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Patch load resistance of longitudinally stiffened webs: Modeling via support vector machines

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Abstract. Steel girders are the structural members often used for passing long spans. Mostly being subjected to patch loading, or concentrated loading, steel girders are likely to face sudden deformation or damage e.g., web breathing. Horizontal or vertical stiffeners are employed to overcome this phenomenon. This study aims at assessing the feasibility of a machine learning method, namely the support vector machines (SVM) in predicting the patch loading resistance of longitudinally stiffened webs. A database consisting of 162 test data is utilized to develop SVM models and the model with best performance is selected for further inspection. Existing formulations proposed by other researchers are also investigated for comparison. BS5400 and other existing models (model I, model II and model III) appear to yield underestimated predictions with a large scatter; i.e., mean experimental-to-predicted ratios of 1.517, 1.092, 1.155 and 1.256, respectively; whereas the selected SVM model has high prediction accuracy with significantly less scatter. Robust nature and accurate predictions of SVM confirms its feasibility of potential use in solving complex engineering problems.

Keywords: steel girders; patch loading; longitudinal stiffener; support vector machines; machine learning

1. Introduction

The behavior of steel beams used in the passage of high openings has been the subject of many studies over the last 30 years. Stiffeners are used to prevent unwanted sudden deformations of steel beams. Based on the experimental and theoretical examinations, it has been observed that the stiffeners increase the strength of steel beams subjected to patch loads, or concentrated loads (Fig. 1) (Bergfelt 1979, 1983, Carretero and Lebet 1998, Dogaki *et al*. 1990, Dubas and Tschamper 1990, Galea *et al*. 1987, Graciano 2002, 2003, 2005, Graciano and Edlund 2003, Graciano and Johansson 2003, Graciano and Lagerqvist 2003, Janus *et al*. 1988, Johansson and Lagerqvist 1995, Lagerqvist and Johansson 1996, Marković and Hajdin 1992, Roberts and Newark 1997, Roberts and Rockey 1979, Rockey *et al*. 1978, Salkar 1992, Shimizu *et al*. 1987, Walbridge and Lebet 2001, Yang and Lui 2012, Kim *et al*. 2018). In order to account for the effect of shear reinforcement on the behavior of steel beams under a patch load, a correction factor obtained by regression is multiplied by the strength value of beams without shear. However, some studies have shown that other parameters that are not taken into account have significant effect on the strength of steel beams. Many of the suggestions presented in the literature are based on empirical formulations obtained by regression, most of which are based on the multiplication of the stiffness of un-stiffened webs with a coefficient.

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In this study, a new model is developed by using experimental data on the strength of steel beams with longitudinal stiffeners. This experimental data obtained from the literature is modelled using a new method, support vector machines (SVM), and the prediction performance of this model is compared with the existing formulations and experimental results. In the proposed SVM model, unlike existing design formulations, the effect of all parameters on the steel beam strength is accounted for.

2. Steel girders subjected to patch loading

Steel beams are often exposed to patch load, which is directly related to steel beam design. Therefore, the determination of final patch load is important in terms of cost and safety. During the construction of bridge, the patch load can freely circulate in the cranes and bridge bodies, making vertical bracing plates non-functional. Especially in large-span, bridge girder is placed close to flange portion pressurizing longitudinal stiffeners. Thus, the purpose is to increase the resistance of steel body subjected to shear and/or bending and to prevent early damage which may occur accordingly (Graciano 2002, Graciano and Lagerqvist 2003).

2.1 Experimental studies

A number of studies have been carried out to examine the behavior of longitudinally stiffened steel girders subjected to patch load. (Bergfelt 1979, 1983, Carretero and Lebet 1998, Dogaki *et al*. 1990, Dubas and Tschamper

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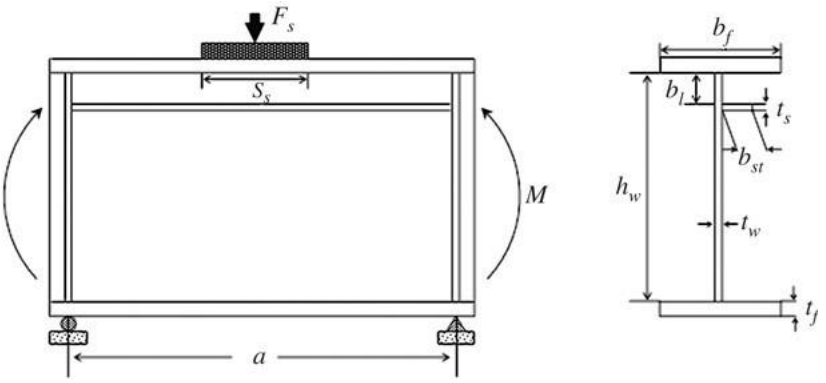


