Predicting the Capacity of Slender Steel Columns at Elevated Temperature with Finite Element Method and Machine Learning

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Abstract
This work applies finite element (FE) modeling and machine learning (ML) techniques to investigate the resistance of slender steel columns at elevated temperatures. First, a numerical study is performed with the FE software SAFIR to evaluate the columns' response for a range of cross-sections and boundary conditions. The FE model is used to generate a large dataset for training and testing three types of ML models: support vector regression (SVR), artificial neural network (ANN), and polynomial regression (PR). The trained models are compared against experimental data and an analytical model. The results show that the ML models provide more accurate predictions in the training and testing datasets compared with the analytical model. The predictions from the ANN and SVR also reasonably agree with the experimental data. These results suggest that ML techniques can be used to derive efficient surrogate models for capacity prediction of such members in fire.

Keywords: Finite element method, Machine learning, Slender steel column, Fire

1 INTRODUCTION

The fire behavior of slender steel columns is influenced by the complex interaction between local, global, and distortional instability modes at elevated temperatures. This behavior has been investigated in the literature using high-fidelity FE models, but the computational cost limits the ability to conduct parametric analyses needed to derive robust design methods. An alternative is the use of analytical methods derived from mechanics-based principles and experimental observations. For predicting the resistance of slender steel members at elevated temperature, a simple analytical method is provided in the Eurocode 3 part 1.2 (CEN 2005). Couto et al. (Couto *et al*. 2015) recently proposed an improvement to this method based on the effective cross-section and the yield strength at 2% total strain for Class 3 and Class 4 cross-sections. While analytical methods are very useful for design, they are necessarily based on simplifying assumptions.

Machine learning (ML) techniques, increasingly used in many engineering fields, provide an opportunity to derive efficient surrogate models and identify prevailing parameters for capacity prediction (Salehi and Burgueño 2018). The adoption of ML techniques in structural fire engineering could provide a way to derive low-cost models for predicting the behavior of complex members and structural assemblies subject to fire (Naser 2019, Chaudary *et al*. 2020, Naser 2021). This work studies the application of three types of ML techniques to determine the resistance of I-shaped cross-section slender steel columns at elevated temperature. To build the dataset required for training of the ML models, high-fidelity FE simulations with shell elements are carried out using the software SAFIR. The trained ML models are compared with Couto et al.'s analytical model and with experimental data not included in the training dataset.

