparisons among elements at the same level to determine their relative importance, and ultimately synthesizing the weights across all levels to obtain

the priority ranking of the alternatives with respect to the overall goal. The core steps of the method are as follows:

- (1) A hierarchical model comprising the goal level, criterion level, and alternative level is constructed, thereby structurally expressing the decision problem as a multi-level and multi-factor analytical framework.
- (2) The elements within the same level are compared pairwise using a nine-point scale to form a judgment matrix, the entries of which characterize the decision-maker's assessment of the relative importance between two factors.
- (3) The weight allocation for the elements at that level is obtained by solving for the maximum eigenvalue of the judgment matrix and its corresponding eigenvector. Subsequently, the logical consistency of the judgment matrix is examined via the consistency ratio. When this ratio falls below 0.1, the judgment matrix is considered to possess satisfactory consistency; otherwise, the pairwise comparisons should be adjusted.

Through the mechanisms of hierarchical decomposition, pairwise comparison, and layer-by-layer aggregation, the AHP incorporates the decision-maker's subjective experience into the analytical process in a systematic and verifiable manner, and has therefore been extensively adopted in engineering decision problems that require the simultaneous handling of quantitative indicators and qualitative judgments [56].

4.4.2. Technique for Order Preference by Similarity to Ideal Solution

The TOPSIS represents a multi-criteria decision-making method based on distance-based comprehensive evaluation. Its fundamental concept consists of simultaneously measuring the closeness of each alternative to the positive ideal solution and the negative ideal solution within a normalized decision space, and subsequently ranking the alternatives accordingly.

- (1) The decision matrix is first normalized to eliminate the dimensional disparities among the different evaluation criteria.
- (2) A weighted normalized matrix is constructed by incorporating the weight vector provided by the decision-maker, on the basis of which the positive ideal solution and the negative ideal solution are determined.
- (3) The Euclidean distances from each alternative to the positive ideal solution and to the negative ideal solution are calculated separately, and the relative closeness coefficient, derived by dividing the distance to the negative ideal solution by the sum of the distances to both the positive and negative ideal solutions, is employed to comprehensively reflect the proximity of an alternative to the ideal state.
- (4) The alternatives are ranked according to their relative closeness coefficients, where a larger coefficient indicates that the alternative lies closer to the positive ideal solution and farther from the negative ideal solution, thus signifying superior overall performance.

The TOPSIS method features a transparent computational procedure, imposes minimal restrictions on sample size and the number of indicators, and avoids the construction of complex preference functions while fully exploiting the original data information, thereby gaining widespread application in the selection of optimal engineering schemes [57].

4.4.3. Screening of Pareto Optimal Solutions Using AHP and TOPSIS

To rationalize the decision-making process for the multi-objective optimization of shear connectors in steel–concrete composite beams, the present study integrates the AHP with the TOPSIS method, establishing a two-stage multi-criteria decision-making

framework that combines subjective and objective considerations. First, a weighting system for the evaluation indicators that reflects engineering preferences is established through the AHP. The resulting weight vector is then incorporated into the TOPSIS ranking procedure, enabling the extraction of the design scheme with the most favorable comprehensive performance from the Pareto solution set.

4.4.4. Distribution of Parameters and Objectives for the Pareto Optimal Solutions

In this study, the NSGA-II parameters were configured as follows: a population size of 100, a maximum number of generations of 400, a simulated binary crossover probability of 0.9, a polynomial mutation probability of 0.05, and distribution indices for crossover and mutation of 15 and 20, respectively. All other parameters were set to their default values. As a result, a total of 100 Pareto-optimal solutions were obtained from the optimization process.

Figure 13 illustrates the distribution of the Pareto optimal solution set obtained from the multi-objective optimization of the SCCB, which comprises both the parameter optimization solution set and the objective optimization solution set, where all indicators have been normalized to the interval $[0, 1]$ to facilitate the analysis.

