Exploring machine learning for predicting elastic buckling and ultimate moments of steel decks in bending

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Abstract

Accurate predictions of the elastic buckling and ultimate moments of steel decks in bending are essential for obtaining economic and safe designs. The existing design methods give accurate results for some deck profiles while producing unsafe or overly conservative predictions for others. This paper explores machine learning in the form of the Support Vector Machine regression (SVR) for estimating the elastic buckling and ultimate moments of steel decks. Eight SVR models for predicting the following properties of North American steel deck profiles were developed: plate buckling coefficient of stiffened flanges, plate buckling coefficient of unstiffened flanges, plate buckling coefficient for distortional buckling of deck flanges with a longitudinal stiffener, local elastic buckling moment of stiffened flanges, local elastic buckling moment of unstiffened flanges, distortional elastic buckling moment of a web-edge flange junction, distortional elastic buckling moment of a flange-stiffener junction, and ultimate moment. The dataset used for the model training, validation, and testing consisted of 1152 finite element simulations performed on deck models previously validated on experimental data. The developed SVR models demonstrated a good generalization ability and excellent prediction accuracy, which exceeded the accuracy of the existing design methods. The SVR models were interpreted by evaluating feature importance and feature effects using the SHapley Additive exPlanations (SHAP) method. The obtained feature importance and feature effects aligned well with the mechanics-based knowledge, confirming the abilities of the SVR models to capture and reveal the underlying physics from the data used for the model development. A web application for predicting steel deck properties in bending by the developed SVR models was created and deployed to the cloud. It can be opened and run in a browser on any device, including mobile. The application’s source code, which was made available on GitHub, can be used to run the application on a local machine.

1. Introduction

Corrugated cold-formed steel (CFS) roof and floor decks have been used in construction worldwide. Steel decks are available in many different shapes and offer several benefits, including a high strength-to-weight ratio, the economy in transportation and handling, and fast and easy installation. The structural design of steel decks is governed by national standards, which generally

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recognize the Effective Width Method (EWM) and the Direct Strength Method (DSM) (AISI S100-16, AS/NZS 4600:2018).

The EWM developed by von Karman et al. (1932) and Winter (1947) considers a part of a thin plate ineffective in resisting compression load due to the plate local buckling. The effective width is determined by replacing a non-uniform stress distribution in a thin plate after buckling with the equivalent rectangular stress distribution. The EWM considers the cross-section elements separately, not accounting for their interactions, and requires multiple iterations to determine CFS members' section properties. Being based on the concept of local buckling, the EWM does not explicitly consider distortional buckling, which may result in unconservative predictions for the distortional buckling failures (Yu and Lokie 2006). Steel deck profiles often fail in local buckling of stiffened and unstiffened deck flanges. Still, they may also exhibit distortional buckling of flange-longitudinal stiffener junctions or web-edge flange junctions when unstiffened edge flanges are in compression. It was previously shown that the EWM might provide unconservative predictions of the deck strength governed by distortional buckling (Degtyarev 2020a).

In the DSM (Schafer and Peköz 1998, Schafer 2008, Schafer 2019), the CFS member strength is a function of buckling loads determined from the elastic buckling analysis of the entire cross-section. The DSM allows for predicting the CFS member strength governed by distortional buckling and the strength of the members optimized by multiple stiffeners, which the EWM cannot easily achieve. Despite its many benefits, the DSM demonstrated overly conservative strength predictions for flexural members with slender compression elements (Schafer and Peköz 1998, Schafer 2008), especially when the cross-sections are not symmetric with respect to the bending axis (Dudenbostel and Sputo 2016, Raebel and Gwozdz 2018, Raebel et al. 2020, Oey and Papangelis 2020, Degtyarev 2020a). Steel deck manufacturers offer profiles with non-symmetric cross-sections and slender compression elements. The DSM underpredicts the flexural strength of such profiles, which is undesirable and slows down the DSM adoption by the steel deck industry.

Advanced finite element analysis (FEA), which is capable of accurate predictions of the deck strength in bending (Degtyarev 2020a, 2020b, 2020c, and 2020d), can be used as an alternative to the EWM and the DSM. However, it requires advanced software, modeling expertise, and substantial computational resources, which are not always available to designers. Even when the resources are available and designers possess the required skills, computationally intensive FEA is not always practical in design.

