XGBoost Correction of Codified Flexural Resistance for Hybrid Double-I-Box Cold-Formed Steel Beams

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Abstract: Codified flexural-resistance equations give a clear mechanical estimate for cold-formed steel beams, but they do not represent the combined effect of hybrid steel grades and changing buckling behaviour uniformly. We compile 240 experimental and validated finite-element results for Hybrid Double-I-Box Beams (HDIBBs). This study retains the regime-specific code moment as the mechanical base and trains XGBoost only to predict the measured-to-code resistance ratio. The corrected resistance follows $M_{\mathrm{AI}} = \eta_{\mathrm{AI}} M_{\mathrm{code}}$ using the section geometry, material strengths, hybrid ratio, slenderness, elastic critical moment and code resistance as pre-test inputs. The correction reduces the overall mean absolute percentage error from 13.71% for the code estimate to 2.30%. Regime-wise out-of-fold R^2 values reach 0.932, 0.931 and 0.978 for local, distortional and lateral-torsional buckling tracks, respectively. The residual mean equals -0.093 kN·m, which indicates low overall bias. The proposed correction improves resistance screening while retaining the codified calculation as the visible mechanical reference.
Keywords: Cold-formed steel; Hybrid Double-I-Box Beam; flexural resistance; code correction; XGBoost

1. Introduction

Hybrid Double-I-Box Beams (HDIBBs) combine a closed web box with flange elements made from cold-formed steel. The section places higher-strength steel in the flange region and uses the web box to improve torsional rigidity. Earlier HDIBB studies show that short, intermediate and long beams do not follow one common failure pattern. Local buckling governs the short beams, distortional buckling controls several intermediate beams, and lateral-torsional buckling governs the long beams [1–3]. The applicable code equation therefore changes with the response track. The code calculation remains necessary because it links resistance to section properties, plate slenderness and member stability [4,5]. However, one simplified equation cannot remove every systematic difference between the calculated and observed moments. We address only this difference. We keep the regime-specific code resistance and learn a correction factor from the beam database. We do not compare several machine-learning models, optimise a section, or include columns in this paper.

2. Related Work

CFS design research connects beam resistance with effective section properties and buckling slenderness [4,5]. Gradient-boosted trees handle nonlinear interaction well in compact tabular datasets [6,7]. Recent CFS studies also use explainable learning for capacity assessment [8–10]. These studies support data-assisted resistance prediction, but the present work asks a narrower question: can XGBoost correct the codified HDIBB moment without hiding the code value? The earlier HDIBB papers supply the mechanical basis and the validated beam results [1–3].

3. Key Contribution

This study proposes one correction model for HDIBB flexural resistance. This model predicts the measured-to-code moment ratio and multiplies it by the applicable code moment. This arrangement keeps the code equation in the calculation and uses XGBoost only for the observed systematic correction across three buckling-response tracks and report their error, bias and track-wise accuracy.

4. Method, Experiments and Results

4.1 Beam database

240 HDIBB results are compiled from the authors' experimental and validated finite-element investigations [1–3]. The database is grouped by the behaviour that controls the applicable resistance expression. Track T1 contains 24 short beams and represents local buckling and effective-section bending. Track T2 contains 56 intermediate beams and represents distortional response. Track T3 contains 160 long beams and represents the lateral-torsional buckling. Figure 1 shows the built-up HDIBB arrangement, while Table 1 gives the final distribution.

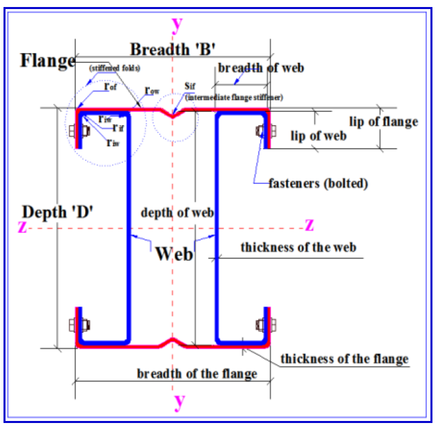

Figure 1. Hybrid Double-I-Box Beam cross-section and component arrangement [1-3].

