Predicting shear strength of CFS channels with slotted webs by machine learning models

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Abstract

Staggered rectangular perforations (slots) are provided in the webs of cold-formed steel (CFS) beams and columns to reduce their thermal conductivity and improve the energy efficiency of CFS buildings. The perforations adversely affect the structural characteristics of the members, especially those governed by the web parameters, such as the shear strength and shear buckling. This paper presents machine learning (ML) models to predict the elastic shear buckling load and the ultimate shear strength of CFS channels with slotted webs. Support vector machine (SVM), decision tree (DT), random forest (RF), and k-nearest neighbor (KNN) regressors were trained using a large dataset of numerical results with 3512 samples. An extensive search was conducted to find optimal hyperparameters of the models that result in the best predictions and prevent overfitting. The models' performances were evaluated employing the ten-fold cross-validation method to make more data available for training and reduce bias and variance. The SVR, DT, and RF models demonstrate good prediction accuracy, which exceeds the accuracy of the existing descriptive equations. Relative feature importance was evaluated using the permutation and SHAP methods for each model. Partial dependence of the buckling load and the shear strength from the channel features was assessed. The predictions of the developed ML models were also compared with the predictions of previously developed artificial neural networks (ANNs). The comparisons demonstrated that ANNs showed higher accuracy in predicting the elastic buckling load, whereas the SVR model provided the most accurate shear strength predictions.

Keywords Cold-formed steel (CFS) · Perforated web · Shear buckling · Shear capacity · Machine learning · Predictive models

Introduction

Cold-formed steel (CFS) framing is structurally efficient and cost-effective due to its advantages, such as high strength-to-weight ratio, durability, sustainability, resilience, and ease of handling, transportation, and installation. CFS, however, possesses a high thermal conductivity, which may affect the energy efficiency of CFS buildings and require special thermal insulation. It has been demonstrated that the thermal conductivity of CFS members can be substantially reduced by providing punched or cut staggered rectangular perforations (slots) in the members' webs [1, 2]. However, the perforations are detrimental to the structural

characteristics of the members [3–11], especially those governed by the web properties, such as shear and web crippling capacities [12, 13].

Degtyarev and Degtyareva conducted extensive numerical parametric studies of the elastic shear buckling load, V_{cr} , and the ultimate shear strength, V_n of CFS channels with slotted webs [14–16] performed on high-fidelity finite element (FE) models validated against the available test results [17]. The studies shed light on the parameters that affect the elastic buckling load and the ultimate shear strength of the perforated channels. Descriptive equations for predicting V_{cr} and V_n of such channels were developed, and a database of the FE simulation results was created and made publicly available [18]. The results of the numerical parametric studies also showed that it is very difficult, if not impossible, to come up with simple empirical equations for predicting V_{cr} and V_n of CFS channels with staggered web perforations due to the complex nature of the problem and many factors affecting the elastic buckling load and the shear strength. In the absence of simple empirical and analytical equations,

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machine learning (ML) methods are deemed a promising option.

Artificial intelligence (AI) and ML are wide-ranging computer science branches that deal with developing machines with simulated human intelligence and data-based predictive models. AI and ML have been successfully deployed in many industries, including healthcare [19], finance and investments [20], autonomous vehicles [21], manufacturing [22], and others. Publications on AI and ML applications in civil/structural engineering span more than three decades [23, 24], and their number has increased exponentially in recent years [25–27]. However, the actual deployment of AI and ML in civil/structural engineering is rather limited compared with other industries, despite their benefits, such as automation with low computational cost and high prediction accuracy.

Several papers have been published on the applications of artificial neural networks (ANNs) for buckling analysis of beam-columns [28] and cellular steel beams [29], as well as for different aspects of CFS structures, including space structure optimization [30], web crippling strength prediction [31], elastic distortional buckling stress determination [32, 33], and rotation capacity prediction [34]. The majority of ML algorithms considered in this work were employed for structural concrete: support vector machines (SVM) were studied in [35–41], decision trees (DT) in [40, 42], random forest (RF) in [40, 42–45], and k-nearest neighbors (KNN) in [37, 40, 42, 46]. Steel and steel-concrete composite structures have also seen limited applications of SVM [47–49] and DT and KNN [50].