Fig. 1 Schematic view of longitudinally stiffened webs

Table 1 Summary of experimental data

References	Number of experiments	a/h_w	b_l/h_w	b_l/t_w	γ_s
(Rockey *et al*. 1978)	2	1.0	0.2	80	88-301
(Bergfelt 1979)	11	0.75-3.24	0.2	52-84	88-336
(Bergfelt 1983)	6	1.5-4.08	0.20-0.35	50-83	144
(Galea *et al*. 1987)	2	1.40	0.20-0.35	44-55	132
(Shimizu *et al*. 1987)	1	1.0	0.20	33	44
(Janus *et al*. 1988)	101	1.0-2.0	0.1-0.5	12-125	3-247
(Dubas and Tschamper 1990)	24	1.76-2.48	0.15-0.2	39-53	133-178
(Dogaki *et al*. 1990)	2	1.0	0.2	56	14-26
(Salkar 1992)	2	1.0	0.2	40	216
(Carretero and Lebet 1998)	6	1.31-2.21	0.20-0.38	27-50	55-169
(Walbridge and Lebet 2001)	5	1.43	0.1-0.18	15-25	73-98.5

1990, Galea *et al*. 1987, Janus *et al*. 1988, Marković and Hajdin 1992, Rockey *et al*. 1978, Salkar 1992, Shimizu *et al*. 1987, Walbridge and Lebet 2001). Details and sample numbers of test specimens are listed in Table 1.

2.2 Models for patch loading resistance of steel girders

2.2.1 Regression models – Model I

Many researchers (Bergfelt 1979, Janus *et al*. 1988, Marković and Hajdin 1992) have used the method of multiplying the strength of the un-stiffened girders with a coefficient to find the strength of the stiffened girders. In general, this coefficient is considered to be a function of the position of the stiffened girder. In this section, a model proposed by Lagerqvist and Johansson and based on the strength of the un-stiffened girders is presented. (Johansson and Lagerqvist 1995, Lagerqvist and Johansson 1996). Accordingly, the strength of the un-stiffened girders subjected to the patch load (F_{ro}) is expressed as follows

$$F_{ro} = F_y \chi(\lambda) \tag{1}$$

Here F_y is the yield strength and the expression is

$$F_y = f_{yw} t_w l_y \tag{2}$$

l_y, the effective loading length is calculated as

$$l_y = s_s + 2t_f (1 + \sqrt{m_1 + m_2}) \tag{3}$$

The unitless parameters m_1 and m_2 are calculated using the following formulas

$$m_1 = f_{yf} b_f / f_{yw} t_w, \qquad m_2 = 0.02(h_w / t_f)^2 \tag{4}$$

For beams $\lambda < 0.5$, $m_2 = 0$

Strength function $\chi(\lambda)$

$$\chi(\lambda) = 0.06 + \frac{0.47}{\lambda} \le 1 \qquad \lambda = \sqrt{\frac{F_y}{F_{cr}}} \tag{5}$$

$$F_{cr} = k_f \frac{\pi^2 E}{12(1-\nu^2)} \frac{t_w^3}{h_w} \tag{6}$$

where F_{cr} is the buckling load.

The buckling coefficient k_f is calculated as

$$k_f = 5.82 + 2.1\left(\frac{h_w}{a}\right)^2 + 0.46\sqrt[4]{\beta}, \qquad \beta = \frac{b_f t_f^3}{h_w t_w^3} \tag{7}$$

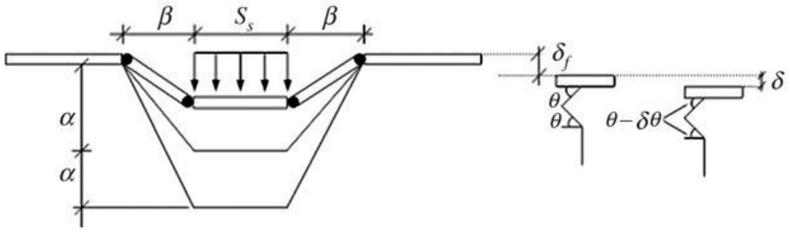


Fig. 2 Collapse mechanism proposed by Roberts and Rockey (1979)

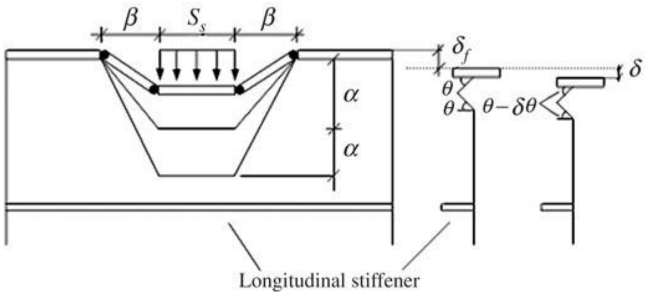


Fig. 3 Modified collapse mechanism for longitudinally stiffened girder (Graciano 2005)

Many correction coefficients based on the relation of the effect of the sheeting plate with the position of the plate have been proposed. (Bergfelt 1979, Janus *et al*. 1988, Marković and Hajdin 1992). Graciano (2003), on the other hand, stated that the flange-to-web thickness ratio and flange-to-web yield strength ratios are also effective in strength (Graciano 2003). Graciano (2003) expressed the resistance of the longitudinally-stiffened steel girders (F_{rl}) in the following way

$$F_{rl} = F_{ro} f_s \tag{8}$$

Here, the correction coefficient f_s is calculated by the regression analysis as follows

$$f_s = 0.556 - 0.277 \ln\left[\frac{b_1}{h_w}\left(\frac{f_{yf} / f_{yw}}{t_f / t_w}\right)\right] \tag{9}$$

And F_{ro} can be found using Eqs. (1)-(9).

