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Application of support vector machine with firefly algorithm for investigation of the factors affecting the shear strength of angle shear connectors

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Abstract. The factors affecting the shear strength of the angle shear connectors in the steel-concrete composite beams can play an important role to estimate the efficacy of a composite beam. Therefore, the current study has aimed to verify the output of shear capacity of angle shear connector according to the input provided by Support Vector Machine (SVM) coupled with Firefly Algorithm (FFA). SVM parameters have been optimized through the use of FFA, while genetic programming (GP) and artificial neural networks (ANN) have been applied to estimate and predict the SVM-FFA models' results. Following these results, GP and ANN have been applied to develop the prediction accuracy and generalization capability of SVM-FFA. Therefore, SVM-FFA could be performed as a novel model with predictive strategy in the shear capacity estimation of angle shear connectors. According to the results, the Firefly algorithm has produced a generalized performance and be learnt faster than the conventional learning algorithms.

Keywords: C-shaped shear connector; channel; estimation; prediction; support vector machine; firefly algorithm

1. Introduction

The estimation of the strength and ductility of shear connectors are important to spot the composite beams in the evaluation process of the ultimate load capacities and the slip in shear connectors (present between the shear connector and the concrete slab) to design the shear connectors (Shariati *et al.* 2016, Khorramian *et al.* 2017, Mansouri *et al.* 2017, Hosseinpour *et al.* 2018, Nasrollahi *et al.* 2018, Paknahad *et al.* 2018, Sedghi *et al.* 2018, Wei *et al.* 2018, Ismail *et al.* 2018). Considering various shear connectors of composite beams, there is a tremendous effort to seek economical and structural superior shear connectors like angle shear connector. The behavior of load displacement and the shear capacity of shear connectors in composite beams, according to the obtained data from push out test or beam-tests, have been conducted for shear connectors' design ((Mohammadhassani *et al.* 2013, Lali and Setayeshi 2011, Shariati *et al.* 2012, Shariati *et al.* 2012, Shariati *et al.* 2012, Shariati *et al.* 2012, Shariati 2013, Shariati 2013, Shariati *et al.* 2013, Mohammadhassani *et al.* 2014, Shariati *et al.* 2014, Shariati *et al.* 2014, Toghroli Ali *et al.* 2014, Fanaie *et al.* 2015, Khalilian 2015, Khorramian *et al.* 2015, Shariati *et al.* 2015, Khorramian *et al.* 2016, Safa *et al.* 2016, Shahabi *et al.* 2016, Shahabi *et al.* 2016, Tahmasbi *et al.* 2016, Tahmasbi *et al.* 2016, Toghroli *et al.* 2016). However, there are some barriers like cost and length of the procedure of nonlinear finite element (FE) analyzing in predicting shear capacity of the angle connectors in composite beams (Toghroli Ali *et al.* 2014, Safa *et al.* 2016, Toghroli *et al.* 2016, Mansouri *et al.* 2017, Stanojevic *et al.* 2017, Sedghi *et al.* 2018). This research has provided another view on predicting the shear capacity of the angle connectors in composite beams through the use of little software as 1) Support Vector Machines (SVM) and 2) Firefly Algorithm (FFA). Though, SVM is a common engineering program with high accuracy in parameters' selection (Mohammadzadeh1a and Kim 2015, Zhang *et al.* 2016), organizational strategies have been used in parameters' selection and alignment such as grid search algorithm (Hsu *et al.* 2003, Friedrichs and Igel 2005, Lorena and De Carvalho 2008, Bao *et al.* 2013), and gradient decent algorithm (Chapelle *et al.* 2002, Chung *et al.* 2003, Hernandez *et al.* 2015). While the grid search algorithm has normally swayed to the local minima, the computation exactness is a main impediment of this algorithm. Regarding the mentioned problems, evolutionary

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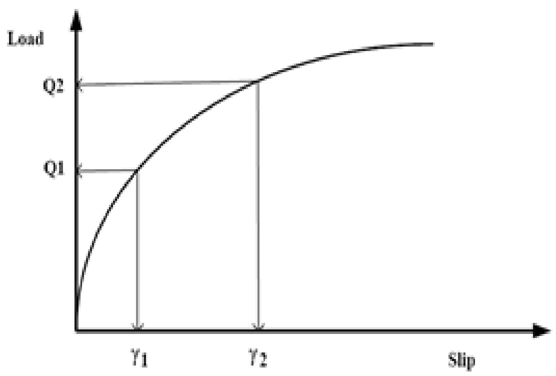


Fig. 1 A typical load slip relationship curve achieved from the standard push out test