ANNs for predicting V_{cr} and V_n of CFS channels with slotted webs were previously developed by the author [51]. In this study, four ML regressors, including SVM, DT, RF, and KNN, for predicting V_{cr} and V_n of CFS channels with slotted webs were evaluated and compared with the ANN predictions. As was demonstrated in the literature review, the considered ML algorithms have been successfully used predominantly for reinforced concrete structures but have been rarely applied to steel structures and never evaluated for predicting the shear strength of CFS channels with slotted webs. The paper first describes the dataset used for training and testing the ML models, followed by a review of the ML algorithms considered in the study. The following section describes the implementation of the models, details of their training, testing, and hyperparameter tuning, and presents the performance of the models with the optimal hyperparameters. Relative feature importance and partial dependence of V_{cr} and V_n are presented and discussed next. Comparisons of V_{cr} and V_n predicted by the developed ML models, the existing descriptive equations, and previously developed ANNs are also presented and discussed. The novelty of this work consists in the application of new ML algorithms, implemented in an open-source framework,

for predicting the buckling load and the shear strength of CFS channels with slotted webs, which allow for rapid predictions with an accuracy that is close to that of nonlinear FE simulations and exceeds the accuracy of the existing descriptive equations. The presented relative feature importance and partial dependence plots explain how different parameters of the channels affect V_{cr} and V_n , resulting in a better understanding of the channels' structural response and may help determine optimal perforation patterns of the channels.

Dataset

The dataset of the elastic shear buckling loads and the ultimate shear strengths of CFS channels with slotted webs [18] was used for training and testing the ML models. The dataset includes FE simulation results for 3512 different channels described in [14–16]. Dimensional parameters of the studied channels are presented in Fig. 1. The 14 independent variables in the dataset are channel depth, D ; channel flange width, B ; channel flange stiffener length, B_f ; channel thickness, t ; length of slots, L_{sl} ; height of slots, W_{sl} ; spacing of slots in the longitudinal direction, S_{sl} ; spacing of slots in the transverse direction, B_{sl} ; the number of perforated regions, N ; the number of slot rows, n ; yield stress of steel, F_y ; type of boundary conditions: realistic and test setup (designated in the models with numbers 1 and 2, respectively); the aspect ratio, a/h ; and height of the longitudinal stiffener, h_{st} . The dependent variables are V_{cr} and V_n . Distributions of the dataset variables shown in Fig. 2 demonstrate that the channels in the dataset are representative of the CFS channels with slotted webs available on the market.

A correlation matrix for the dataset variables is presented in Fig. 3. It shows that channel thickness, t , has the highest positive correlation with V_{cr} and V_n , which can be classified as moderate, with coefficients of correlation of 0.73 and 0.77, respectively. All other independent variables are weakly correlated with V_{cr} and V_n , with a coefficient of correlation not exceeding 0.31. The correlation between the independent variables is weak, except for D and B , and h_{st} and N , which demonstrate a moderate correlation characterized by coefficients of correlation of 0.65 and 0.54, respectively. The correlation between V_{cr} and V_n is moderate, with a coefficient of correlation of 0.77.

Review of machine learning models

Four popular ML regressors, including support vector regressor (SVR), DT, RF, and KNN, were evaluated with respect to their predicting abilities of V_{cr} and

Fig. 1 Dimensional parameters of CFS channels with slotted webs

Fig. 2 Distributions of dataset variables

Fig. 3 Correlation matrix of dataset variables

V_n of CFS channels with slotted webs. All considered ML regressors are supervised algorithms, which learn by example using labeled training data. Figure 4 shows schematic representations of the models for predicting V_{cr} and V_n . The models consist of input parameters (or features), ML algorithms (SVR, DT, RF, or KNN), and output parameters (V_{cr} and V_n). The input parameters are fed into the ML algorithm, which produces the output value. ML algorithms are trained from training data and fine-tuned by finding optimal hyperparameters, which are the algorithm parameters specified before training to control learning. Each ML algorithm has its own hyperparameters, as described in the following subsections. The input parameters of the models for predicting V_{cr} and V_n were D , B , t , L_{sl} , W_{sl} , S_{sl} , B_{sl} , N , n , boundary conditions (BC), a/h , h_{sl} , and F_y (in the V_n models only). The channel flange stiffener length, B_l , was excluded from the models' input

parameters because it has an insignificant influence on V_{cr} and V_n [51]. The ML algorithms considered in this study are briefly described in the following subsections. More information about them and their practical implementation can be found in [52] and [53].