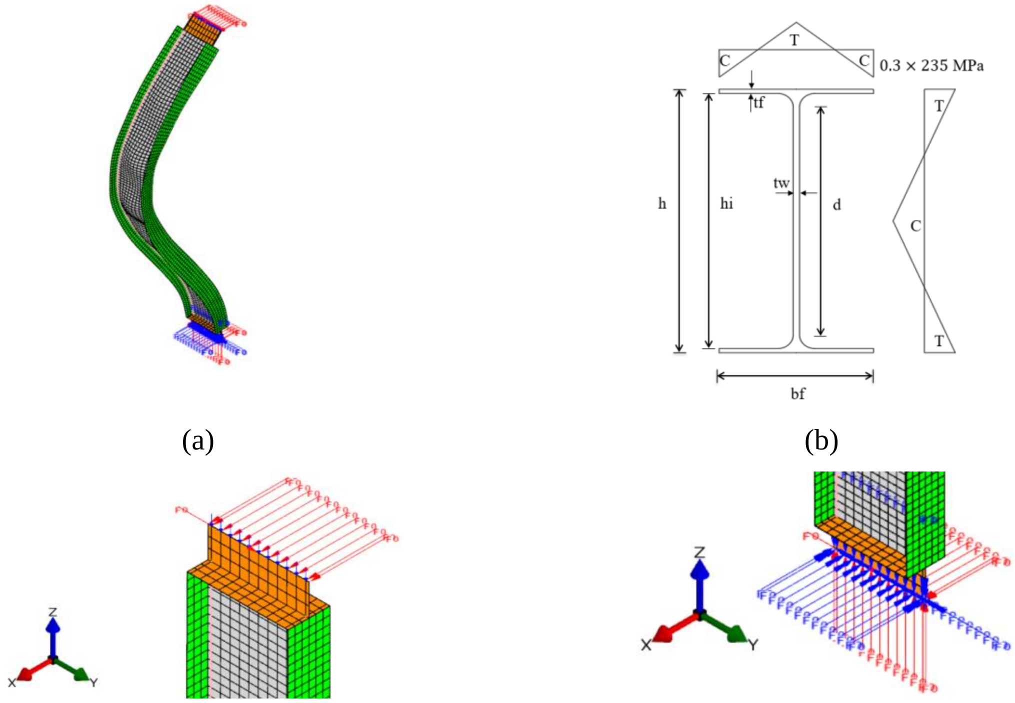
2 FINITE ELEMENT MODELING

The FE software SAFIR (Franssen and Gernay 2017) is applied to predict the resistance of slender steel columns at elevated temperature and generate the datasets to construct the ML models. The ability of the FE models to capture the behavior of slender steel columns subjected to uniform heating is validated against eight experimental tests on Class 3 and 4 I-shaped cross-section columns as described in (Franssen *et al*. 2016). The critical temperature and failure mode observed in the tests are well captured by SAFIR. For critical temperature, the average ratio of *SAFIR/Test* is 1.007 with a standard deviation of 0.03. Therefore, the SAFIR numerical models can be used to generate the datasets for ML.

An extensive FE study is conducted to obtain the load capacity of columns at elevated temperature. Considered cross-sections range from IPE300 to IPE600. Ambient temperature steel grade include S235, S355 and S460. Temperature at which the capacity is evaluated is assumed uniform in the section and ranges from 300-800°C with a 100°C increment. The length of the columns is 4.5 meters, while different boundary conditions are studied. A total of 1728 data points are generated.

To build the numerical models, geometric imperfections are obtained for local and global modes through buckling analyses with the software Abaqus to obtain the eigenmodes. For global imperfection, the amplitude follows the design recommendation, i.e. *L/1000*, where *L* is the length of the column. For local imperfection, the amplitude is calculated as 80% of the geometric fabrication tolerances as recommended in (CEN 2008; Couto and Real 2021). In this study, the amplitudes of local imperfections are calculated following Table 1 in (Couto and Real 2021). The global imperfection and local imperfection are combined following the recommendation of Annex C in Part 1-5 of Eurocode 3 (CEN 2006). The lowest eigenmode is the leading imperfection and the amplitude of the other eigenmode is reduced to 70%.

The coordinates of the nodes with geometric imperfections are then exported to SAFIR. The members are discretized using 4-noded shell elements. A sensitivity analysis on the mesh size is conducted showing convergence of the results with 120 elements on the length, 6 elements on the flange, and 10 elements on the web. Two rigid 100 mm thick end plates are added at both ends of the column, as shown on Figure 1. The size of the horizontal plate equals the web height and flange width. The width of the vertical plate equals the web height and its length is 150 mm. The load is axially applied on the edge of the vertical plate on the top with no eccentricity such that the load can be distributed evenly on the web and flange. The rotations of the shell edge of the vertical plate are either fixed or pinned in *Mx*, *My*, and *Mz* directions. The pattern of residual stresses follows the one for hot-rolled columns (Couto and Real 2021) as shown in Figure 1(b). The residual stress is added to the integration points of the shell element and transformed into residual strains by SAFIR; the detailed procedure can be found in (Lopes 2009). The ultimate load-bearing capacity of the columns is calculated by SAFIR by first uniformly increasing the temperature in the section up to the target value and then progressively loading the column until failure.



(c)

Fig. 1 The numerical model in SAFIR: (a) shell model for IPE500 column at 300 °C; (b) cross-section dimensions and residual stresses; (c) boundary conditions with end plates and pinned-fixed supports

3 MACHINE LEARNING MODELS

The 1728 data points obtained from the FE analysis are randomly divided into two groups for training and testing the ML models, with a ratio of 9:1. The trained ML models are also validated against experimental data published in (Kucukler *et al.* 2020) and in (Wang *et al.* 2014). Cross-validation is applied to tune the parameters in the ML models. The input parameters and output are summarized in Table 1, in which $N_{u,T}$ is the load capacity at elevated temperature, $N_{u,20}$ is the load capacity at 20 °C, h_w/t_w and $b_f/2t_f$ are the adimensional web and flange dimensions, F_{y_web}/E and F_{y_flange}/E are the adimensional web and flange yield strengths, and top and bottom are the boundary conditions at the two ends (either fixed or pinned). The h_w/t_w of the cross-sections ranges from 31.1 to 52.5 while $b_f/2t_f$ ranges from 4.7 to 8.2. Three ML methods are considered herein, namely SVR, ANN and PR as described in the next sections. The Python package Scikit-learn (Pedregosa *et al.* 2011) is used for the implementation.

