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Assessing the Performance of Machine Learning Algorithms in Predicting Buckling Moments of Corrugated Web Beams

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Abstract. I-beams with corrugated webs have higher torsional stiffness than that of flat web beams. Furthermore, the geometrical dimensions of the beam and the web corrugation heavily influence the precision of the currently used traditional pen-and-paper methods for determining the elastic lateral-torsional buckling moment. This study aims to suggest several machine learning models with the intention of predicting the elastic lateral-torsional buckling moment of corrugated web beams. Multiple machine learning models, including Random Forests, Gradient Boosting, Categorical Boosting, and Deep Neural Networks, were deployed to develop and train models to predict the elastic critical lateral-torsional buckling moments of I-beams with corrugated web. The database used for training the different models was compiled through linear bifurcation analyses conducted on shell finite element models. The study evaluates the precision of the various machine learning models by examining their performance against statistical parameters derived from both predicted and test data. The findings from the parametric evaluation highlight the surprisingly high performance and accuracy of the machine learning models.

Keywords. Machine learning, supervised learning, corrugated web girder, lateral-torsional buckling

1. Introduction

Using corrugated sheets as a web enables the application of thin plates without the need for web stiffeners, which leads to a more economical solution in contrast with flat web beams. The most frequently used profiles for corrugations are sinusoidal and trapezoidal but other periodic shapes like zigzags or triangles can also be found in structural engineering practice. Corrugated web I-beams have higher shear resistance and better fatigue behaviour than traditional flat web I-beams [1].

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The most common failure modes of corrugated web beams include global shear buckling of the web, local buckling of the compressed flange, lateral-torsional buckling (LTB) and the interaction between the local and global buckling modes [2]. In the Eurocode 1993-1-1 standard [3], the reduction factor for the LTB moment of a steel beam is based on the non-dimensional slenderness of the member. The main parameter to determine the non-dimensional slenderness is the elastic LTB moment of the member. The traditional pen-and-paper methods to calculate the elastic LTB moments of corrugated web beams can be separated into three ways: 1) increasing the warping constant of the flat web section [4-7], using equivalent thickness [8]; or using equivalent orthotropic plate with uniform thickness [2]. According to Bärnkopf et al. [9], there is no widely accepted analytical formula for the elastic critical LTB moment of a corrugated web beam. The reason for this is that the out-of-plane behavior of the corrugated beam is different compared to the conventional flat web beam. Hajdú and Papp [10] demonstrated that the accuracy of the traditional hand-calculation methods is highly influenced by the geometrical dimensions of the beam and the corrugation.

This study aims to show the reliability of several machine learning models for calculating the elastic LTB moment of the corrugated web girders. A comprehensive overview of applied machine learning (ML) models for various structural engineering tasks is available in [11]. Mukherjee et al. [12] proposed the first machine learning algorithm for column buckling problems in 1996. Since then, several researchers worked on the application of ML models for predicting the elastic global and local buckling capacity of steel members [13-15].

2. Creating the database

2.1. Finite element model

By using a larger number of samples for the training of an ML model, the accuracy of the algorithm can be improved. In this study, the required target values were obtained using shell finite element models. Linear Bifurcation Analyses (LBA) of the different beams were run in the Abaqus CAE simulation software [16]. The numerical models were discretized using the four-noded shell finite elements (S4). This finite element is suitable for thin-walled shell structures. The mesh size depended on the length of the beam in order to keep the elements' width/length ratio close to 1. The flanges and the web equally contain 16 shell elements. Linear multi-point constraints (Equation) were used at the beams' ends to model the fork support boundary conditions. The end moments were applied as nodal forces on the finite element nodes of the flanges. The material model is linear elastic where Young's modulus is 210000 N/mm^2. The left side of Fig. 1 shows the LTB mode. The validation of the used finite element model and the convergence study were presented in [2].

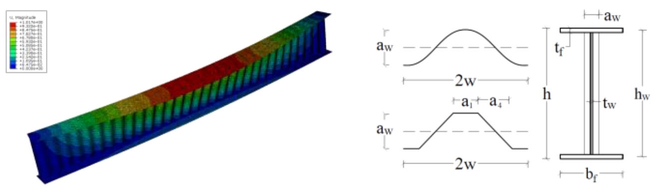

Figure 1. First global buckling mode and geometrical notations.