Support vector regressor

SVR is a regression application of SVM developed by Vapnik et al. [54–56] with the structural risk minimization principle in the basis. The ϵ -SVR algorithm [54, 57] used in this study can be illustrated by considering training data $\{(x_1, y_1), \dots, (x_n, y_n)\} \subset \chi \times \mathbb{R}$, where x_i and y_i are input and output parameters, respectively, and χ denotes the space of the input patterns. The ϵ -SVR algorithm's objective is to find a hyperplane function $f(x)$ that has maximum ϵ deviation from targets y_i and minimum flatness. Errors

Fig. 4 Schematic representations of machine learning models for predicting V_{cr} and V_n

smaller than ϵ are only acceptable in the model. The linear hyperplane function is described by Eq. 1.

$$f(x) = \langle w, x \rangle + b \text{ with } w \in \chi, b \in \mathbb{R} \quad (1)$$

where $\langle \cdot, \cdot \rangle$ represents the dot product in χ .

To minimize the hyperplane flatness, a small w needs to be found by minimizing the norm, i.e. $\|w\|^2 = \langle w, w \rangle$ as follows.

$$\text{minimize } \frac{1}{2} \|w\|^2 \text{ subject to } \begin{cases} y_i - \langle w, x_i \rangle - b \leq \epsilon \\ \langle w, x_i \rangle + b - y_i \leq \epsilon \end{cases} \quad (2)$$

Equation 2 is satisfied when a function $f(x)$ that approximates all pairs (x_i, y_i) with ϵ precision can be found, which is not always possible. The concept of “soft margin” was introduced to allow for errors. It consists of using slack variables ξ_i, ξ_i^* to give the algorithm flexibility in dealing with infeasible constraints. SVR with slack variables is formulated as follows:

$$\begin{aligned} &\text{minimize } \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*) \\ &\text{subject to } \begin{cases} y_i - \langle w, x_i \rangle - b \leq \epsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \end{aligned} \quad (3)$$

The “soft margin” constant C controls the compromise between the flatness of $f(x)$ and the maximum tolerable deviations greater than ϵ .

Nonlinear SVR is obtained by including nonlinear kernel functions into the algorithm. The nonlinear kernel function, which can be in the form of polynomial, radial basis (RBF), and sigmoid functions, transforms the original data into a high-dimensional feature space where a hyperplane function in the linear form can be found. The kernel function type and its parameters, the “soft margin” constant C , and the margin of tolerance ϵ are the SVR hyperparameters.

Decision tree

DT regression models have a tree structure that is incrementally developed by splitting the dataset into smaller subsets. The splitting occurs based on a series of questions determined by the DT algorithm. The learning begins at the root node, which includes all data and is split into two or more subsets. The splitting is repeated for the subsequent-level nodes until a predefined limit (e.g., the maximum tree depth) is reached or when leaf nodes have only one sample. A sub-node that splits into further sub-nodes is called a decision node. Nodes that do not split are called leaves or terminal nodes.

There are various algorithms for growing a DT, which differ by the possible tree structure, the split finding criteria, the splitting stoppage criteria, and the model estimation within the leaf nodes. In this work, the classification and regression trees (CART) algorithm [52] implemented in *scikit-learn* [58] was used. The CART algorithm can be illustrated by considering a dataset (x_i, y_i) for $i = 1, 2, \dots, N$, with $x_i = (x_{i1}, x_{i2}, \dots, x_{ip})$, where x_i and y_i are input and output parameters, N is the number of samples, and p is the number of input parameters. When the dataset is partitioned into M regions $R_1, R_2, \dots, R_M$, the model prediction in each region is a constant c_m described by the following formula:

$$f(x) = \sum_{m=1}^M c_m I(x \in R_m) \quad (4)$$

where $I(x \in R_m)$ is the identity function that returns 1 if x is in the subset R_m and 0 otherwise.

When the criterion of minimization is in the form of the sum of squared errors $\sum (y_i - f(x_i))^2$, the best $\hat{c}_m$ is the average of y_i in region R_m :

$$\hat{c}_m = \text{ave}(y_i \mid x_i \in R_m) \quad (5)$$

The best binary partition in terms of minimum sum of squared errors is found using the following greedy algorithm. The pair of half-planes partitioned by a splitting variable j and split point s is defined as follows.

$$R_1(j, s) = \{X \mid X_j \leq s\} \text{ and } R_2(j, s) = \{X \mid X_j > s\} \quad (6)$$

The splitting variable j and split point s that solve Eq. 7 are sought.

$$\min_{j,s} \left[\min_{c_1} \sum_{x_i \in R_1(j,s)} (y_i - c_1)^2 + \min_{c_2} \sum_{x_i \in R_2(j,s)} (y_i - c_2)^2 \right] \quad (7)$$

The inner minimization is solved by

$$\hat{c}_1 = \text{ave}(y_i \mid x_i \in R_1(j, s)) \text{ and } \hat{c}_2 = \text{ave}(y_i \mid x_i \in R_2(j, s)) \quad (8)$$

After finding the best split, the dataset is partitioned into two resulting subsets, the splitting process for which is repeated. The process is repeated for the subsequent-level nodes. DT is prone to overfitting when the tree is very large [59, 60]. Therefore, it is important for a DT to be small enough to avoid overfitting and large enough to capture the important relationships between the input and output parameters. The DT hyperparameters include the maximum depth of the tree, the minimum number of samples required to split an internal node, the minimum number of samples required to be at a leaf node, and others.