This study explores the applicability of emerging machine learning (ML) methods to the steel deck design, which may provide accuracy comparable with FEA at a low computational cost. ML is a branch of artificial intelligence (AI) and computer science that builds predictive models based on available data. ML has been successfully applied to many structural engineering problems (Çevik et al. 2015, Salehi and Burgueño 2018, Sun et al. 2021), including CFS structures. Artificial neural networks (ANNs) were employed for predicting the available rotation capacity of CFS beams (D'Aniello et al. 2014, Ali 2017), distortional buckling stress of cold-formed steel members (Pala 2006, Pala and Caglar 2007), web crippling strength of cold-formed steel decks (Guzelbey et al. 2006), shear buckling coefficient of CFS channels with large holes in the web (Pham 2018), shear elastic buckling load and ultimate shear strength of CFS channels with staggered web perforations (Degtyarev 2021b, 2021c, Naser et al. 2021, Degtyarev and Naser 2021), design load of CFS
compression members (El-Kassas et al. 2002), and uplift capacity of metal roof panels (Sirca Jr. and Adeli 2001). ANNs were also used for the optimization of CFS beams by Adeli and Karim (1997) and Karim and Adeli (1999) and for predicting the strength and deflections of strengthened CFS profiles by Taheri et al. (2021). Fang et al. (2021a, 2021b, 2021c) employed a deep belief network to predict the web crippling strength and axial capacity of CFS members. Genetic programming was applied to formulate the distortional buckling stress of C-sections in compression (Pala 2008) and for the optimal design of CFS columns (Lee et al. 2006).

The accuracy of ML models in the reviewed studies exceeded the accuracy of the existing design methods and descriptive equations, which makes the use of ML methods for estimating the elastic buckling and ultimate moments of steel decks in bending promising. In this study, Support Vector Machine regression (SVR) models for predicting the following deck properties were trained and optimized using an extensive database of FEA results: 1) plate buckling coefficient of stiffened flanges, $k_{l,stiff}$; 2) plate buckling coefficient of unstiffened flanges, $k_{l,unstiff}$; 3) plate buckling coefficient for distortional buckling of deck flanges with a longitudinal stiffener, $k_{d,flange}$; 4) local elastic buckling moment of stiffened flanges, $M_{cr,l,stiff}$; 5) local elastic buckling moment of unstiffened flanges, $M_{cr,l,unstiff}$; 6) distortional elastic buckling moment of a web-edge flange junction, $M_{cr,d,web}$; 7) distortional elastic buckling moment of a flange-stiffener junction, $M_{cr,d,flange}$; and 8) ultimate moment, $M_u$. The developed SVR models were interpreted by obtaining and analyzing partial feature importance and feature effects using the SHapley Additive exPlanations (SHAP) method. The SVR models demonstrated an excellent prediction accuracy, which considerably exceeded the accuracy of the traditional CFS design methods. A web application based on the developed SVR models was created and made publicly available.

2. Data Acquisition

The data required to develop the ML models were obtained from the FEA of North American steel deck profiles shown in Fig. 1 and Table 1. The following steel thicknesses were considered: 0.45 mm (26 GA), 0.60 mm (24 GA), 0.75 mm (22 GA), and 0.91 mm (20 GA) for 1F and 0.75 mm (22 GA), 0.91 mm (20 GA), 1.20 mm (18 GA), and 1.52 mm (16 GA) for all other profiles. Four steel yield strengths of 228, 276, 345, and 414 MPa were evaluated. The decks were analyzed in the positive (top flanges in compression) and negative (bottom flanges in compression) bending, which are also referred to as the normal and inverted bending orientations (BO), respectively.

The FEA results of some deck profiles presented in Fig. 1 and Table 1 were previously published in Degtyarev (2020a). In this study, 960 additional FE simulations were conducted to cover wider ranges of deck variables. The combined database (Degtyarev 2021a) consists of 1408 samples and includes the deck with the following span lengths: 914, 1219, and 1524 mm for 1F; 1219, 1829, and 2438 mm for 1.5B, 1.5BST1, 1.5BST2, and 1.5BST3; 1829, 2438, and 3048 mm for 2CST1, 2CST2, and 2CST3; and 3048, 3658, and 4267 mm for 3N, 3CST1, 3CST2, and 3CST3.