2.2. Dataset

The samples in the dataset were created using the finite element model mentioned in the preceding section. Based on the geometrical dimensions of the beams each sample is defined by seven features. Table 1 contains the lowest and the highest values for each feature. The geometrical dimensions of the tested members were compiled to include a broad range of practical cases. In total, the dataset includes 216 samples for sinusoidal and 216 samples for trapezoidal corrugation, with three distinct beam heights (h), five distinct flange widths (b), three distinct web thicknesses (t_w), five individual corrugation amplitudes (a_w), and five different wavelengths ($2w$). The transformation technique proposed in [3] was applied to turn the sinusoidal curve into an equivalent trapezoidal geometry. The following geometrical parameters are necessary for trapezoidal corrugation: $a_1 = 0.1 \cdot 2w$ and $a_4 = 2w/2 - a_1$. Fig. 2 shows the correlation matrix between the input and output parameters.

Table 1. Minimum and maximum values of the different features

Input values	Minimum [mm]	Maximum [mm]
L	3840.0	21 000.0
h	500.0	1000.0
b	200.0	300.0
t_w	2.5	4.0
t_f	18.0	25.0
a_w	30.0	46.0
2w	120.0	155.0

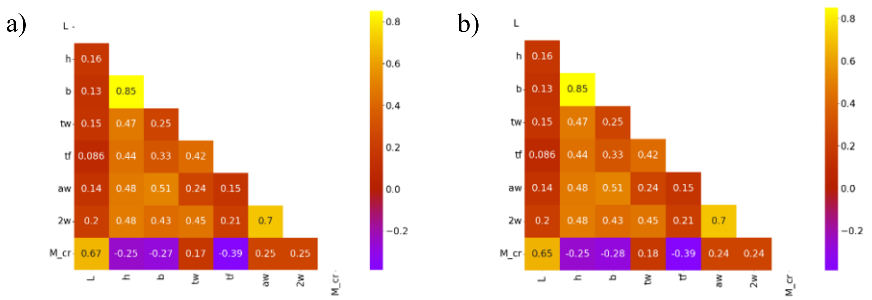

Figure 2. Correlation matrices a) for sinusoidal and b) for trapezoidal corrugation.

3. Applied machine learning models

In this part, the applied ML models and the used hyper-parameters are presented. The used algorithms are the following: random forest (RF), gradient boosting (GB), gradient boosting with categorical variables (CatBoost) and deep neural network (DNN). In structural engineering, these supervised ML methods are often applied [17].

Breiman [18] introduced Random Forest, an ensemble-learning method that employs decision trees as its weak learners. The core concept involves building a forest of decision trees by randomly selecting features and aggregating the predictions of each tree, typically by averaging, in regression problems. Leveraging decision trees as weak learners mitigates the likelihood of overfitting. The optimized hyper-parameters for the used RF models are the following: the complexity parameter is *0.0*, the function of the split quality is *poisson/squared_error*, the maximum depth of the three is 10/*None*, the minimum number of the samples is *1*, with the required split number *2*, the weight fraction is *0.0*, with the number of folds where *k*=9 for sinusoidal and trapezoidal corrugations.

Friedman [19] developed the boosting algorithm, which is an ensemble method that combines multiple individual models to enhance predictive accuracy. Similar to Random Forest, the Gradient Boosting algorithm also employs decision trees as its weak learners. During the training phase, GB minimizes the loss function of each weak learner through a general optimization technique, typically gradient descent. Additionally, it incorporates the residual loss from previous trees to inform the training of subsequent trees. The optimized hyper-parameters for the GB models are: the quality of the split is *friedman_mse*, the contribution of the trees is *0.3*, the depth of the regression estimators is *3* and *4*, the number of features is *None*, the minimum number of the samples is *5*, the tolerence is *0.0001*, with the number of folds where *k*=10 for sinusoidal and *k*=9 for trapezoidal corrugations, respectively.

CatBoost was originally designed to speed up GB's training time, but it concentrates on categorical variables. However, it can be seamlessly applied to various data types, including numerical and text features, eliminating the need for data conversion during pre-processing. Prokhorenkova et al. [20] introduced a permutation-driven boosting approach within CatBoost to optimize prediction accuracy shifts. By leveraging minimal variance sampling techniques, the algorithm enhances split scoring accuracy, which is particularly beneficial in scenarios with limited data, effectively curbing overfitting. The optimized hyper-parameters for the CatBoost models are: the fraction of the features is *0.8* and *0.9*, the tree depth is *4*, the number of trees is *300*, the L2 regularization term on weights is *0.1*, the learning rate is *0.1*, the fraction of samples is *0.9* and *0.7*, with the number of folds where *k*=8 and 10 for sinusoidal and trapezoidal corrugations, respectively.