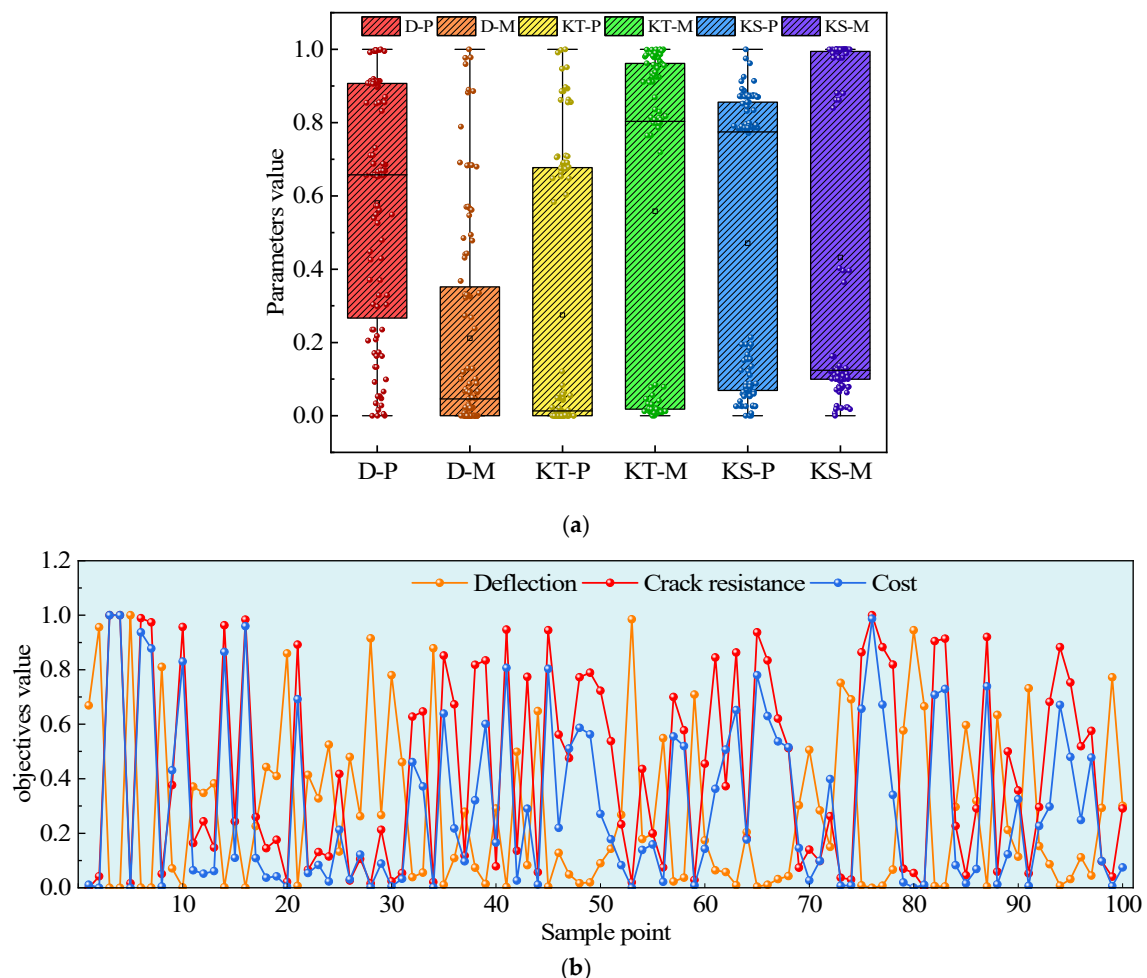


Figure 13. Distribution of parameters and objectives: (a) Optimal solution set of stud parameters. (b) Optimal solution set of objectives.

Figure 13a presents the parameter optimization solution set by means of box plots overlaid with scatter points, illustrating the distribution characteristics of the six design parameters, across the 100 Pareto optimal solutions. On the whole, the optimal distribu-

tions of the individual parameters differ substantially, reflecting their varying degrees of sensitivity to the multi-objective optimization outcomes. Specifically, the optimization result sets for D-M and D-P appear relatively dispersed, and favorable objective values can be achieved whether the stud spacing at the pier or at the mid-span assumes a relatively large or small value when combined with other parameters. This observation indicates that these two parameters offer the highest flexibility in terms of optimal value selection, as Pareto optimal solutions can be identified across a broad interval, and their sensitivities to the objectives remain comparatively low. In contrast, the values of shear stiffness and uplift stiffness are concentrated near the extremes, suggesting that, within the parameter ranges adopted in this study, intermediate values are incapable of yielding optimal solutions; only by selecting either the maximum or the minimum value within the optimization domain can the optimal objective values be attained.