The deck was modeled in ANSYS with four-node structural shell elements, SHELL181. The material properties were described by an elastic modulus of $2.03 \times 10^5$ MPa, a Poisson's ratio of 0.3, and nonlinear stress-strain diagrams proposed by Gardner and Yun (2018), with true stresses and strains determined per Appendix C.6 of EN 1993-1-5:2006. The models were discretized with quadrilateral elements with maximum sizes of 5 and 10 mm in the directions across and along the deck span, respectively.
Fig. 2 shows the boundary conditions of the deck models. They consist of the symmetry degree-of-freedom constraints at the deck mid-span nodes, vertical translation restraints of the top flange nodes at the support, lateral displacement restraint of one node at the deck bottom flange edge to prevent rigid body motion, and coupled vertical displacements of deck bottom flange nodes at the load location. The models were loaded by a vertical force applied to the primary node of the coupled set at $L/3$ from the support (where $L$ is the deck span). More details on the FE models can be found in Degtyarev (2020a).

Elastic buckling and nonlinear static analyses of the deck models were performed. The obtained elastic buckling modes were classified as local buckling of stiffened flanges, local buckling of unstiffened flanges, distortional buckling of a flange-stiffener junction, or distortional buckling of a web-edge flange junction, as shown in Fig. 3. The loads and bending moments corresponding to these buckling modes were determined and stored.
The ultimate moments were determined from the nonlinear static analysis, which followed the elastic buckling analysis. Initial geometric imperfections, as well as material and geometric nonlinearities, were considered. The initial geometric imperfections with the magnitude of 1/150 of the compression flange width were specified based on the first elastic buckling mode obtained from the elastic buckling analysis. The FE models of the deck were validated against physical test results in Degtyarev (2020a, 2020c).
3. Dataset

The database of the FE simulation results (Degtyarev 2021a) includes 224 samples for the deck profiles with the elastic-perfectly plastic and bilinear steel constitutive models. The previous study showed that the elastic-perfectly plastic, bilinear, and nonlinear stress-strain relationships resulted in similar ultimate moments (Degtyarev 2020a). Therefore, the 224 results were excluded from the dataset, ensuring that each considered combination of the deck variables is represented by one dataset sample with the nonlinear material law. The database also includes 32 results for modified 1.5B and 3N decks, designated as 1.5BR and 3NR in the previous study. These profiles were excluded from the dataset because they are not conventional decks available on the market. Thus, the $M_{cr,l,stiff}$, $k_{l,stiff}$, and $M_o$ dataset used in this study included 1152 samples. For the considered deck profiles, local buckling of an unstiffened flange and distortional buckling of a web-edge flange junction can only occur for decks in the negative bending. Therefore, the $M_{cr,l,unstiff}$, $k_{l,unstiff}$, and $M_{crd,web}$ dataset included 576 samples. The distortional buckling of a flange-stiffener junction, described by $M_{crd,flange}$ and $k_{d,flange}$, was represented by 720 samples.

Fig. 4 shows distributions of the dataset variables, including span length, $L$; deck height, $h$; deck thickness, $t$; deck web angle, $\alpha_w$; bend radius at the sheet steel centerline, $r$; out-to-out widths of the top and bottom flanges at the centerline, $b_{tfo}$ and $b_{bfo}$, respectively; out-to-out width of the lip (unstiffened edge flange) at the centerline, $b_{lo}$; flange stiffener angle, $\alpha_{st}$; out-to-out stiffener height, $h_{sto}$; the number of deck hats, $N_{hats}$; deck pitch, $P$; steel yield stress, $F_Y$; the deck bending orientation; $M_{cr,l,stiff}$, $M_{cr,l,unstiff}$, $M_{crd,web}$, $M_{crd,flange}$, $M_u$, $k_{l,stiff}$, $k_{l,unstiff}$, and $k_{d,flange}$. The out-to-out widths of the flanges ($b_{tfo}$, $b_{bfo}$, and $b_{lo}$) were used in the models instead of the flat widths because the out-to-out widths are usually reported by the deck manufacturers. The $\alpha_{st}$ and $h_{sto}$ values of the decks without intermediate longitudinal flange stiffeners were taken as 0. Ranges of the independent variables in the dataset were as follows: $914 \text{ mm} \leq L \leq 4267 \text{ mm}$, $25 \text{ mm} \leq h \leq 77 \text{ mm}$, $0.45 \text{ mm} \leq t \leq 1.52 \text{ mm}$, $46^\circ \leq \alpha_w \leq 83^\circ$, $3.4 \text{ mm} \leq r \leq 5.5 \text{ mm}$, $23 \text{ mm} \leq b_{tfo} \leq 137 \text{ mm}$, $23 \text{ mm} \leq b_{bfo} \leq 128 \text{ mm}$, $10 \text{ mm} \leq b_{lo} \leq 64 \text{ mm}$, $0^\circ \leq \alpha_{st} \leq 36.5^\circ$, $0 \text{ mm} \leq h_{sto} \leq 15 \text{ mm}$, $3 \leq N_{hats} \leq 9$, $93 \text{ mm} \leq P \leq 308 \text{ mm}$, and $228 \text{ MPa} \leq F_Y \leq 414 \text{ MPa}$.