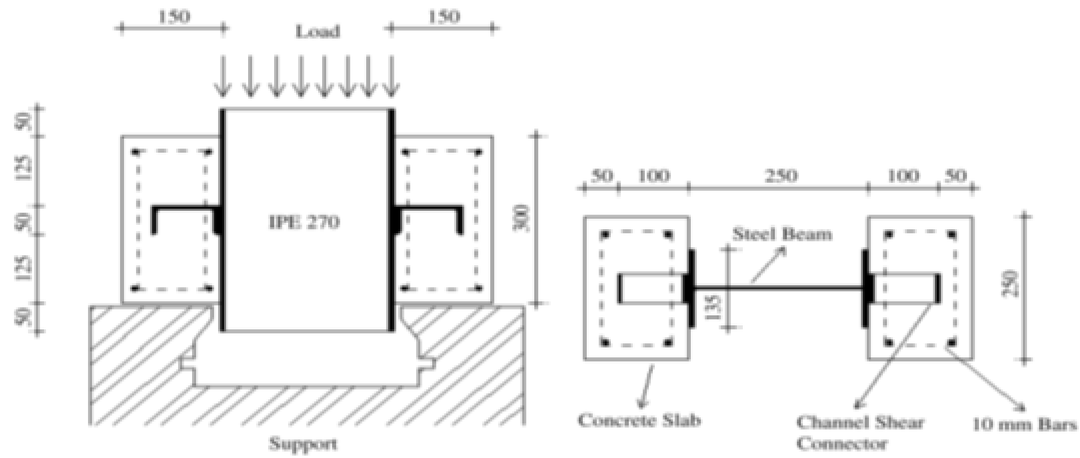


Fig. 2 A schematic setup for the push-out test

algorithms are more appropriate approach in providing the global solution for optimizing cases.

The present study has introduced a non-linear tool through the use of SVM to seek the factors affecting the angle shear connectors' shear strength and FFA to select the parameters. The achieved data have been compared to GP and ANN. The proposed reliable SVM-FFA model has been confirmed to predict the connector's load slip relationship in different dimensions and in different strengths of the concrete with and without reinforcement bars.

2. Shear connector test

Some various push out specimens tests have been designed following the concrete strength and the angle shear connector' size in concrete slabs. Push out test has included the steel I beam with double slabs connected to the both flanges of the beam and a channel that has been welded to each flange. While various concretes with different compression strengths have been used for samples, air dry aggregates have been applied in all mixes such as the fine aggregate graded by silica sands (4.75 mm), the coarse aggregate graded by crushed granite (10 mm), and the cement is Ordinary Portland Cement (OPC). Rheobuild 1100, a super plasticiser (SP), has been applied in both mixes to gain the effective workability (Table 1). On assuming a reliable concrete for each slabs of two sides of specimen, they have been designated as normal (N), high strength (H) and light weight (LW) concrete. Soaking in water for twenty eight days prior to test, the load has been applied in a 600 kN capacity (universal testing machine) with a precise support during the slabs' loading in 0.04 mm/s ratio. The monotonic loading has been gradually increased until the failing and the steel I-beams have been occurred in the universal test machine deck to automatically record the practical loading and related slip(s) between the I-beam and the concrete block (Shariati *et al.* 2010, Shariati *et al.* 2011, Andalib *et al.* 2014, Bazzaz *et al.* 2015, Bazzaz *et al.* 2015, Mansouri *et al.* 2017, Andalib *et al.* 2018, Shariati *et al.* 2011). Push-out specimens and the compressive strength have been cast simultaneously by applying standard cylinders (150 mm in diameter and 300 mm long) and standard cubes (100 mm long) soaked in water. The mean of the compression tests have been calculated to measure the strength of the concrete following ASTM C39 (ASTM 2005) procedure. Additionally, shear connectors have been applied to simulate the composite

Table 1 Mix proportions of concrete materials (weight based)

Mix	Cement (kg/m^3)	Coarse aggregate (kg/m^3)	Leca (kg/m^3)	Fine aggregate (kg/m^3)	Water (kg/m^3)	Silica fume (kg/m^3)	Limestone (kg/m^3)	SP (%)	W/C	Compressive Strength (MPa)
High strength	460	910	-	825	168	35	-	0.5	0.37	78
Light weight	495	180	147	-	218	55	165	1	0.43	27
Normal	360	910	-	825	168	65	55	0.5	0.37	38

action in a beam, when the connectors are capable to relay the shear forces (even in severe load reversals). The current study has been performed to reveal the channel shear connectors' behavior embedded in the solid concrete slabs.

The load has been used by a universal testing machine (600 kN capacity). For loading the slabs, the load has been controlled (0.04 mm/s) for all specimens. The specimens have been re-arranged prior to any loading process to simulate the unidirectional nature of the loading test. Despite of several mathematical expressions for describing the shear connector load slip curves (Fig. 1), providing a common regression formula for the shear connector stiffness is slightly hardship due to the scatter plot's magnitude against other parameters. Besides, the knowledge of the shear connectors' stiffness is essential for using the equation of partial interaction theory of composite steel-concrete beams.