This model is only applicable for cases where the cantering plate is placed at a distance $b_l \leq 0.3h_w$.

2.2.2 Collapse mechanism model – Model II

Roberts and Rockey (1979) developed a model to estimate the resistance of un-stiffened steel girders with a slender profile and exposed to patch loading. This model is based on the draw line mechanism, which consists of three flow lines on the web and four plastic hinges on the flange. (Fig. 2) (Graciano 2005). The BS 5400 Part 3 regulations applicable to patch loading have been obtained based on work by Roberts and Rockey (1979). This model was later modified by Roberts and Newark (1997) based on flow lines' $\alpha = 25t_w$ positions $\alpha = 20t_w f_{yw} / f_{yf}$. Thus, it is bounded by 2α position of the flow lines in the web, which is approximately equal to 40 times the web thickness. It has also been experimentally observed that steel beams subjected to patch loads and with rigid bending plates exhibit similar collapse mechanisms (Graciano 2005).

The model proposed by Roberts and Newark was later improved by Graciano and Edlund (2003). Fig. 3 shows the fracture mechanism provided by this model for longitudinally stiffened girders. The position (a) of the flow lines is restricted by the rigid stiffener plate at the rigid portion of the loaded flange. In this collapse model, the middle portion of the underlying flow line may form at the junction of the stiffener plate, as well as on the loaded panel (Fig. 3) (Graciano 2005).

2.2.3 Post-critical strength approach – Model III

This method is developed by Lagerqvist and Johansson (1996) depending on the critical post-thrust resistance of the steel girders and is applied by controlling the stability with buckling curves. In this context, Graciano and Johansson (2003) have developed a model based on the design philosophy of Eurocode 3 Part 1.5. The goal in this model is to include the longitudinal stiffener effect, which is not present in earlier Eurocode versions, in the calculation.

2.3 Design approach in BS5400

In BS 5400 Part 3, the design approach is based on the regression analysis by Markovic and Hajdin (1992), and the ultimate resistance of steel girder subjected to patch load F_{rl} is determined as follows

$$F_{rl} = \left\{ 0.5 t_w^2 \sqrt{\frac{E f_{yw} t_f}{t_w}} \left[1 + \frac{3 s_s}{h_w}\left(\frac{t_w}{t_f}\right)^{3/2} \right] \sqrt{1 - \left(\frac{\sigma_b}{f_{yw}}\right)^2} \right\} f_s \tag{10}$$

where correction coefficient is f_s

$$f_s = 1.28 - 0.7(b_l / h_w) \tag{11}$$

In this formula f_s coefficient is between 1.0 and 1.21.

In addition to these models, resistance of steel girders exposed to patch loads is also modelled by methods such as artificial neural networks, fuzzy logic, genetic programming and regression (Cevik 2007, Cevik *et al*. 2010, Fonseca *et al*. 2003a, b, 2007).

In this study, resistance of longitudinally stiffened steel girders subjected to patch loads is modelled with a new approach namely, support vector machines, and the proposed model is compared with the existing models.

3. Support vector machines

Support vector machines (SVM) were first developed by Boser *et al*. (1992) is an artificial intelligence learning method developed for solving classification problems. However, researchers have begun to use SVM to solve regression problems and have called this method Support Vector Regression (SVR).

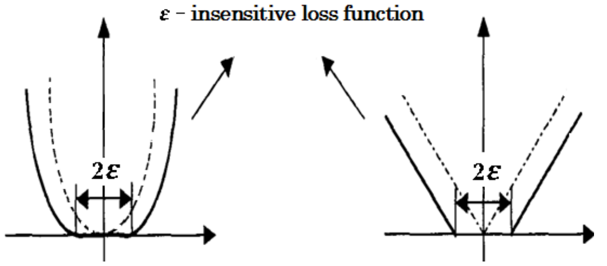
In addition to its robust numerical basis in statistics learning theory, SVMs have performed extremely well in many applications such as text analysis, face recognition, image processing and bioinformatics. This fact proves that SVMs are one of the most modern approaches in machine learning and data mining, along with some other computational methods such as neural networks and fuzzy systems (Wang 2005).

3.1 Support vector regression (*SVR*)

In SVR, the objective is to obtain a function that estimates the real output values by a maximum deviation of ε and to obtain two hyper planes parallel to this function. The distance between these hyper planes should be minimal (Chen *et al*. 2004).