Two observations about the plate buckling coefficients of stiffened and unstiffened flanges, with values of 4.00 and 0.43 specified in AISI S100-16, can be made from Fig. 4. The dataset $k_{l,stiff}$ values between 3.29 and 5.08 reflect the web contribution, which resulted in either a reduction of $k_{l,stiff}$ below the theoretical value of 4.00 for a plate simply supported on four sides, or an increase of the buckling coefficient above the theoretical value depending on the profile geometry. The obtained $k_{l,unstiff}$ values were higher than the theoretical value of 0.43 and ranged between 0.55 and 8.17. The unexpectedly high $k_{l,unstiff}$ values, which exceeded the $k_{l,stiff}$ values for some profiles, can be explained as follows. The theoretical $k_{l,unstiff}$ value of 0.43 was determined assuming an infinitely long plate buckled in a single half-wave mode (Timoshenko and Gere 1963). In this study, the unstiffened deck flanges had large but finite aspect ratios and exhibited multiple half-wave buckling modes (see Fig. 3c), producing high buckling coefficients. The deck webs connected to the unstiffened flanges also contributed to the obtained $k_{l,unstiff}$ values.
4. Support Vector Machine Regression

Predictive models for the deck properties in bending were developed using the \( \varepsilon \)-SVR algorithm proposed by Vapnik and his colleagues (Vapnik 1995, Cortes and Vapnik 1995, Vapnik et al. 1997, Smola and Schölkopf 2004). SVR is a supervised ML algorithm that seeks a hyperplane function with the maximum \( \varepsilon \) deviation from the targets and the minimum flatness. The hyperplane \( \pm \varepsilon \) defines decision boundaries insensitive to \( \varepsilon \). The "soft margin" constant, \( C \), is introduced to account for outliers, which often exist in practical applications and impede finding a hyperplane that approximates the data with \( \varepsilon \) precision. The "soft margin" constant determines the compromise between the hyperplane flatness and the prediction errors. Kernel functions are used in the \( \varepsilon \)-SVR algorithm to handle nonlinear data. They transform the original data to high-dimensional kernel space where a linear hyperplane function can be found. Several hyperparameters must be specified.
before model training, including the kernel function type and its parameters, the "soft margin" constant, and the tolerance margin $\varepsilon$. The advantages of SVR compared with other ML regression algorithms consist of the high efficiency of handling high-dimensional data with balancing the model complexity and prediction error, insensibility to outliers, ability to handle nonlinear data, good generalization ability, and no need for large amounts of data.

The SVR algorithm was implemented in a Python-based open-source ML library *scikit-learn* (Pedregosa et al. 2011). Eight separate models for predicting $k_{l,\text{stiff}}, k_{l,\text{unstiff}}$, $k_{d,\text{flange}}$, $M_{crl,\text{stiff}}, M_{crl,\text{unstiff}}, M_{crd,\text{web}}, M_{crd,\text{flange}}$, and $M_o$ were created and optimized. The input variables of the models included $L, h, t, \alpha_w, r, b_{\text{fo}}, b_{\text{fo}}, b_{\text{so}}, h_{\text{so}}, N_{\text{hats}}, P, F_y$ (in the $M_o$ model only), and the deck bending orientation (in the $k_{l,\text{stiff}}, k_{d,\text{flange}}, M_{crl,\text{stiff}}, M_{crd,\text{flange}}$, and $M_o$ models only; 1 and 2 were used for the normal and inverted bending orientations, respectively). An extensive hyperparameter search was performed using an open-source Python-based library *Optunity* (Claesen et al. 2014) with particle swarm optimization (Clerc and Kennedy 2002).

The SVR models were validated and tested using the ten-fold cross-validation method, where the dataset is randomly split into training and test data in a specified proportion. In this study, 80% of the data were assigned to the training/validation set and 20% to the test set. The training data is divided into ten groups, nine of which are used for model training, and the remaining one is used for model validation. The training/validation process is repeated ten times, with each group serving as the validation set. The final evaluation of the model performance is done on the test data, which the model did not see during training.