The concept of neural networks traces back to the 1940s, with foundational work by McCulloch and Pitts [21], followed by advancements from Hebb [22], and further elaborated by Minsky and Papert [23]. Originating from the logical representation of signal transmission among individual neurons in biological nervous systems, deep learning techniques have evolved significantly and are now extensively utilized across diverse fields such as architecture, engineering, and construction. This surge in adoption is propelled by factors like the availability of large datasets, the accessibility of graphics processing units, advancements in algorithms, and easier entry into the machine learning domain through high-level libraries and APIs compared to previous decades.

Deep Neural Networks (DNNs), also known as Deep Nets, are neural networks characterized by their complexity. They are essentially stacked neural networks, comprising multiple layers - typically two or more - including output, input, and minimum one hidden layer in between. DNNs are commonly applied to handle unlabeled and unstructured data. Presently, these sophisticated neural networks have become the go-to solution for addressing a wide range of computer vision tasks. The optimized hyper-parameters for the DNN models are: number of hidden layers is *4*, the activation function is *ReLU*, the adaptive optimizer is *Adam*, the learning rate is low with *0.0005*, the number of epochs is *6000*, the used batch size is *128* for sinusoidal and trapezoidal corrugations, respectively.

4. Results

The findings of this investigation for various supervised ML models are presented in this section. *Scikit-learn* and *TensorFlow* are two open-source Python libraries that were used for the implementation of ML algorithms. The *k-fold cross-validation* method was applied for the optimization, validation and testing of the different models. An 80/20 ratio was used to randomly split the dataset into training and test sets. Table 2 summarizes the different statistical parameters of the ratio of the test ($M_{cr,Abaqus}$) and the predicted ($M_{cr,ML}$) critical moments. As can be seen, the mean values of the $M_{cr,Abaqus}/M_{cr,ML}$ ratios are 1.00 or very close to 1.00 in every case. The CatBoost algorithm has the highest scatter for both corrugation geometry and the DNN is the most stable. The maximum deviation is between 1-6%. However, the precision of the distinct ML models is acceptable and these algorithms can be used to predict the elastic LTB moment of corrugated web beam. The scatter plots of the different methods are in Fig. 3 and Fig. 4. As Table 2 indicates, the standard deviation is small in all cases. A similar conclusion was drawn in [24].

Table 2. Statistical parameters of the different algorithms ($M_{cr,Abaqus}/M_{cr,ML}$)

	RF (sin)	RF (trap)	GB (sin)	GB (trap)	CatBoost (sin)	CatBoost (trap)	DNN (sin)	DNN (trap)
Mean	1.00	1.00	0.97	1.00	0.97	1.00	1.00	1.00
Std.	0.01	0.02	0.01	0.02	0.02	0.02	0.00	0.00
C.o.V.	1.19	1.47	1.21	1.49	2.04	1.51	0.13	0.23
Min.	0.99	0.99	0.99	0.99	0.94	0.99	0.99	0.99
Max.	1.05	1.06	1.05	1.06	1.04	1.06	1.00	1.01