Random forest

RF is an ensemble of DTs generally trained via the *bootstrap aggregating* (or *bagging* for short) method, which consists of training the same algorithm (DT) many times on different random subsets of the training set. In bagging, the sampling is performed with replacement, meaning that one sample may appear in different subsets. In the RF algorithm, multiple randomly generated DTs make independent predictions, which are averaged to obtain the final output value. Unlike DT, RF with multiple independent DTs is robust against overfitting.

The RF regression algorithm can be described as follows [52]:

1. For $b=1$ to B , where b is an individual DT and B is the total number of DTs (estimators):
 - (a) Draw a bootstrap sample of size N from the training data.
 - (b) Grow a tree T_b to the bootstrapped data by repeating the following steps for each node until the minimum node size or the maximum tree depth is reached:
 - (i) Randomly select m variables from p variables.
 - (ii) Find the best variable among m and the best split point.
 - (iii) Split the node into two nodes.
2. Output the ensemble of trees $\{T_b\}_1^B$.
3. Make the final prediction as $\hat{f}_{RF}^B(x) = \frac{1}{B} \sum_{b=1}^B T_b(x)$.

The RF hyperparameters include those for DTs plus the number of trees in the forest.

K-nearest neighbors

KNN regression algorithm forecasts the output value by local interpolation of the k nearest neighbors' output values in the training set. The number of neighbors k is a hyperparameter set prior to training. The distance function used to define the distance between the neighbors can be expressed by the Minkowski metric, which is a generalization of the Euclidean and Manhattan distances:

$$D(X, Y) = \left(\sum_{i=1}^k |x_i - y_i|^p \right)^{\frac{1}{p}} \quad (9)$$

The Minkowski distance with the power parameter, p , being 1 and 2 corresponds to the Manhattan distance and the Euclidean distance, respectively.

The KNN regressor predicts output values by taking either an average (10) or an inverse distance weighted

average (11) of the k nearest neighbors with similar features. In the latter approach, closer neighbors have a more significant influence than the neighbors that are farther away.

$$\hat{f}(x) = \frac{1}{k} \sum_{x_i \in N_k(x)} y_i \quad (10)$$

$$\hat{f}(x) = \frac{\sum_{x_i \in N_k(x)} \frac{1}{d_i} y_i}{\sum_{x_i \in N_k(x)} \frac{1}{d_i}} \quad (11)$$

where $N_k(x)$ is the neighborhood of x defined by the k closest points x_i in the training data, d_i is the distance from the i^{th} point to the estimated point.

The KNN hyperparameters are the number of neighbors, the weight function (uniform or inverse distance weighted), and the distance metric.

Implementation and results

The ML algorithms were implemented in *scikit-learn* [58], a Python-based open-source ML library. Optimal hyperparameters of the models were found through an extensive search, which was performed using *Optunity* [61] for SVR and the *scikit-learn's* *GridSearch* function for other models. *Optunity* is an open-source library that contains various optimizers for hyperparameter tuning. The *Optunity's* default particle swarm optimization [62] was used in this study. The *GridSearch* function conducts an undirected grid search by testing a predefined set of hyperparameter values.

The ML models were validated and tested employing the ten-fold cross-validation method, where the dataset is randomly divided into test and training data, which is further split into ten groups. The model is trained on nine groups of the training data and validated on the remaining group. The process is repeated ten times until each group has served as the validation set. The model's final performance is evaluated on the test data, which was not used for the model training. Such cross-validation method offers several benefits over the more traditional hold-out method, where the dataset is partitioned into training, validation, and test sets, with each set used for its purpose only. The benefits include the availability of more samples for the model training and avoiding the model dependence on a particular random choice of the samples selected for the training, validation, and test sets. Training models on multiple train-validation splits usually results in more accurate models with better generalization abilities. In this study, 80% of the dataset samples (2808) were used for training and 20% of the samples (704) for final testing.