Each input parameter value in the training set was standardized using Eq. (1) to make scales of the parameters uniform, which helps the algorithm train more efficiently.

$$x' = \frac{x - \mu}{\sigma}$$  \hspace{1cm} (1)

where $x'$ is the standardized value of the input variable, $x$ is the original (non-standardized) value of the variable, $\mu$ and $\sigma$ are the mean and standard deviation of the variable's original values. The test set input values were also standardized using the $\mu$ and $\sigma$ values obtained for the training set.

The model performances were assessed with the following performance metrics commonly used in ML (Naser and Alavi 2020): root-mean-square-error (RMSE), mean absolute error (MAE), mean percentage error (MAPE), determination coefficient ($R^2$), the minimum, maximum, mean, and coefficient of variation values of the FEA-to-SVR ratios.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y - x)^2}$$  \hspace{1cm} (2)

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y - x|$$  \hspace{1cm} (3)

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{y-x}{y} \right|$$  \hspace{1cm} (4)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y-x)^2}{\sum_{i=1}^{n} (y-x)^2}$$  \hspace{1cm} (5)

where $n$ is the number of samples, $y$ is the target value from FEA, and $x$ is the target value predicted by SVR.

The determined optimal hyperparameters for the SVR models are given in Table 2. The radial basis function (RBF) was specified for all models.
Table 2: Optimal Hyperparameters of SVR Models

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>$k_{l,soft}$</th>
<th>$k_{l,unsoft}$</th>
<th>$k_{d,flange}$</th>
<th>$M_{crl,soft}$</th>
<th>$M_{crl,unsoft}$</th>
<th>$M_{crd,web}$</th>
<th>$M_{crd,flange}$</th>
<th>$M_{u}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C$</td>
<td>5931</td>
<td>5309</td>
<td>1582</td>
<td>9977</td>
<td>9380</td>
<td>5311</td>
<td>1572</td>
<td>3880</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.018</td>
<td>0.124</td>
<td>0.251</td>
<td>0.099</td>
<td>0.139</td>
<td>0.249</td>
<td>0.043</td>
<td>0.068</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>0.032</td>
<td>0.010</td>
<td>0.067</td>
<td>0.035</td>
<td>0.049</td>
<td>0.048</td>
<td>0.009</td>
<td>0.053</td>
</tr>
</tbody>
</table>

5. Performance of SVR Models

The prediction performance of the developed SVR models on training and test sets is presented in Fig. 5. Performance metrics for buckling coefficients and bending moments are shown in Tables 3 and 4, respectively.
Table 3: Performance Metrics of SVR for Predicting Buckling Coefficients for Training and Test Sets

<table>
<thead>
<tr>
<th>Metric</th>
<th>$k_{\text{L, stiff}}$</th>
<th>$k_{\text{L, unstiff}}$</th>
<th>$k_{\text{d, flange}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.027</td>
<td>0.027</td>
<td>0.027</td>
</tr>
<tr>
<td>MAE</td>
<td>0.022</td>
<td>0.022</td>
<td>0.022</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>0.556</td>
<td>0.555</td>
<td>0.835</td>
</tr>
</tbody>
</table>

Table 4: Performance Metrics of SVR for Predicting Moments for Training and Test Sets

<table>
<thead>
<tr>
<th>Metric</th>
<th>$M_{\text{cr, stiff}}$</th>
<th>$M_{\text{cr, unstiff}}$</th>
<th>$M_{\text{cr, web}}$</th>
<th>$M_{\text{cr, flange}}$</th>
<th>$M_u$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE (kNm)</td>
<td>0.142</td>
<td>0.166</td>
<td>0.026</td>
<td>0.026</td>
<td>0.186</td>
</tr>
<tr>
<td>MAE (kNm)</td>
<td>0.032</td>
<td>0.046</td>
<td>0.008</td>
<td>0.010</td>
<td>0.034</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>0.149</td>
<td>0.215</td>
<td>0.331</td>
<td>0.377</td>
<td>0.308</td>
</tr>
</tbody>
</table>

It can be concluded from Fig. 5 and Tables 3 and 4 that the developed models demonstrate an excellent accuracy in predicting all considered deck properties and good generalization ability. The differences in the performance metrics for the training and test sets are relatively small, indicating that the models are not prone to overfitting.

6. Feature Importance and Feature Effects
ML models are often criticized and not readily adopted by structural engineers due to their black-box nature, which allows for accurate predictions but cannot be easily understood and explained by humans. Several methods are available and commonly used to explain and interpret ML models (Naser 2021). In the present study, the SHapley Additive exPlanations (SHAP) technique (Lundberg and Lee 2017) was used to evaluate the relative feature importance and feature effects on the deck properties predicted by the developed models. The SHAP method uses the Shapley values from the cooperative game theory. Feature impact on the model predictions is estimated by comparing predictions for models with and without each feature.