Table 1. Parameters for the ML models

input parameters							output
h_w/t_w	$b_f/2t_f$	F_{y_web}/E	F_{y_flange}/E	$temperature$(°C)	top	$bottom$	$N_{u,T}/N_{u,20}$

3.1 Support vector machine regression (SVR)

SVR is developed as an extension of the support vector machine (SVM), which aims to find a hyperplane in an n-dimensional space (n is the number of features, i.e. input parameters) that classifies the training datasets in different classes. While the objective of SVM is to find a hyperplane that has the maximum margins ($\pm\varepsilon$), the extension SVR aims to find a flat hyperplane with margins ($\pm\varepsilon$) that accept the data points within or on the margins while rejecting the data points outside the margins. The hyperplane can be written in Equation (1) for linear SVR:

$$y_i = w^T x_i + b \tag{1}$$

in which x_i and y_i are the ith input and output in the training dataset, w is the weight matrix and b is the bias.

For nonlinear SVR, the hyperplane can be written as:

$$y_i = w^T \varphi(x_i) + b \tag{2}$$

in which $\varphi(x_i)$ is the nonlinear kernel function that maps the input vectors to a higher dimension space. The deviation of points within the margins ($\pm\varepsilon$) is zero. The deviation of points outside the margins ($\pm\varepsilon$) is the distance of these points to the margins (ξ_i and ξ_i^*). The loss function of SVR is written as:

$$minimize: \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{3}$$

Constraints:

$$y_i - wx_i - b \leq \varepsilon + \xi_i$$

$$wx_i + b - y_i \leq \varepsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \geq 0$$

in which $\frac{1}{2}\|w\|^2$ is the regularization term added to seek the flattest hyperplane with a small weight. C is a trade-off between the accepted tolerance of deviation ε and the flatness of the solution.

3.2 Artificial neural network (ANN)

The ANN consists of several neurons arranged in multiple layers (input layer, hidden layer, and output layer) and the connections between them. The neurons are the main process unit which is a linear or nonlinear function describing the relationship of input and output of the neuron. In this work, a feed-forward and backpropagation algorithm is used to build the ANN. The feed-forward means the information is transmitted from the input layers to the output layers. Once the ANN model is built, the training process starts to assign random values to the weights connecting the neurons in the input, hidden, and output layers. The input parameters are fed in the neurons in the input layers and multiplied by the weighted values. The sums of the multiplication and bias are put through a transfer function or activation function to generate the output of the neurons in the hidden layers or the output layers. Typical activation functions include linear, logistic sigmoid, hyperbolic tan function and rectified linear unit function. The output of neurons can be written as:

$$output_j = f(\sum_{i=1}^{n} w_{ij}x_i + bias_j) \quad (4)$$

in which $output_j$ is the output of jth neuro and x_i is the input from ith neuron in the last layer. f is the transfer function. $bias_j$ is the bias for jth neuro. The predicted values in the output layer are compared to the known observations. The difference of predicted and known values are used to adapt the weights through the backpropagation algorithm. The forward feed and backpropagation algorithm is repeated to adjust the weights iteratively until the error between known and predicted value reaches an accepted tolerance. The optimal hidden layer in this work is 6.

3.3 Polynomial regression (PR)

The general form for polynomial regression is written as:

$$Y = X\omega + \varepsilon \quad (5)$$

in which Y is the vector of responses, X is the feature matrix, ω is the coefficient and ε is the bias. The polynomial regression extends the inputs of the linear model, which is obtained by raising the initial inputs to a power. The new inputs are created with degrees less than or equal to the specific order. The new feature matrix includes 1) bias; 2) converting the initial inputs to their higher-order terms for each degree; 3) combination of all pairs of initial inputs. For instance, if there are two inputs, $[x_1, x_2]$, a degree-2 polynomial expansion would produce a new feature matrix $[1, x_1, x_2, x_1^2, x_1x_2, x_2^2]$. Models with higher degrees may closely fit most of the data in the training dataset, however, it may also capture the noises in the data, resulting in a larger error on the testing dataset (i.e. over-fitting). To prevent over-fitting in polynomial regression, ridge regression is applied to fit the polynomial feature matrix. The ridge regression adds a regularization term to the sum of squares of residuals. The loss function of ridge regression is written as:

$$minimize: \sum_{i=1}^{n} \|y_i - \sum_{j=0}^{m} x_{ij}w_j\|^2 + \lambda \sum_{j=0}^{m} \|w_j\|^2 \; (\lambda > 0) \quad (6)$$

in which the y_i is the known observation, $\sum_{j=0}^{m} x_{ij}w_j$ is the predicted value, and λ is the tuning parameter which controls the complexity of the model. As λ grows larger, the ridge regression effectively shrinks coefficient w_j to be 0 and selects a small subset of features to build the model, which prevents training a more complex model and thus avoid over-fitting.