For a given set of training data in SVR, the main purpose is to obtain a function with maximum difference from the exact found targets for all the training data, and at the same time, is at most flat i.e., we do not focus on errors as long as they are less than a certain amount, but any deviation larger than this amount is not acceptable (Chen *et al*. 2004), The (linear) ε-insensitive loss function $L(x, y, f)$ is described as

$$L^\varepsilon(x,y,f)=|y-f(x)|_\varepsilon=\begin{cases}0 & if\,|y-f(x)|\le\varepsilon\\ |y-f(x)|-\varepsilon & otherwise\end{cases} \tag{12a}$$



(a) Quadratic (b) Linear

Fig. 4 The form of linear and quadratic ε-insensitive loss function for zero and non-zero ε

where f is a real-valued function on a x and the quadratic ε-insensitive loss is defined by

$$L_2^\varepsilon(x,y,f)=|y-f(x)|_\varepsilon^2 \tag{12b}$$

Fig. 4 illustrates the form of linear and quadratic ε-insensitive loss function for zero and non-zero ε.

The loss function $L(y, f(x, \omega))$ determines the performance of accuracy. Performing linear regression in the high-dimension feature space by the use of ε-insensitive loss function, SVM attempts to decrease model complexity by performing the minimization of $||\omega||^2$. By introducing (non-negative) slack variables $\xi_j, \xi_i^* i = 1, \dots n$

$$L(y,f(x,\omega))=|y-f(x)|_\varepsilon^2, \qquad L_2^\varepsilon(x,y,f)=|y-f(x)|_\varepsilon^2 \tag{12c}$$

to determine the deviation of training data outside ε -zone. Following formulation is utilized for the minimization of SVM regression

$$\frac{1}{2}\|\omega\|^2+c\sum_{i=1}^{n}(\xi_{i+}\xi_i^*) \qquad \text{subject to} \qquad \xi_{j,}\xi_i^* i=1,..n \tag{12d}$$

$$\xi_{j,} \qquad \xi_i^* i=1,..n \tag{12e}$$

The solution of this optimization problem can be found by transforming it into the dual problem

$$f(x)=\sum_{i=1}^{n_{sv}}(\alpha_j-\alpha_i^*)K(x_j,x)+b \qquad \text{subject to} \quad 0\le\alpha_i^*\le C, \quad 0\le\alpha_j\le C \tag{12f}$$

where n_{sv} is the number of support vectors (SVs), a_i^* and a_j are the Lagrange multipliers and $K(x_j, x)$ is a kernel function and b is the bias term. Generalization capability (accuracy of estimation) of SVM is dependent on a proper setting of meta-parameters C, ε and the kernel parameters. Currently available software applications enable users to manually define the meta-parameters of support vector regression (Cherkassky and Ma 2002).

The model complexity and the degree, to which deviations larger than ε are tolerated, are controlled by a parameter C controls in optimization formulation. Parameter ε describes the width of ε -insensitive zone, which is utilized to fit the training data. Value of ε can affect the number of support vectors used to form the regression function. On the other hand, greater ε -insensitive values cause more 'flat' predictions. Although in different ways, both C and ε values affect model complexity (flatness) (Cherkassky and Ma 2002).

While there are many kernel functions used in machine learning, four different kernel functions are used in this study. These functions are:

Linear function

$$K(x_i,x)=x_i x \tag{13a}$$

Table 2 Inputs and statistical values of developed SVM models

SVM model	Model type	Kernel function	Epsilon/Nu	Gamma	Cost	R2
E-R	Epsilon-SVR	Radial basis	0	0.11112	55555.6	0.994
E-P	Epsilon-SVR	Polynomial	0	0.0909	11111.1	0.997
E-S	Epsilon-SVR	Sigmoid	0.3333	0.0909	1	0.927
E-L	Epsilon-SVR	Linear	0	0.0909	11111.1	0.943
N-R	Nu-SVR	Radial basis	1.00E-06	0.0909	100000	0.946
N-P*	**Nu-SVR**	**Polynomial**	**0.1111**	**0.0909**	**22222.2**	**0.996**
N-S	Nu-SVR	Sigmoid	0.1111	0.0909	1	0.937
N-L	Nu-SVR	Linear	0.4444	0.0909	1	0.95
E-R	Epsilon-SVR	Radial basis	0	0.11112	55555.6	0.994
E-P	Epsilon-SVR	Polynomial	0	0.0909	11111.1	0.997
E-S	Epsilon-SVR	Sigmoid	0.3333	0.0909	1	0.927

* Selected model

Polynomial function

$$K(x_i, x) = (x_i(x+1))^d \tag{13b}$$

Radial-based function

$$K(x_i, x) = \exp\left[-\frac{(\mathrm{x_i} - x)(\mathrm{x_i} - x)}{2\sigma^2}\right] \tag{13c}$$

Sigmoid function

$$K(x_i, x) = \tanh(x_i(x+1)) \tag{13d}$$

where x_i and x, are the training and test inputs, respectively, σ is the Gaussian kernel function and d is the polynomial degree of kernel function.