The dataset features span varying degrees of magnitude and ranges (see Fig. 2), which may be an obstacle for

Fig. 5 Performance of the machine learning models for predicting V_{cr}

ML algorithms. To bring the input parameters to the same scale, each input parameter value in the training set was standardized using Eq. 12. The mean and standard deviation values obtained for the training set were used to standardize the test set's input values.

$$x' = \frac{x - \mu}{\sigma} \quad (12)$$

where x' is the standardized value of the input parameter, x is the original (non-standardized) value of the input

parameter, μ is the mean of the original values of the input parameter, and σ is the standard deviation of the original values of the input parameter.

Mean squared error (MSE) values for the test set were used to evaluate the model performance and select the optimal hyperparameters.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y - \hat{y})^2 \quad (13)$$

Fig. 6 Performance of the machine learning models for predicting V_n

Table 1 Performance metrics of optimized ML models for predicting V_{cr}

Model	MSE (kN ²)			MAE (kN)			MAPE (%)		
	Train	Test	All	Train	Test	All	Train	Test	All
SVR	3.78	20.39	7.16	0.63	2.05	0.93	1.83	10.35	3.57
DT	16.58	80.57	29.38	1.46	3.61	1.89	4.28	9.49	5.33
RF	4.84	49.09	13.70	0.90	2.77	1.27	2.79	7.07	3.65
KNN	93.16	223.92	119.34	5.28	9.10	6.04	39.95	70.82	46.24
ANN ¹	3.85	20.08	7.11	1.25	2.42	1.49	11.63	16.87	12.68
ANN ²	16.00	43.55	21.52	1.36	2.57	1.60	3.98	6.23	4.43
ANN ³	2.86	13.73	5.04	0.60	1.64	0.81	4.64	7.98	5.31
ANN ⁴	3.55	17.32	6.31	0.70	1.78	0.92	2.28	5.04	2.83

¹ ANN with one hidden layer and MSE loss function

² ANN with one hidden layer and MAPE loss function

³ ANN with two hidden layers and MSE loss function

⁴ ANN with two hidden layers and MAPE loss function

where n is the number of samples, y is the output value, and $\hat{y}$ is the predicted output value.

Other common performance evaluation metrics [63] were also determined for the training and test sets, including mean absolute error (MAE), mean absolute percentage error (MAPE), the coefficient of determination (R^2), the minimum, maximum, mean, and coefficient of variation values of the prediction-to-FEA ratios.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y - \hat{y}| \quad (14)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y - \hat{y}}{y} \right| \quad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y - \hat{y})^2}{\sum_{i=1}^n (y - \bar{y})^2} \quad (16)$$

where $\bar{y}$ is the mean of the y values.

The optimal hyperparameters found for each ML model are listed below, with the *scikit-learn*'s hyperparameter names shown in parentheses. *Scikit-learn*'s default values were used for the hyperparameters not listed.

- SVR:
 - kernel function (kernel): RBF for V_{cr} and V_n ,
 - the “soft-margin” constant C : 838867 for V_{cr} and 357047 for V_n ,
 - RBF's gamma (gamma): 0.07 for V_{cr} and 0.03 for V_n ,
 - a margin of tolerance ϵ (epsilon): 2.16 for V_{cr} and 0.69 for V_n .
- DT:
 - the maximum depth of the tree (max.depth): None for V_{cr} and V_n ,

Table 2 Performance metrics of optimized ML models for predicting V_n

Model	MSE (kN ²)			MAE (kN)			MAPE (%)		
	Train	Test	All	Train	Test	All	Train	Test	All
SVR	0.55	1.52	0.75	0.40	0.73	0.46	2.10	3.72	2.43
DT	2.12	14.38	4.57	0.91	2.22	1.17	4.83	10.95	6.06
RF	0.61	5.62	1.61	0.53	1.47	0.71	2.92	7.41	3.82
KNN	11.31	22.59	13.57	2.39	3.25	2.56	15.97	20.16	16.82
ANN ¹	0.54	1.68	0.77	0.51	0.84	0.57	3.23	5.05	3.60
ANN ²	0.52	1.88	0.79	0.43	0.81	0.50	2.31	4.08	2.66

¹ ANN with one hidden layer and MSE loss function

² ANN with one hidden layer and MAPE loss function

- the minimum number of samples required to split an internal node (min_samples_split): 2 for V_{cr} and V_n ,
- the minimum number of samples at a leaf node (min_samples_leaf): 2 for V_{cr} and V_n .
- RF:
 - the number of trees in the forest (n_estimators): 500 for V_{cr} and 100 for V_n ,
 - the maximum depth of the tree (max_depth): None for V_{cr} and V_n ,
 - the minimum number of samples required to split an internal node (min_samples_split): 2 for V_{cr} and V_n ,
 - the minimum number of samples at a leaf node (min_samples_leaf): 1 for V_{cr} and V_n .
- KNN
 - the number of neighbors (n_neighbors): 3 for V_{cr} and 5 for V_n ,
 - weight function (weights): uniform for V_{cr} and V_n ,
 - the power parameter for the Minkowski metric (p): 1 for V_{cr} and V_n .