4 RESULTS

To quantify the performance of the different models, the R^2 value is evaluated for the models against the training and testing dataset and the experimental data. Table 2 gives the results for the SVR, ANN, and PR (degree 2) models. Predictions by the analytical model by (Couto *et al*. 2015) with χ_{fi} from Eurocode 3 Part 1.2 (CEN 2005) are also included. The three ML models provide better agreement with the training and testing dataset than the analytical model. For the validation against experimental data, 16 data points obtained from (Kucukler *et al.* 2020) and (Wang *et al*. 2014) are used. The predicted capacity from the ANN agrees best with the experimental data with R^2 of 0.945, followed by PR and the analytical model. The SVR model does not agree well with the experimental data.

Table 2. Performance of ML and analytical models

Regressor (R^2)	Train	Test	Experiment
SVR	0.999	0.998	0.087
ANN	0.999	0.999	0.945
PR (degree 2)	0.976	0.980	0.864
Analytical (Couto et al. 2015)	0.948	0.943	0.838

Figure 2 (a)-(d) plot the predicted capacity $N_{u,T}/N_{u,20}$ using SVR, ANN, PR, and analytical models against the numerical estimations from SAFIR. For training and testing datasets, the predicted capacities are scattered in six groups, corresponding to the elevated temperature levels. The results from SVR, ANN, and PR agree well with the capacity evaluated by SAFIR. The ANN and PR models are also able to predict the capacity in the experimental datasets with good agreement. Overall, the trained ANN and PR models, which are built on extensive validated FE analysis data, can predict the resistance of the slender steel columns at elevated temperature with high accuracy. The performance of the ML models can be further improved by considering a larger dataset including a greater range of inputs. For instance, different column lengths can be included in the training dataset to improve prediction of capacity when global buckling occurs.