Only the quantities available before the ultimate moment becomes known and are used. The input matrix contains the flange-width-to-depth ratio, flange and web thicknesses, beam length, flange and web yield strengths, hybrid strength ratio, plate and member slenderness, elastic critical moment, effective-section resistance and the applicable code moment. Specimen identity, source labels, reported failure descriptions, remarks and every variable derived from the measured moment are removed. The track labels are used only to select the mechanical base and to examine performance after prediction.

Table 1. Behaviour-based HDIBB database used for code correction.

Track	Beam classification; Behaviour	Cases	Purposes
T1	Short beam; local buckling	24	Section response
T2	Intermediate beam; distortional buckling	56	Flange-web response
T3	Long beam; lateral-torsional buckling	160	Member stability
Total	All beam tracks; Regime-specific	240	Correction model

4.2 Code-correction formulation

For beam i, the correction target is calculated as the ratio between the observed ultimate moment $M_{u,i}$ and the regime-specific code moment $M_{\text{code},i}$: $\boxed{\eta_{\text{AI},i} = \frac{M_{u,i}}{M_{\text{code},i}}}$

XGBoost maps the pre-test feature vector $\boldsymbol{X}_i$ to the correction factor. The corrected flexural resistance is obtained from: $\boxed{M_{\mathrm{AI},i} = \eta_{\mathrm{AI},i} M_{\mathrm{code},i}}$

where:

- $M_{u,i}$ = observed ultimate flexural resistance of beam i;
- $M_{\mathrm{code},i}$ = flexural resistance predicted using the applicable code expression;
- $\eta_{\mathrm{AI},i}$ = XGBoost-predicted code-correction factor;
- $M_{\mathrm{AI},i}$ = corrected flexural resistance.

Equation (2) gives the paper its single working idea. The code moment remains visible, and η_{AI} shows the magnitude and direction of the learned adjustment. A value above 1.0 increases the code estimate; a value below 1.0 reduces it. We therefore avoid a stand-alone black-box moment prediction.

4.3 Model execution and checking

At first, the units and variable names are standardised. Secondly, the measured and code moments, remove duplicate identifiers and check missing values are verified. Then, the modelling matrix are freezed before training. The XGBoost builds boosted regression trees and updates the residual through successive trees [6,7]. Model depth, learning rate, number of trees, row sampling, feature sampling and L1/L2 regularisation during cross-validation are controlled. The corrections are calculated only from out-of-fold predictions so that the performance does not represent a fit to the same rows used to train each fold. The corrected moment is evaluated through: Coefficient of determination, R^2; Root-mean-square error, RMSE; Mean absolute error, MAE; Mean absolute percentage error, MAPE; Mean residual. Each response track is examined separately because a high overall score can hide poor prediction in a smaller buckling group. As a secondary audit, feature contributions are inspected with SHAP [8]. This audit only used to check whether the correction follows mechanics-related variables; SHAP is not considered as a second research contribution.

4.4 Correction performance

The uncorrected code moment gives an overall MAPE of 13.71%. The XGBoost-corrected moment reduces the MAPE to 2.30%. This change removes 11.41 percentage points of error and gives an 83.2% relative reduction:

$$\text{Relative error reduction} = \frac{13.71 - 2.30}{13.71} \times 100 = 83.2\%$$

The corrected residual mean equals -0.093 kN·m. The residual standard deviation equals 1.001 kNm, while RMSE and MAE equal 1.003 kN·m and 0.712 kNm, respectively. These values show a narrow error range with small average bias.

Table 2. Performance of the attentive HDIBB code-correction model.