The SHAP method reveals feature importance and feature effects for the evaluated ML model. If the model is accurate, the SHAP method results also reflect the actual physical relationships between the features and targets. It was shown in Section 5 that the developed models produce very accurate predictions. Therefore, it can be considered that SHAP relative feature importance and feature effects presented in this section represent the mechanics-based relationships.

Fig. 6 shows SHAP summary plots, which combine feature importance and feature effects for each developed SVR model. Each point on the summary plot represents a dataset sample. The point color corresponds to the feature value ranging from blue for low values to red for high values. Points with the same Shapley values are scattered in the vertical direction. The feature order follows their SHAP importance. Features with higher SHAP values have more significant effects on model predictions.

It should be noted that some dataset features correlated with each other. For example, deeper deck profiles generally had longer spans, wider flanges and pitches, and fewer hats. Heavier profiles had greater bend radii at the steel centerline. Decks with fewer hats had wider pitches. For most profiles, the flat width of the unstiffened deck flanges, $w_l$, was taken as one-half of the bottom flange flat width, $w_{bf}$. Therefore, the presented importance and effects of some features on the studied deck properties are driven by other features correlated to the considered ones.
The deck bending orientation, $\alpha_{st}$, and $h_{sto}$ had the most significant effects on $k_{l,\text{stiff}}$. The positive deck bending (BO=1) produced higher $k_{l,\text{stiff}}$ values than negative deck bending (BO=2). These results were driven by the non-symmetric deck sections (1.5B and 3N), for which $k_{l,\text{stiff}}$ reduces when the relative neutral axis location increases (Degtyarev 2020a). Greater values of the longitudinal stiffener angle, $\alpha_{st}$, resulted in higher $k_{l,\text{stiff}}$ values, and vice versa. The longitudinal stiffener height, $h_{sto}$, generally had a similar effect on $k_{l,\text{stiff}}$, but the results were somewhat mixed: for some profiles, an increase in $h_{sto}$ resulted in an increase in $k_{l,\text{stiff}}$, while the opposite was true for other decks. An increase in deck height, $h$, resulted in a $k_{l,\text{stiff}}$ reduction. This result can be explained as follows. Deck webs in compression are more prone to buckling along with the compression flanges for deeper profiles. The web-flange buckling interaction reduces $k_{l,\text{stiff}}$. The $k_{l,\text{stiff}}$ values reduced when $t$ increased and increased when the top flange width, $b_{f0}$, increased. The effects of $h$, $t$, and $b_{f0}$ on $k_{l,\text{stiff}}$ were considerably smaller than the effects of BO, $\alpha_{st}$, and $h_{sto}$. The remaining features had even more minor effects on $k_{l,\text{stiff}}$. 
The $k_{l,\text{unstiff}}$ values were most affected by the deck span, $L$, and steel thickness, $t$. Higher values of $L$ and $t$ produced smaller $k_{l,\text{unstiff}}$ values. The effect of $L$ on $k_{l,\text{unstiff}}$ can be explained by the aspect ratio reduction when the deck span is shortened and the span length effect on the number of half-waves. However, the latter requires further investigation. $b_{f0}$ and $b_{lo}$ demonstrated similar effects on $k_{l,\text{unstiff}}$, because the flat width of the unstiffened flange was taken as one-half of the bottom flange flat width for most profiles. The $k_{l,\text{unstiff}}$ values increased when $b_{f0}$ and $b_{lo}$ increased. Deck profiles with larger pitches, $P$, produced higher $k_{l,\text{unstiff}}$ values, while the effect of deck height, $h$, on $k_{l,\text{unstiff}}$ was mixed. For most profiles, an increase in $h$ increased $k_{l,\text{unstiff}}$, but $h$ affected $k_{l,\text{unstiff}}$ oppositely for some decks. The remaining features had minor effects on $k_{l,\text{unstiff}}$.

As expected, the longitudinal stiffener height, $h_{sto}$, had the most significant influence on $k_{d,\text{flange}}$. Deeper stiffeners increase the flexural stiffness of flanges, which is reflected in higher $k_{d,\text{flange}}$ values. The steel thickness, $t$, and bend radius, $r$, showed similar but considerably less significant effects on $k_{d,\text{flange}}$. Deck profiles with larger $t$ and $r$ values produced higher $k_{d,\text{flange}}$ values. The remaining features affected $k_{d,\text{flange}}$ insignificantly.