Previously, SVM has been used in several applications e.g., modelling concrete strength, corrosion, structural safety and self-compacting concrete properties as well as other subject areas (Camoes and Martins 2017, Kundapura and Hegde 2017, Ozcan *et al*. 2017, Mirhosseini 2017), Çevik *et al*. has carried out a review study summarizing the works carried out using support vector machines in structural engineering (Çevik *et al*. 2015). Zhang and Song (2012) employed SVM to predict the residual mechanical characteristics of fly ash concrete specimens exposed acidic environment. Yang *et al*. (2014) investigated the mechanical properties of corroded concrete and performed tests on specimens under repeated loads.

Deflection and maximum crack with parameters were predicted using least squares support vector machines (LS-SVM). Cao *et al*. (2013) presented a predictive SVM based model for elastic modulus of SCC. Also, a SVM based approach was implemented for structural reliability analysis by Li and Lu (2007).

4. Numerical application

4.1 Modelling patch loading resistance of longitudinally stiffened steel girders with SVM

Table 3 Statistics of training and testing sets

	Model	Mean experimental-to-predicted ratio	Std. deviation	Coefficient of variation
Training data	Model I	1.07	0.147	0.138
	Model II	1.15	0.226	0.197
	Model III	1.26	0.197	0.157
	BS5400	1.52	0.245	0.161
	SVM (N-P) model	1.00	0.054	0.054
Testing data	Model I	1.10	0.148	0.134
	Model II	1.17	0.227	0.194
	Model III	1.25	0.199	0.160
	BS5400	1.51	0.263	0.175
	SVM (N-P) model	0.99	0.053	0.054

The main purpose of this study is to assess the feasibility of SVM approach in predicting the patch loading resistance of longitudinally stiffened steel girders. For this, an entensive experimental database was created using experiments available in literature as summarized in Table A.1. Database consists of 162 experimental data. Input parameters include geometrical and mechanical parameters (a, h_w, t_w, t_f, b_f, f_{yf}, f_{yw}, s_s, t_{st}, b_l, b_{st}) of steel girders. The cross-sectional view of the steel girders subjected to the test is shown in Fig. 1. Support vector regression models were created using a software named DTREG (Sherrod 2008). A cross-validation test (v-fold cross validation) was used to avoid over-fitting problems, and randomly selected 25% of the data was used as the testing set. Control variables (e.g., epsilon/Nu, gamma, cost) were selected by the program based on a grid search generated using predetermined ranges for each variable. Entries and statistical results for all SVM models are presented in Table 2.

Although the statistical indicators suggest the high estimation capacity of produced models, high generalization capability is also required for the validation of a model.

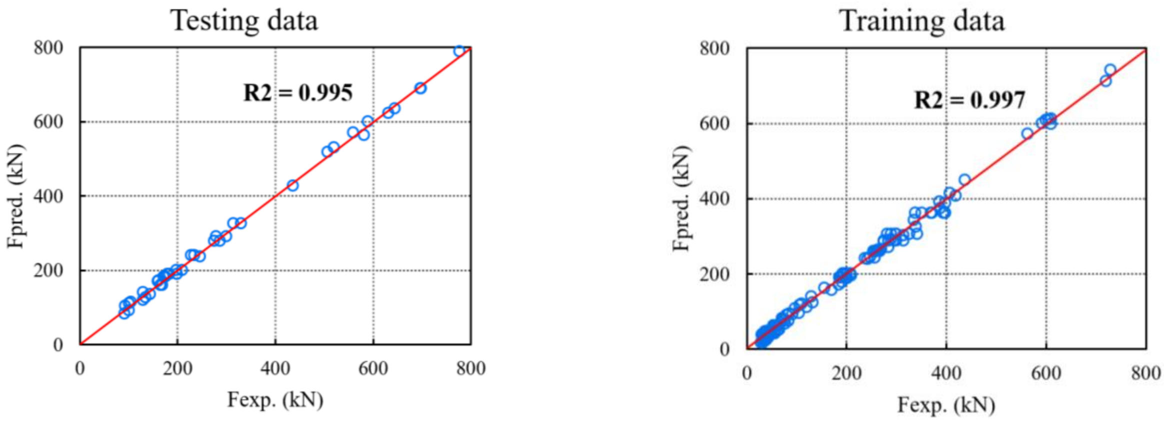


Fig. 5 Comparison of test results versus corresponding SVM predictions

Generalization capability implies the competence of the model in estimating the results for any given data different than the one used as input.

Among eight models, polynomial function based models with epsilon-SVR (E-P) and Nu-SVR (N-P) types exhibited the best performance in terms of correlation coefficient (R^2) and root mean squared error (RMSE). N-P model was selected for parametric analyses despite the statistical indicators, due to the deficiencies in preliminary assessment of parametric analysis of E-P model. Table 3 summarizes the performance statistics of all models for training and testing sets.