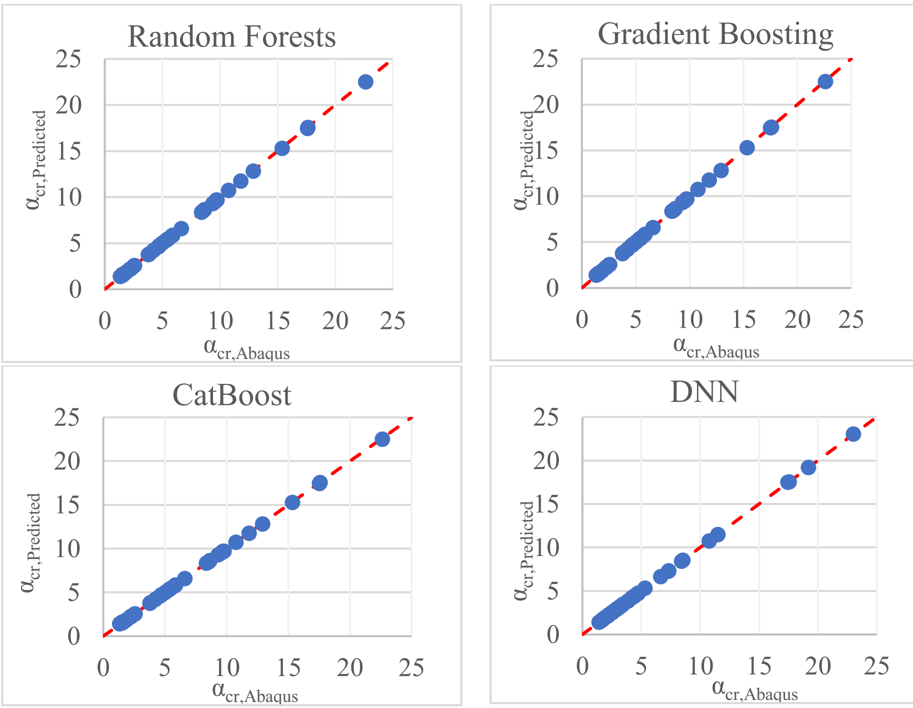

Figure 3. Scatter plots for sinusoidal corrugation.

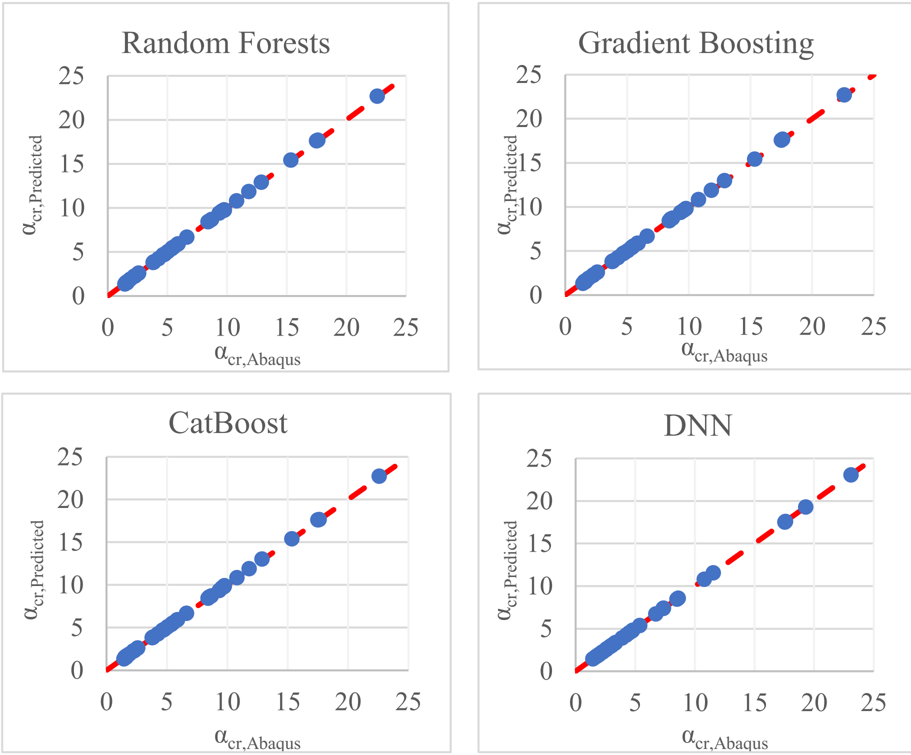

Figure 4. Scatter plots for trapezoidal corrugation.

5. Conclusions

This study explores various supervised machine learning methods to determine the elastic critical LTB moment of I-beams with corrugated webs. The out-of-plane buckling behavior of corrugated web beams differs from that of flat web beams. Past research indicates that the accuracy of existing pen-and-paper methods significantly relies on the geometrical dimensions of the beam and web corrugation. In order to calculate the elastic critical LTB moment of a corrugated web beam the most precise way is to apply a full shell finite element model. However, the model-creating process requires a significant amount of time, particularly when the web involves numerous corrugations.

Given these challenges, employing an ML approach could offer a robust method for determining the elastic critical LTB moment. The safety evaluation of various machine learning models demonstrates promising overall performance. Through detailed statistical analysis, the DNN algorithm emerges as the most precise in determining the elastic LTB moment of sinusoidal and trapezoidal corrugated web girders. In the examined cases, GB algorithm has the largest scatter, which is 2.04. The maximum deviation 6% that is still acceptable.

In the future, this research can be extended for the plastic buckling behavior and the ML models can be combined with a hand-calculation method to improve its accuracy.

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