Assessment	Result	Engineering reading
Uncorrected code	MAPE = 13.71%	Mechanically clear but wider scatter
XGBoost-corrected code	MAPE = 2.30%	83.2% relative error reduction
Corrected residual	Mean = -0.093 kNm	Low overall bias
Residual spread	SD = 1.001 kNm	Narrow corrected scatter
Moment error	RMSE = 1.003; MAE = 0.712 kNm	Low error in resistance units

The track-wise out-of-fold results remain consistent with the overall improvement. T1 gives $R^2 = 0.932$, T2 gives $R^2 = 0.931$, and T3 gives $R^2 = 0.978$. The two smaller tracks show similar accuracy even though they represent different section-level mechanisms. The long-beam track gives the highest R^2 because it contains more cases and the lateral-torsional variables provide a strong mechanical description. Table 3 summarises these results. Figure 2 checks the predicted correction factor against the observed ratio.

Table 3. Out-of-fold performance across the three beam-response tracks.

Track	Cases	Governing response	R2	Interpretation
T1	24	Local buckling	0.932	Good short-beam correction
T2	56	Distortional buckling	0.931	Good intermediate-beam correction
T3	160	Lateral-torsional buckling	0.978	Highest track accuracy

The feature audit identifies lateral-torsional slenderness, elastic critical moment, effective-section resistance, code moment, beam length and hybrid strength ratio as the dominant correction variables. These inputs agree with the expected transition from section bending to member instability. The low contribution of web thickness follows its limited variation in the available records. This check indicates that the model does not rely mainly on an identifier or a post-test label.

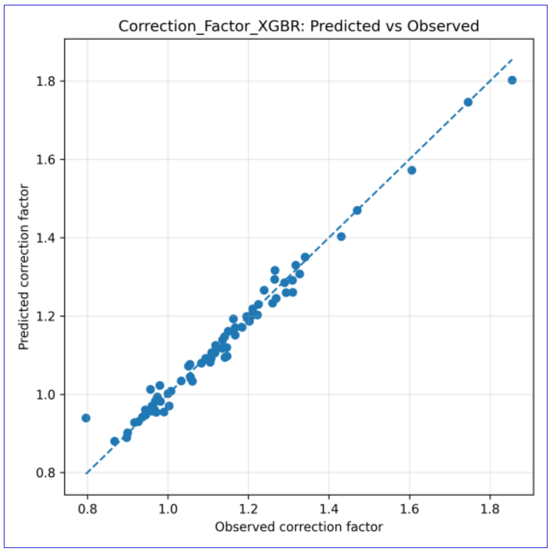

Figure 2. Observed and XGBoost-predicted correction factors for HDIBB beams.

5. Discussions

The result shows why a correction-factor formulation suits this problem. The code equation supplies the resistance scale and the appropriate mechanics for each beam track. XGBoost then learns the remaining nonlinear difference caused by geometry, hybrid material arrangement and interacting slenderness. The method does not apply one fixed multiplier to all beams. It changes the correction according to the section and member variables. The correction gives a large error reduction, but the low MAPE does not convert the model into a design resistance equation. The result are calibrated within the geometry, material, connection and loading conditions represented by the 240 beams. A designer must still complete the effective-width, local-buckling, distortional and lateral-torsional checks required by the selected code. A new section family, restraint system, load arrangement or code expression requires fresh validation. The present database contains unequal track sizes, and the T1 group contains only 24 cases.

6. Conclusions

This study addresses one problem i.e., systematic error in the codified flexural resistance of HDIBB beams across three buckling-response tracks. The data is compiled of 240 experimental and validated finite-element beam results and using pre-test geometry, material, slenderness and code-resistance inputs

1. Based on the results the predicted equation is : $\eta_{\mathrm{AI}} = \frac{M_u}{M_{\mathrm{code}}}$ and that is calculated using $M_{\mathrm{AI}} = \eta_{\mathrm{AI}} M_{\mathrm{code}}$. Hence, the code moment remains the visible mechanical base.
4. The correction reduces overall MAPE from 13.71% to 2.30%, which gives an 83.2% relative reduction in code error.
5. Track-wise out-of-fold R^2 values equal 0.932, 0.931 and 0.978 for local, distortional and lateral-torsional buckling tracks, respectively. Declarations

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Conflict of interest: The author declares no competing interests.

Data availability: The author compiles the beam data from published experimental and validated finite-element studies [1–3] and can share the processed data subject to publication and institutional conditions.

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