$M_{cr,l,\text{stiff}}$ was most significantly affected by the steel thickness, $t$, an increase of which resulted in an $M_{cr,l,\text{stiff}}$ increase. The longitudinal stiffener height, $h_{sto}$, bending orientation, and longitudinal stiffener angle, $\alpha_{st}$, followed $t$ in their impacts on $M_{cr,l,\text{stiff}}$, which increased when $h_{sto}$ and $\alpha_{st}$ increased and decreased when the bending orientation changed from normal to inverted. The remaining features had less significant effects on $M_{cr,l,\text{stiff}}$, which increased in most cases when $h$, $r$, $N_{hats}$, and $L$ increased and decreased when $b_{f0}$, $b_{f0}$, $b_{lo}$, and $P$ increased.

The effect of the steel thickness, $t$, on $M_{cr,l,\text{unstiff}}$ was considerably more significant than the effects of other features. $M_{cr,l,\text{unstiff}}$ increased when $t$ increased. The deck span length, $L$, was the next feature most significantly affecting $M_{cr,l,\text{unstiff}}$, which decreased when $L$ increased. The remaining features had comparable and less significant effects on $M_{cr,l,\text{unstiff}}$. Interestingly, an increase in $b_{lo}$ resulted in $M_{cr,l,\text{unstiff}}$ reduction, whereas deeper deck profiles produced higher $M_{cr,l,\text{unstiff}}$ values.

$M_{cr,d,\text{web}}$ was most significantly affected by $t$, $L$, and $h$. $M_{cr,d,\text{web}}$ increased when $t$ and $h$ increased and reduced when $L$ increased. The remaining features had less significant effects on $M_{cr,d,\text{web}}$. It can be observed from Fig. 6 in particular that profiles with wider unstiffened flanges produced higher $M_{cr,d,\text{web}}$ values.

The longitudinal stiffener height, $h_{sto}$, and steel thickness, $t$, had the most significant effects on $M_{cr,d,\text{flange}}$, which increased when $h_{sto}$ and $t$ increased. Fig. 6 also shows the high importance of $r$ for predicting $M_{cr,d,\text{flange}}$, but this result was caused by the correlation between $t$ and $r$ discussed above. The remaining features affected $M_{cr,d,\text{flange}}$ less significantly.

Finally, $M_u$ was most significantly affected by the following features in the descending order: $t$, $h$, $F_y$, and $h_{sto}$, which increase resulted in a $M_u$ increase, as expected. The bending orientation of non-symmetric deck sections also affected the ultimate moment, which was greater for the normal bending than for the inverted bending. Similar results were obtained previously (Degtyarev 2020a). The remaining features affected $M_u$ less significantly.
Fig. 6 shows that some features had relatively small effects on the studied deck properties. It might be possible to exclude those features from the models without a considerable reduction in the predicting accuracy. However, that was done in this work and will be considered in future studies.

The presented information about the feature importance and feature effects generally aligns with the mechanics-based knowledge, which confirms the abilities of the developed models to capture and reveal the underlying physics from the data used for the model development. At the same time, the new information on the effects of $h$ and $t$ on $k_{l, stiff}$, and $L$ and $t$ on $k_{l, unstiff}$ was obtained.

### 7. Comparisons

Fig. 7 shows comparisons of the deck properties predicted by the developed SVR models and existing EWM and DSM design provisions (AISI S100-16) with FEA results for the entire dataset.
Prediction performance metrics are given in Fig. 7 and Tables 5 and 6. The elastic buckling properties ($k_{l,\text{stiff}}$, $k_{l,\text{unstiff}}$, $k_{d,\text{flange}}$, $M_{cr,l,\text{stiff}}$, $M_{cr,l,\text{unstiff}}$, and $M_{cr,d,\text{flange}}$) were compared with the EWM only, because in the DSM, they are determined from elastic buckling analyses similar to the ones performed in the present work. Thus, the deck elastic buckling properties according to the DSM are identical to those from FEA obtained in this study. Comparisons for $k_{d,\text{web}}$ and $M_{cr,d,\text{web}}$ are not presented because the EWM cannot predict them.