Performance of the developed ML models for predicting V_{cr} and V_n is presented in Figs. 5 and 6, respectively. The performance metrics are given in Figs. 5 and 6 and Tables 1 and 2.

Figure 5 and Table 1 show that the KNN regressor demonstrates considerably worse performance than SVR, DT, and RF, which predict V_{cr} from the FE simulations reasonably well. SVR shows the best performance in terms of MSE and R^2 for the test set, but the SVR's coefficient of variation of the prediction-to-FEA ratios for the test set is considerably worse compared with RF and DT. It should also be noted that the SVR's minimum prediction-to-FEA ratio is negative, and the maximum prediction-to-FEA ratio is considerably greater than those for RF and DT. Therefore, it is concluded that RF demonstrates the best performance in predicting V_{cr} among all evaluated models. SVR is the best model for predicting V_n in terms of all performance metrics considered in the study. RF, DT, and KNN follow it. It should also be noted that all ML models predict V_n significantly better than V_{cr} . The information presented in Figs. 5 and 6 and Tables 1 and 2 also indicate that the developed models possess good generalization ability, which is the ability to make good predictions of new data that have not been used in training.

Fig. 7 Permutation feature importance of the machine learning models for predicting V_{cr}

Relative feature importance and partial dependence

To find out which property of the analyzed CFS channels with slotted webs has the most significant effect on the V_{cr} and V_n predictions, the relative feature importance was determined using permutation and SHAP methods. The permutation feature importance shows a reduction in the model score, usually in the form of R^2 , when the feature is replaced with randomly permuted values. The model evaluation metric for the dataset modified by random shuffling of a single feature is determined and compared with the original dataset's evaluation metric. The process is repeated for each feature multiple times to obtain the mean and the standard deviation of the permutation importance score. The permutation feature importance, i_j is computed as follows:

$$i_j = s - \frac{1}{K} \sum_{k=1}^K s_{k,j} \quad (17)$$

where subscript j denotes each feature, s is the model score for the original data with unpermuted features, k is a permutation repetition, K is the total number of the

permutation repetitions, and $s_{k,j}$ is the model score for the data with the j^{th} feature permuted at the k^{th} repetition.

The permutation importance of the features in predicting V_{cr} and V_n is shown in Figs. 7 and 8, respectively. The evaluation metric (score) used in the permutation analysis was the coefficient of determination R^2 . Therefore, a permutation feature importance value of 1 means that R^2 of the model reduced by 1 after the feature was permuted (see Eq. 17). The permutation feature importance values for t are greater than one in Figs. 7 and 8, indicating that R^2 became negative for the data with permuted t . It means that, after shuffling, greater t values corresponded to lower values of V_{cr} and V_n , making the models trained on the original data (where V_{cr} and V_n increased when t increased) unable to follow the trend of the permuted data. The permutation feature importance is model-dependent, which is reflected by a slightly different order of the relative feature importance values for the evaluated ML models observed in Figs. 7 and 8.

The channel thickness, t , has the most significant impact on V_{cr} . The channel thickness importance is considerably greater than the importance of all other features. The length of slots, L_{sl} , is the second most significant feature for predicting V_{cr} , followed by boundary conditions. The boundary conditions importance, however, is significantly

Fig. 8 Permutation feature importance of the machine learning models for predicting V_n

smaller than the importance of L_{sl} . All other features demonstrate even smaller permutation importance values for predicting V_{cr} , with the channel depth, D , the channel flange width, B , the number of perforated regions, N , and the spacing of slots in the longitudinal and transverse directions, S_{sl} and B_{sl} being at the bottom of the list.

In the models for predicting V_n , the channel thickness importance also significantly exceed the permutation importance of all other features. The importance of the channel depth, D , varies widely among the evaluated ML models, but in the most accurate model for predicting V_n , SVR, it is the second most important feature, followed by the number of slot rows, n , the length of slots, L_{sl} , the height of slots, W_{sl} , and the aspect ratio, a/h . The longitudinal stiffener height, h_{st} , the number of perforated regions, N , the steel yield stress, F_y , and boundary conditions have even more minor effects on V_n in the SVR model, with the importance of the remaining features (channel flange width,

B , and the spacing of slots in the longitudinal and transverse directions, S_{sl} and B_{sl}) being close to zero.