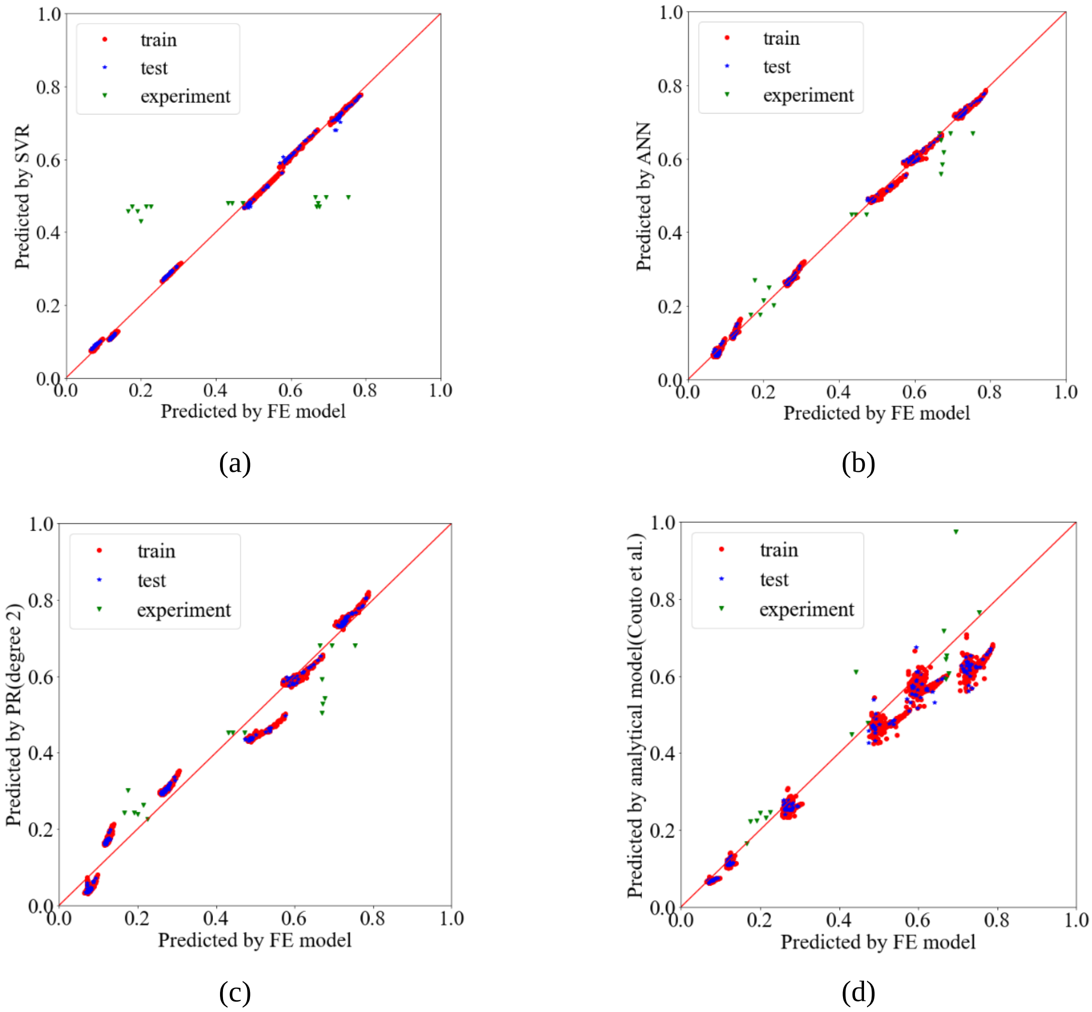


Fig. 2 Predicted capacity $N_{u,T}/N_{u,20}$ for slender steel columns at elevated temperature: Comparison between SAFIR finite element model and (a) SVR; (b) ANN; (c) PR; (d) Analytical model (Couto et al.)

5 CONCLUSIONS

This study investigated the potential of Machine Learning (ML) models to capture the capacity at elevated temperature of slender steel columns. A numerical study based on validated nonlinear finite element modeling with shell elements was conducted to build a dataset of 1728 data points for columns with a range of cross-sections, temperature, yield strength and boundary conditions. The columns exhibited failure by local, global, and distortional buckling. The dataset was used to train and test three ML models, namely based on support vector regression (SVR), artificial neural network (ANN), and polynomial regression (PR).

The results indicate that the three tested ML models are able to predict the resistance of the columns in the training and testing dataset with an excellent accuracy (R^2 greater than 0.998 for SVR and ANN, and greater than 0.976 for PR). The ML models agreed better with the FE data than a state-of-the-art analytical model. The ANN and PR models were also able to capture experimental data not used to train the model with a R^2 of 0.945 and 0.864, respectively. It is expected that the accuracy against test data could be further improved by increasing the training dataset and including other inputs in the ML models. This work shows that the ML models are able to accurately predict the resistance of columns under uniform heating while also being computationally efficient. In future works, more complex configurations such as structural assemblies or localized fire exposures will be explored.

REFERENCES

CEN, EN., 2008, 1090-2: execution of steel structures and aluminium structures–part 2: technical requirements for steel structures, European Committee for Standardisation, Brussels.

CEN. EN.,2005,1993-1-2, Eurocode 3: design of steel structures — part 1–2: general rules —structural fire design. Brussels: European Committee for Standardisation.

CEN. EN.,2006, 1993-1-5, Eurocode 3 — design of steel structures — part 1-5: plated structural elements. Brussels: European Committee for Standardisation.

Chaudhary R.K., Jovanović B., Gernay T., Van Coile R., 2020. Generalized fragility curves for concrete columns exposed to fire through surrogate modelling. In Proceedings of the 11th International Conference on Structures in Fire (SiF2020).

Couto C, Real P.V., 2021. The influence of imperfections in the critical temperature of I-section steel members, Journal of Constructional Steel Research, 179: 106540.

Couto C, Real P.V., Lopes N, Zhao B., 2015. 'Resistance of steel cross-sections with local buckling at elevated temperatures', Journal of Constructional Steel Research, 109: 101-14.

Franssen J.M, Gernay T., 2017. Modeling structures in fire with SAFIR®: Theoretical background and capabilities, Journal of Structural Fire Engineering.

Franssen J.M, Zhao B, Gernay T., 2016. Experimental tests and numerical modelling on slender steel columns at high temperatures, Journal of Structural Fire Engineering.

Kucukler M, Xing Z, Gardner L., 2020. Behaviour and design of stainless steel I-section columns in fire, Journal of Constructional Steel Research, 165: 105890.

Lopes N., 2009. Behaviour of Stainless Steel Structures in Case of Fire, Ph.D. thesis Universidade de Aveiro, Portugal.

Naser M.Z., 2019. Fire resistance evaluation through artificial intelligence-A case for timber structures. Fire safety journal, 105, 1-18.

Naser M.Z., 2021. Mechanistically Informed Machine Learning and Artificial Intelligence in Fire Engineering and Sciences. Fire Technology, 1-44.

Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V., 2011. Scikit-learn: Machine learning in Python, the Journal of machine Learning research, 12: 2825-30.

Salehi H, Burgueño R., 2018. Emerging artificial intelligence methods in structural engineering, Engineering structures, 171: 170-89.

Wang W, Kodur V, Yang X, Li G., 2014. Experimental study on local buckling of axially compressed steel stub columns at elevated temperatures, Thin-Walled Structures, 82: 33-45.