Figure 13b depicts the optimal dependent variable solution set in the form of line charts, illustrating the variation trends of the three core optimization objectives, namely deflection, crack resistance, and cost, across the 100 Pareto optimal solutions. The horizontal axis denotes the sample point number, while the vertical axis represents the normalized objective values, where a smaller deflection value corresponds to superior structural stiffness, a larger crack resistance index signifies enhanced durability, and a larger cost value indicates higher construction expenditure. With regard to the distribution characteristics, the values of all three objectives span the entire interval $[0, 1]$ with considerable fluctuations, demonstrating that the multi-objective optimization performed in this study generates a rich design alternative space capable of accommodating diverse design requirements. More importantly, a pronounced trade-off relationship exists among the three objectives, and no ideal solution can simultaneously optimize all three, which constitutes the essential nature of multi-objective optimization. For instance, sample points with lower deflection typically correspond to higher crack resistance and higher cost, whereas those with lower cost are often accompanied by larger deflection and lower crack resistance. Meanwhile, the vast majority of sample points are capable of maintaining all three objectives above 0.2, thereby avoiding extreme deterioration in any single objective. This finding indicates that the overall performance of the optimized solution set is satisfactory and can fulfill the fundamental requirements of engineering design.

4.4.5. Analysis of the Optimal Solution

In the present study, the deflection, crack resistance, and stud consumption of the composite beam are selected as the optimization objectives, and pairwise comparisons among them are performed, wherein crack resistance is assigned an importance three times that of deflection, deflection is assigned an importance five times that of stud consumption, and crack resistance is assigned an importance seven times that of stud consumption. Cracking resistance receives the highest weight because it directly governs long-term durability; once cracks develop beyond the allowable limit, the damage is largely irreversible and accelerates corrosion of reinforcement and steel girders, threatening the structure's service life [58]. Deflection is given the second highest weight because it mainly affects ride comfort and appearance. For steel-concrete composite structures, deflection under vehicle loading is generally an elastic and reversible deformation, and even if it exceeds the code limit, the consequence is primarily a serviceability issue rather than a threat to structural safety [52]. The number of studs receives the lowest weight because it is primarily an economic indicator.

Following the judgment matrix construction method proposed in Ref. [55], the corresponding judgment matrix is established, as presented in Table 10. It should be noted that the resulting weights represent the authors' engineering judgment and are intended to

illustrate the decision-making procedure; in practice, designers may substitute their own preference matrix to reflect project-specific priorities.

Table 10. Judgment matrix.

Optimization Objective	Deflection	Cracking Resistance	Number of Studs
Deflection	1.000	0.333	5.000
Cracking resistance	3.000	1.000	7.000
Number of studs	0.200	0.143	1.000

Based on the judgment matrix presented in Table 10, a series of calculations were performed using the AHP, from which the weight coefficients for each optimization objective were derived, as summarized in Table 11.

Table 11. Weight coefficients of indicators.

Optimization Objective	Deflection	Cracking Resistance	Number of Studs
Weight coefficient	0.279	0.649	0.072

By integrating the derived weight coefficients of the optimization objectives with the TOPSIS method, the Pareto optimal solution set was ranked, and the global optimal solution was subsequently identified. The optimal parameter values are presented in Table 12, and the corresponding optimal objective outcomes are summarized in Table 13, with the optimal deflection reaching 0.053 m, the optimal axial force equaling 13,256.65 kN, and the stud consumption amounting to 1019. It should be noted that prior to optimization, both stiffness parameters (KT and KS) were set to 1×10^{10} N/m, a value several orders of magnitude higher than typical connector stiffnesses. This deliberately chosen value numerically approximates the classical full composite action limit (i.e., no relative slip or uplift), and is not intended as a physically realizable design; it serves solely as a theoretical reference benchmark for comparison. All improvements reported for the optimized cases are measured relative to this idealized full-composite state, because the central premise of this work is to intentionally introduce a controlled degree of partial interaction to enhance the global structural performance.

Table 12. Optimal parameter solution.

Optimization Parameter	D-P (m)	D-M (m)	KT-P (N/m)	KT-M (N/m)	KS-P (N/m)	KS-M (N/m)
Before optimization	0.5	0.5	1×10^{10}	1×10^{10}	1×10^{10}	1×10^{10}
Optimal value	4.1	0.9	6.7×10^7	1.1×10^9	2.4×10^9	2.5×10^9
Engineering value	4	0.5	6.7×10^7	1.1×10^9	2.4×10^9	2.5×10^9

Unit: D in meters; KT and KS are measured in N/m (as used in the FE model).

Table 13. Optimal objective solution.