5. Parametric analysis

A Matlab program using a given database to generate parametric data was utilized. Experimental data with 11 input parameter (a, h_w, t_w, t_f, b_f, f_{yf}, f_{yw}, s_s, t_{st}, b_l, b_{st}) was introduced to program and 3 points were generated for each input parameter, thus, 3^{11} = 177147 rows of data were generated for this study. Program code uses the minimum and maximum values of each input and generates predetermined number of points within this interval. Later, the generated data were scored using produced SVM model and the outputs were analyzed through ANOVA analysis, using main effect plots, interaction plots and 3D surface plots.

Main effect graphs are useful tools to evaluate the effect of each input on the output parameter. Interaction and surface plots show the combined effect of any two parameters on the output, thus these plots are useful to assess the generalization capability of the proposed model.

6. Results and discussion

Statistical norms were used for the evaluation of produced models. These norms are correlation ratio (R^2) and root mean squared error ($RMSE$), whose formulations are given in Eqs. (14)-(15). Also, mean experimental-to-predicted ratio, standard deviation and coefficient of variation (CoV) were also used for evaluation of the models.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (o_i - t_i)^2}{\sum_{i=1}^{N} (o_i - o')^2} \right) \quad (14)$$

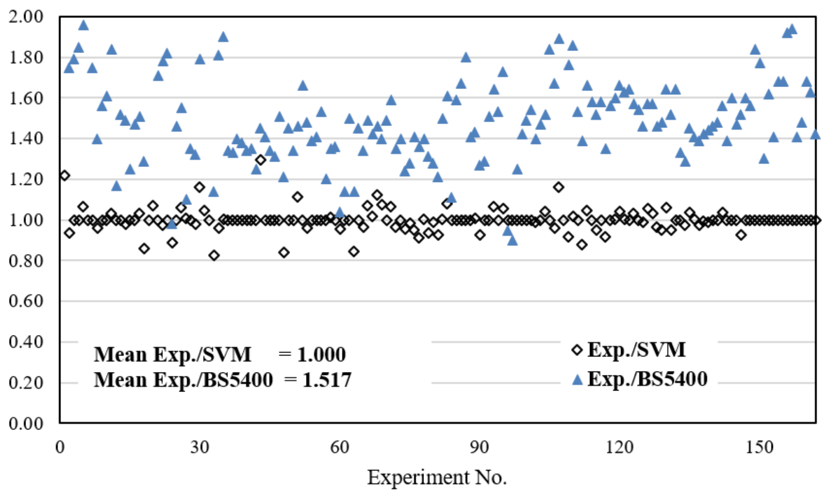


Fig. 6 Experimental/predicted ratio comparison of SVM and BS5400

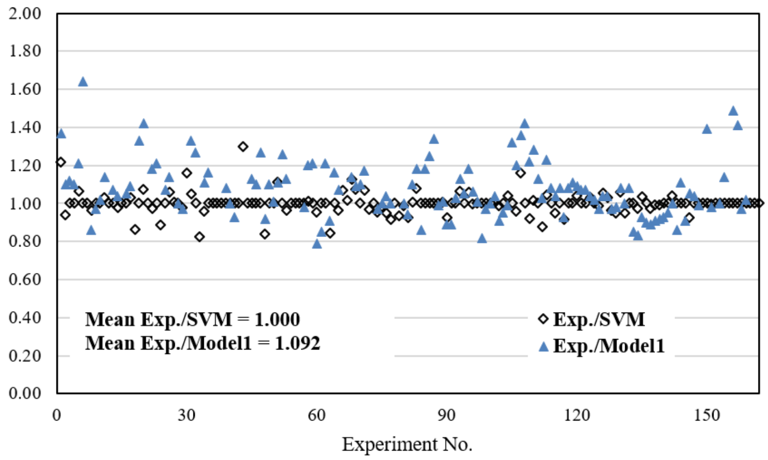


Fig. 7 Experimental/Predicted ratio comparison of SVM and Model I

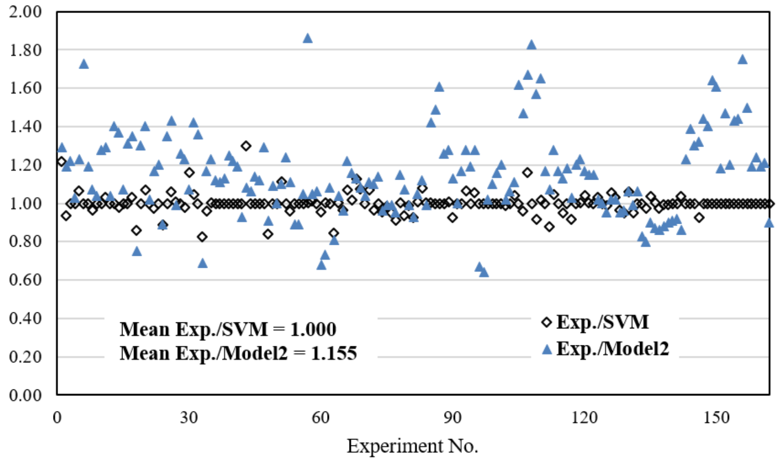


Fig. 8 Experimental/Predicted ratio comparison of SVM and Model II

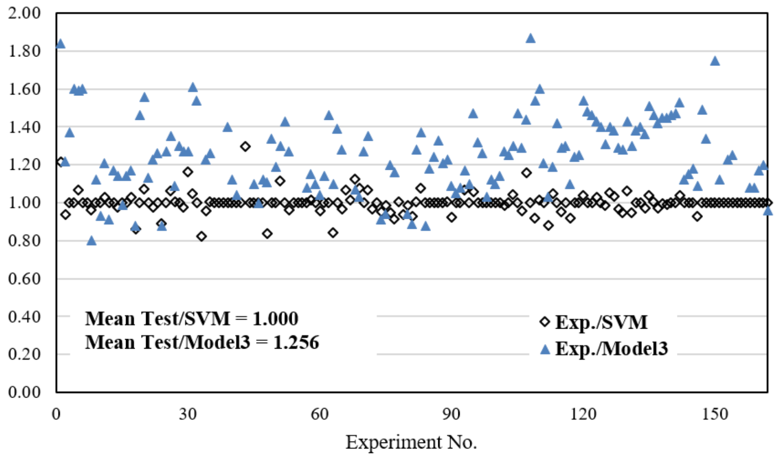


Fig. 9 Experimental/predicted ratio comparison of SVM and Model III

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(o_i - t_i)^2}{N}} \tag{15}$$

where o_i is the experimental value of ith data, t_i is the predicted value of *ith* data, N is the number of data used for training and testing of SVM model.

Among the generated models, Nu-SVR model with polynomial function (N-P), which has the highest estimation capacity was selected for further inspection. Fig. 5 shows the correlation between the estimated values and the actual experimental data. The correlation ratio (r-square, R^2), whose ideal value is 1, was found to be 0.995 and 0.997