The SHAP method, which stands for Shapley Additive Explanations [64], relies on the Shapley values from the cooperative game theory. The SHAP feature importance is estimated by comparing predictions for models with and without each feature. In contrast to the permutation feature importance, which is based on the decrease in model performance, SHAP is based on the magnitude of feature attributions. Figures 9 and 10 show the SHAP relative feature importance of the evaluated ML models for predicting V_{cr} and V_n , respectively. In the models for predicting V_{cr} , the SHAP feature importance orders are similar to those from the permutation method discussed previously, except the channel depth, D , demonstrates slightly greater importance per the SHAP method. For the most accurate model for predicting V_n , SVR, the SHAP relative importance of the features is also similar

Fig. 9 SHAP feature importance of the machine learning models for predicting V_{cr}

Fig. 10 SHAP feature importance of the machine learning models for predicting V_n

to the permutation feature importance, except the number of perforated regions, N , and boundary conditions show noticeably greater importance, while the aspect ratio, a/h , has smaller importance per the SHAP method.

The relative feature importance described above provides valuable information about how each feature affects the target, but it does not show the magnitude of the target change due to the change of each feature, which partial dependence plots can illustrate. Partial dependence plots demonstrate the effect of each feature on the predicted variable. They can reveal whether the relationships between the target and features are linear or nonlinear. Figures 11 and 12 show partial dependence plots for the developed ML models for predicting V_{cr} and V_n . It can be seen from these figures that the shapes of the relationships between the features and the targets for different models are relatively similar. However, there are some differences in the effect magnitudes. An increase of the channel depth, D , results

in a negligible reduction of V_{cr} and a noticeable increase of V_n , especially for the SVR model, which is the most accurate in predicting V_n . An increase of the channel flange width, B , practically does not affect V_{cr} and V_n . An increase of the channel thickness, t , causes significant increases in V_{cr} and V_n . The relationship between V_n and the channel thickness, t , within the considered range, is linear, whereas V_{cr} shows a greater increase when t changes from 2 to 3 mm than when it changes from 1 to 2 mm. Both V_{cr} and V_n decrease when the length of slots, L_{sl} , increased. The relationship is nonlinear, with greater V_{cr} and V_n reductions occurring when L_{sl} increases from 60 to 75 mm than when it changes from 75 to 90 mm. The effects of the slot height, W_{sl} , on V_{cr} and V_n are linear: both values reduce when W_{sl} increases. Increases in the spacing of slots in the longitudinal and transverse directions, S_{sl} and B_{sl} , result in slight increases in V_{cr} and practically no change in V_n . V_{cr} is not affected by changes in the number of perforated regions,

Fig. 11 Partial dependence plots for V_{cr}

N , whereas V_n reduces moderately when N increases from 1 to 2. An increase in the number of slot rows, n , results in practically linear reductions of V_{cr} and V_n , with V_n showing a greater reduction. The CFS channels with the realistic boundary conditions (designated with number 1 in the figures) demonstrate slightly smaller V_{cr} and greater V_n than the channels with the test setup boundary conditions. The effects of the aspect ratio a/h on V_{cr} and V_n are nonlinear. Both predicted variables reduce considerably when a/h increases from 0.5 to 1 and practically do not change with the further increase in a/h from 1 to 1.5. The longitudinal web stiffener's introduction results in a slight increase in V_{cr} , whereas the increase in the stiffener height, h_{st} , does not affect V_{cr} . The V_n values are approximately the same for the channels without the longitudinal stiffener and with a 20-mm high longitudinal stiffener. Further increase in the stiffener height results in a nonlinear decrease of V_n , with with more significant reductions occurring for larger stiffeners. Finally, V_n increases when the steel yield stress, F_y , increases.

Comparisons of V_{cr} and V_n predicted by ML models and descriptive equations

The following descriptive equations for predicting V_{cr} and V_n were previously developed from the nonlinear regression analysis of the FE simulation results [14–16].

$$V_{cr} = \frac{\pi^2 E k_v}{12(1 - \mu^2) \left(\frac{h}{t k_t}\right)^2} A_w = \frac{0.904 E k_v}{\left(\frac{h}{t k_t}\right)^2} A_w \quad (18)$$

$$V_n = V_y \text{ for } \frac{h}{t k_t} \leq b \sqrt{\frac{E k_v}{F_y k_f}} \text{ (Shear yielding)} \quad (19)$$

$$V_n = \left[1 - a \left(\frac{V_{cr}}{V_y}\right)^\alpha\right] \left(\frac{V_{cr}}{V_y}\right)^\alpha V_y \text{ for } \frac{h}{t k_t} > b \sqrt{\frac{E k_v}{F_y k_f}} \text{ (Shear buckling)} \quad (20)$$

where E is modulus of elasticity of CFS; k_v is shear buckling coefficient of the whole channel section with flat solid web;