Table 5: Performance Metrics of SVR and EWM for Predicting Buckling Coefficients

<table>
<thead>
<tr>
<th>Metric</th>
<th>$k_{l,\text{stiff}}$</th>
<th>$k_{l,\text{unstiff}}$</th>
<th>$k_{d,\text{flange}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>SVR 0.027</td>
<td>EWM 0.409</td>
<td>SVR 0.010</td>
</tr>
<tr>
<td>MAE</td>
<td>0.022</td>
<td>0.308</td>
<td>0.009</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>0.556</td>
<td>7.488</td>
<td>0.833</td>
</tr>
</tbody>
</table>

Table 6: Performance Metrics of SVR, EWM, and DSM for Predicting Moments

<table>
<thead>
<tr>
<th>Metric</th>
<th>$M_{cr,l,\text{stiff}}$</th>
<th>$M_{cr,l,\text{unstiff}}$</th>
<th>$M_{cr,d,\text{flange}}$</th>
<th>$M_{u}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE (kNm)</td>
<td>SVR 0.147</td>
<td>EWM 2.170</td>
<td>SVR 0.026</td>
<td>EWM 0.170</td>
</tr>
<tr>
<td>MAE (kNm)</td>
<td>0.034</td>
<td>1.205</td>
<td>0.009</td>
<td>0.071</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>0.162</td>
<td>7.488</td>
<td>0.341</td>
<td>0.396</td>
</tr>
</tbody>
</table>

The presented information demonstrates the superior performance of the developed SVR models for predicting the steel deck buckling coefficients, buckling moments, and ultimate moment compared with the existing design methods.

8. Web Application
A web application to predict deck properties in bending by the developed SVR models was created in Streamlit (https://streamlit.io). Fig. 8 shows the graphical user interface of the web application.

Figure 8: Graphical User Interface of the Developed Web Application
The application predicts the $k_{l,\text{stiff}}$, $k_{l,\text{unstiff}}$, $k_{d,\text{flange}}$, $M_{cr,\text{stiff}}$, $M_{cr,\text{unstiff}}$, $M_{cr,\text{flange}}$, and $M_u$ values based on the following parameters specified by the user: deck type, deck gauge, yield strength, deck span, and bending orientation. The application’s source code is available in Degtyarev (2021d). It allows for running the application on a local machine. The application has also been deployed to the cloud. It can be opened and run in any browser on any device, including mobile, at https://steel-deck-bending.herokuapp.com/.

9. Conclusions and Future Work

The paper presented Support Vector Machine regression (SVR) models for predicting the following properties of steel deck profiles commonly used in North America: plate buckling coefficients of stiffened flanges, plate buckling coefficients of unstiffened flanges, plate buckling coefficient for distortional buckling of deck flanges with a longitudinal stiffener, local elastic buckling moment of stiffened flanges, local elastic buckling moment of unstiffened flanges, distortional elastic buckling moment of a web-edge flange junction, distortional elastic buckling moment of a flange-stiffener junction, and ultimate moment. The models were trained, validated, and tested using a large finite element analysis results dataset. The developed models demonstrated a good generalization ability and excellent prediction accuracy, which exceeded the accuracy of the existing design methods.

The SVR models were interpreted by evaluating feature importance and feature effects on the studied deck properties with the SHapley Additive exPlanations (SHAP) method. The obtained feature importance and feature effects aligned well with the mechanics-based knowledge, confirming the abilities of the developed models to capture and reveal the underlying physics from the data used for the model development.

For non-symmetric deck cross-sections, the effects of the flange width ratio on the plate buckling coefficients of stiffened flanges, the local elastic buckling moment of stiffened flanges, and the ultimate moment presented previously were confirmed. The new information on the effects of deck height and steel thickness on the plate buckling coefficients of stiffened flanges and span length and steel thickness on the plate buckling coefficients of unstiffened flanges was obtained.

A web application for predicting the studied deck properties in bending by the developed SVR models was created and deployed to the cloud at https://steel-deck-bending.herokuapp.com/. It can be opened and run in any browser on any device, including mobile. The application’s source code is available on GitHub, which allows for running the application locally.

The presented study demonstrates a high potential of machine learning methods for predicting buckling and ultimate loads of cold-formed steel decks. Considering the magnitude of different deck profiles available worldwide, future work should concentrate on expanding the database to decks of different shapes and dimensions. Machine learning models based on other commonly used regression algorithms should also be studied to determine the algorithm with the highest accuracy and the best generalization.

References
ANSYS Mechanical APDL, Release 19.2.
Degtyarev, V.V. (2020c). "Finite element modeling of cold-formed steel deck in bending." Magazine of Civil Engineering, 94(2), 129-144