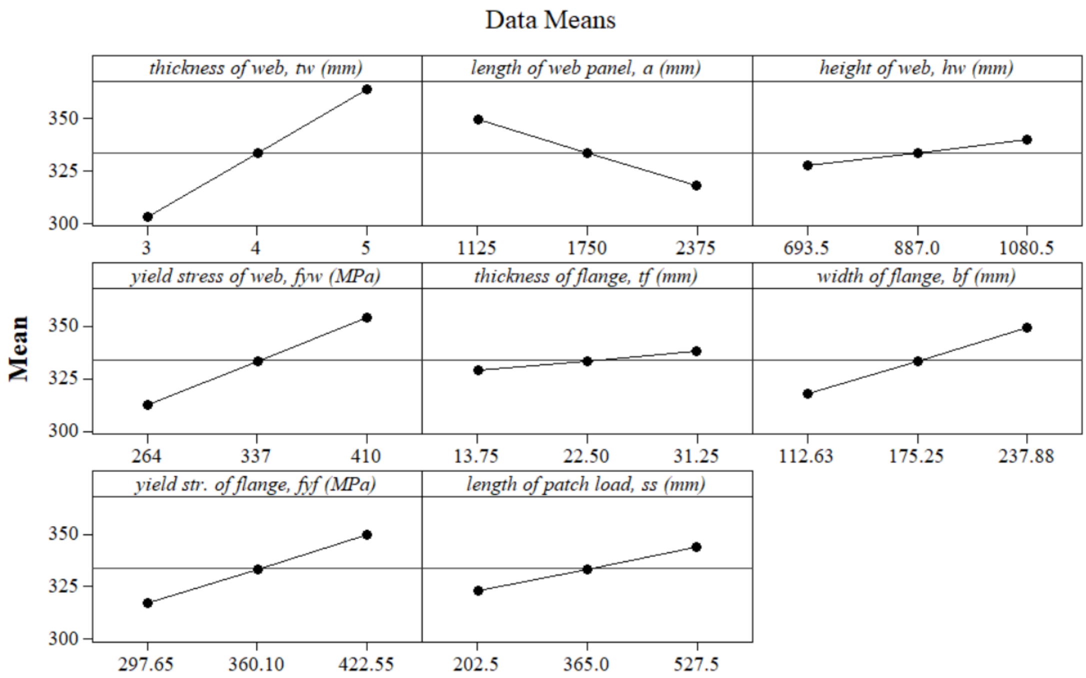


Fig. 10 Influences of input parameters on $F_{pred.}$

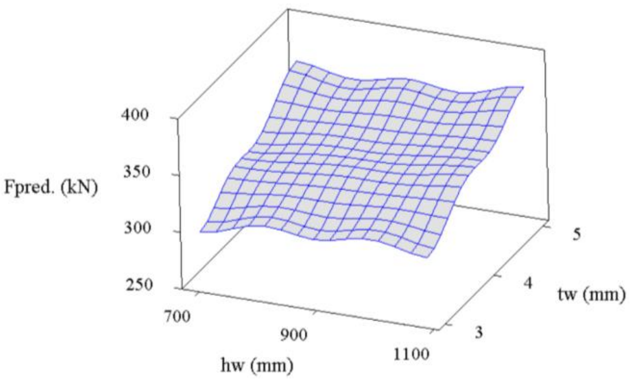


Fig. 11 Surface plot of $F_{pred.}$ vs thickness of web and height of web

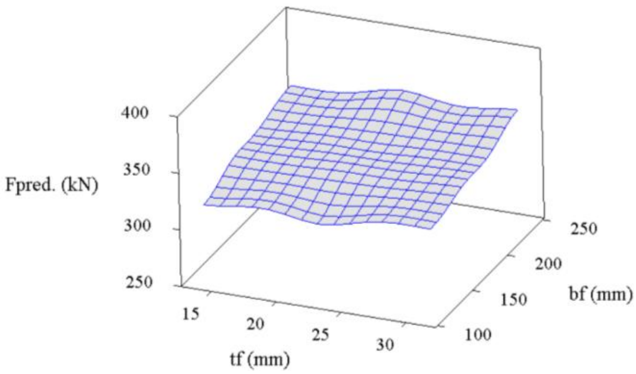


Fig. 12 Surface plot of $F_{pred.}$ vs thickness of flange and width of flange

for testing and training data, respectively. Therefore, this confirms the high predictive performance of the SVM model in estimating the patch load resistance of longitudinally stiffened webs.

Further inspection was carried out for testing the validity of proposed model by comparing the mean experimental-to-predicted ratio of current and proposed models as illustrated in Figs. 6-9. BS5400 model estimates are quite conservative with an average ratio of 1.517 and the large scattering of data is evident. Model I, Model II and Model III, on the other hand, have conservative estimations as well as un-conservative results at a moderate level, with less scattering compared to BS5400 model. The performance of proposed SVM model is further validated and it predicts experiment results with much higher accuracy and very less scattering.

Fig. 10 shows that input variables, except for web panel length (a), have increasing effect on patch load resistance. Web thickness (t_w) appears to be the most influential parameter whereas the flange thickness (t_f) has a relatively lower influence. Mechanical properties (i.e., yield stress of web, f_{yw} and yield stress of flange, f_{yf}) have an increasing

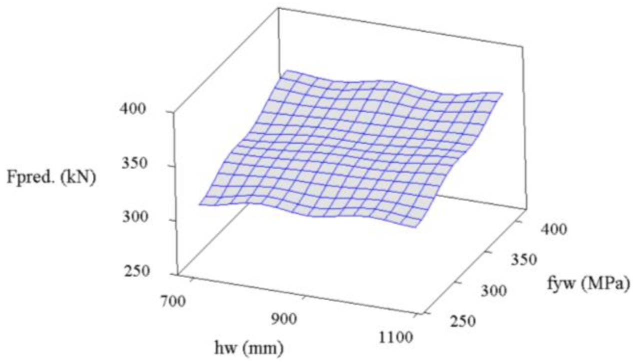


Fig. 13 Surface plot of $F_{pred.}$ vs height of web and yield stress of web

tendency on patch load resistance.

Figs. 11-13 shows 3D surface plots generated using ANOVA analysis. The smooth shape of plots illustrates that the parameter effects on patch load resistance is acceptable since no fluctuation is apparent in any of the graphs. This further confirms the generalization capability of proposed model.

7. Conclusions