Fig. 12 Partial dependence plots for V_n

μ is Poisson's ratio of steel; h is depth of channel web excluding thickness of flanges and rounded corners between the flanges and the web; t is base steel thickness; $A_w=ht$ is vertically projected web area irrespective of the stiffener size determined not accounting for web perforations and stiffener; V_y is shear yielding strength; F_y is yield stress of steel; k_t and k_f are web thickness modification coefficient and shear strength reduction coefficient due to web perforations determined as described in [14–16]; a , b , and α are coefficients (a is equal to 0.18 and 0.15 for channels

with flat and longitudinally stiffened webs, respectively; b is equal to 0.697 and 0.789 for channels with flat and longitudinally stiffened webs, respectively; and α is equal to 0.27 and 0.23 for channels with flat and longitudinally stiffened webs, respectively).

Comparisons of V_{cr} and V_n predicted by the developed optimized ML models and the descriptive equations are shown in Figs. 13 and 14. The comparisons demonstrate that SVR, DT, and RF predict V_{cr} and V_n from FE simulations with better accuracy than the descriptive equations, whereas

Fig. 13 Comparisons of V_{cr} predicted by the machine learning models and descriptive equations

Fig. 14 Comparisons of V_n predicted by the machine learning models and descriptive equations

KNN shows worse prediction abilities. As was mentioned previously, RF and SVR are the best models for predicting V_{cr} and V_n , respectively.

It is also interesting to compare the performance of the ML models considered in this study with the performance of previously developed ANNs [51]. Tables 1 and 2 present performance metrics for the train, test, and entire sets for SVR, DT, RF, KNN, and ANN models for predicting V_{cr} and V_n . The model prediction abilities are compared in terms of MSE, MAE, and MAPE for the test set not seen by the models during their training. Table 1 shows that ANNs demonstrate the highest accuracy in predicting V_{cr} than SVR, DT, RF, and KNN. Table 2 shows that the best predictions of V_n for all considered performance metrics are provided by SVR, followed by ANNs, RF, DT, and KNN.

Conclusions

Four machine learning regressors, including support vector machine (SVR), decision tree (DT), random forest (RF), and k-nearest neighbor (KNN), for predicting the elastic shear buckling load, V_{cr} , and the ultimate shear strength, V_n , of CFS channels with slotted webs were developed using a large dataset of FE simulation results with 3512 samples. The models' input parameters were channel depth, channel flange width, channel thickness, length of slots, height of slots, the spacing of slots in the longitudinal and transverse directions, the number of perforated regions, the number of slot rows, type of boundary conditions, the aspect ratio, height of the longitudinal stiffener, and yield stress of steel (in the models for predicting V_n only).

The models were validated and tested through ten-fold cross-validation, with randomly selected 80% of the samples used for training and validation and 20% of the samples used for final testing. The models were fine-tuned by specifying optimal hyperparameters obtained from an extensive search. The optimal hyperparameters were selected based on the models' performance metrics determined for the test set, which was not used for the model training. Predictions of SVR, DT, and RF models with the optimal hyperparameters compare reasonably well with the FE simulation results, whereas KNN demonstrates considerably worse performance. RF and SVR are the best models, among the ones considered in this study, for predicting V_{cr} and V_n , respectively. The models were implemented in an open-source Python-based framework and allow for a quick and accurate assessment of the elastic shear buckling load and the ultimate shear strength of CFS channels with slotted webs.

The relative feature performance analyses performed for each model using the permutation and SHAP methods

allowed for determining the impact of the CFS channel features on the predicted V_{cr} and V_n values. It was found that channel thickness, length of slots, and channel boundary conditions have the most significant impact on V_{cr} , with channel thickness, channel depth, and the number of slot rows being the most important features for predicting V_n . The relative importance of channel thickness for predicting V_{cr} and V_n significantly exceeds the importance of other features. Partial dependence analysis allowed for obtaining partial dependence plots, demonstrating how V_{cr} and V_n change with the change of each feature.

V_{cr} and V_n predicted by the developed ML models were compared with the predictions by the existing descriptive equations and previously developed ANNs. SVR, DT, and RF demonstrate superior performance compared with the descriptive equations. Among the ML models, ANNs show the best performance in predicting V_{cr} , whereas SVR is the best model for predicting V_n .

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