Case	Deflection (m)	Axial Force in Deck Slab (kN)	Number of Studs
unoptimized	0.051	15,021.60	8316
optimization	0.053	13,256.65	1019
change (%)	+3.9%	−11.7%	−88%
constraint limits	0.106	14,850	200

Based on the optimal solution set presented in Table 12, the stud spacing over the pier appears relatively sparse, whereas that at the mid-span is comparatively dense, a configuration that contributes to a reduction in the axial force within the deck slab over the pier. Furthermore, the shear stiffness of the studs determined in the present study ranges from $2.9 \times 10^9 \sim 5.82 \times 10^9$, and the pull-out stiffness ranges from $3 \times 10^7 \sim 1.1 \times 10^9$.

Within these ranges, lower shear stiffness values for the studs in both the pier and mid-span regions prove more favorable, while adopting a smaller pull-out stiffness for the studs over the pier and a larger pull-out stiffness at the mid-span is conducive to attaining the optimal solution. Substituting the optimized parameter values listed in Table 12 into the finite element model yields the optimal objective outcomes summarized in Table 13. As revealed by Table 13, following optimization, the SCCB deflection increases by 3.9%, whereas the axial force in the concrete slab decreases by 11.7% and the stud consumption is reduced by 88%, this demonstrates a highly favorable trade-off between material savings and deformation control, confirming the practical value of the proposed multi-objective optimization approach.

This study validates a multi-objective optimization method for steel–concrete composite beams, aiming to identify the Pareto optimal trade-offs among cracking resistance, deflection control, and stud quantity, rather than to provide a ready-to-use design for specific applications. Issues concerning code requirements, stud fatigue, interface slip, group effects, and constructability pertain to detailed design verification under specific conditions and, owing to space limitations, are not discussed in depth herein. These aspects are nevertheless of practical value and merit further investigation in future work.

Beyond these practical considerations, the shear stiffness and pull-out stiffness of studs are governed by physical parameters such as stud diameter and concrete strength, and are not independent free design variables. Although shear stiffness can be regulated by specifying stud dimensions according to code provisions [49], no accurate formula exists for pull-out stiffness, and the two stiffness parameters are inherently coupled. The uplift-restricted and slip-permitted (URSP) connector approach [59], in which studs are wrapped with low-elastic-modulus materials such as rubber, offers a feasible decoupling strategy to adjust shear stiffness while preserving pull-out resistance. However, a quantitative relationship between the design parameters of a URSP connector (e.g., rubber thickness and modulus) and the resulting KT and KS has not yet been established. For this reason, a sensitivity analysis or design diagram linking the optimized stiffness values directly to physical dimensions currently lacks a sound theoretical basis and remains a topic for further investigation. The optimized stiffness values should therefore be interpreted as theoretical design targets to guide the experimental and theoretical work required to build this quantitative mapping in the future.

5. Conclusions

A multi-objective optimization methodology that integrates machine learning surrogate models with the NSGA-II algorithm is proposed for the layout optimization of stud connectors in SCCB, and the following principal conclusions are drawn:

- (1) In the prediction tasks involving the three mechanical indicators of deflection, axial force in the concrete slab, and steel girder stresses, the MLP model achieves the best overall predictive performance, outperforming RF and XGBoost in terms of both RMSE and R^2 across all 16 load cases. The strong capability of the MLP model in capturing nonlinear relationships renders it particularly suitable as a surrogate model for the mechanical responses of SCCB.
- (2) Feature importance analysis reveals that the shear stiffness of the studs over the pier constitutes the absolutely dominant feature governing the axial force in the deck slab, accounting for 48% of the total importance. The mid-span stud spacing exerts the greatest influence on deflection, with an importance proportion of 35%, and the shear stiffness of the studs at both the pier and mid-span, together with the mid-span stud spacing, collectively contribute most significantly to the steel girder stresses, representing approximately 77% of the total importance. By contrast, the pull-out

stiffness parameters exhibit extremely low importance across all load cases, and their contribution to the optimization objectives is negligible.

- (3) By employing the AHP-TOPSIS approach, the global optimal solution is identified from the Pareto solution set. Following optimization, the SCCB deflection increases from 0.051 m to 0.053 m, the axial force in the deck slab decreases from 15,021.6 kN to 13,256.65 kN, and the stud consumption is drastically reduced from 8316 to 1019. The optimized scheme significantly lowers the construction cost while satisfying the structural safety and serviceability requirements, thereby validating the effectiveness and practical engineering value of the proposed methodology.

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