This paper gives a contribution towards the implementation of support vector machines (SVM) approach in predicting the test results of a complex problem, i.e., the resistance of longitudinally stiffened webs subjected to patch loading. It is aimed to explore the feasibility of SVM in estimating the patch load resistance of steel beams with longitudinal stiffeners. SVM has been successfully applied to solve many engineering problems before (Çevik *et al*. 2015, Zhang *et al*. 2016). For the solution of this problem, support vector machines (SVM) method is used for the first time in the literature. For the modelling process, a database (Table A.1) is created with the experimental results available in the literature, and multiple SVM models are developed using this database. Among these models, the model with the highest correlation ratio (R^2 = 0.996, CoV = 0.169) and better parametric study results is selected for further analysis. The effect of each parameter on the patch load resistance are studied and interpreted. In addition, the results of available design models are analyzed, and these results are compared against the predictions of SVM model. Following conclusions can be drawn based on these findings:

- Predicted values are significantly close to actual test results both for training and testing data. SVM model with Nu-SVR model type and polynomial kernel function exhibits the best prediction performance.
- The model proposed by BS5400 overestimate the experimental results with a large scattering of data. Predictions of Model I, Model II and Model III (proposed by other researchers) have relatively less scatter. Proposed SVM model, however, has the lowest scattering of data (mean predicted-to-experimental ratio of 1.00) and the estimations closely agree with experimental values.
- Parametric study confirms that the proposed SVM model has generalization capability; thus, the model can give accurate results not only for given experimental database but also for different inputs within the experimental limits.
- SVM models have high applicability and reliability in estimating the patch load resistance of steel girders with longitudinal stiffeners, can give results in significantly short time and with low error rates.
- Machine learning methods may provide a promising alternative for complex problems (e.g., prediction, classification and optimization) in various disciplines of civil engineering.

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