Conducting diverse tests to measure the shear strength, majority of them is based on the load slip relationship and failure mode. Push out test looks convenient and economic than the composite beam test. Push-out test has accurately explained the very properties of the shear connectors across the stress state variations between push out test and beam. Some literatures have focused on the behavior of channel shear connector (Khorramian *et al*. 2015, Shariati *et al.* 2015, Safa *et al.* 2016, Shahabi *et al.* 2016, Shahabi *et al*. 2016, Shariati *et al.* 2016, Tahmasbi *et al*. 2016) following the push out test's process (Maleki and Bagheri 2008, Maleki and Mahoutian 2009) (Fig. 2).

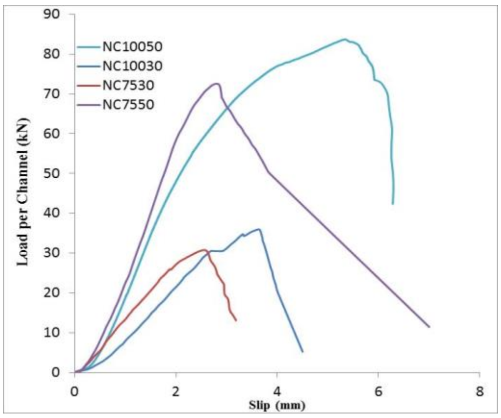


Fig. 3 Typical push-out test results for channel shear connector

Regarding monotonic load simulation, the load has been raised till the failure and the steel I- beams have been fixed on the deck of universal test machine. The channel connector has made the ultimate strength's variations and the related stiffness in the orientation changing (Maleki and Bagheri 2008, Maleki and Mahoutian 2009, Shariati 2017). The starting phase of any test is push out test conduction considering the same orientated channel. The related slip between the concrete block and I-beam across the practical load at different intervals has been automatically recorded by the universal test machine (Fig. 3).

3. Soft computing techniques with prediction algorithms

3.1 SVM (Support Vector Machine)

SVM has applied not only in computing, hydrology and environmental research (Lee and Verri 2003, Lu and Wang 2005, Asefa *et al.* 2006, Ji and Sun 2013, Sun 2013), but also in pattern recognizing, forecasting, classifying and regression analyzing by demonstrating an acceptable function comparing to the neural network and other statistical methods (Vapnik *et al.* 1997, Joachims 1998, Collobert and Bengio 2000, Huang *et al.* 2002, Mukkamala *et al.* 2002, Sung and Mukkamala 2003). SVM follows the core of statistical machine learning process and the structural risk minimizing (Vapnik 2013). Likewise the traditional machine learning methodologies, SVM has reduced the upper bound generalization error than the local training error (Vapnik and Vapnik 1998). Extra advantages of SVM are its unique solutions for convex optimized errors and applying a high spaced set of dimension from kernel functions. SVM has comprised a non-linear transformation mightily prevent from any functional transformation assumption making data linearly separable and indispensable. SVM equations have been presented in the equation (1, 4) by assuming dataset of $\{x_i, d_i\}_i^n$, when x_i(input space vector), d_i(target value) and *n* (data size) have represented the data samples. Approximate SVM functions are as follows (Eqs. (1) and (2))

$$f(x) = w\varphi(x) + b \tag{1}$$

$$R_{SVMs}(C) = \frac{1}{2}\|w\|^2 + C\frac{1}{n}\sum_{i=1}^{n} L(x_i, d_i) \tag{2}$$

While $\varphi(x)$ is the greatest space factor dimension (mapped input space vector x), w is the normal vector, b is the scalar vector, and $C\frac{1}{n}\sum_{i=1}^{n} L(x_i, d_i)$ is the empirical error (risk).
scalar vector (b) and normal vector (w) have been calculated through the regularized risk function reduction (Eq. (2)).The regularized risk function has been achieved after the positive slack factors' presentation ξ_i and ξ_i^*(upper and lower excess deviation) (Govindaraju and Rao 2010).

$$\text{Minimize} R_{SVMs}\left(w, \xi^{(*)}\right) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (3)$$

$$\text{Subject to } \begin{cases} d_i - w\varphi(x_i) + b_i \le \varepsilon + \xi_i \\ w\varphi(x_i) + b_i - d_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, i = 1 \dots\dots\dots\dots l \end{cases}$$

Accordingly, $\frac{1}{2}\|w\|^2$ is the regularized unit, C is the error penalty factor (regulate difference between the regularized unit and empirical error risk), ε is the loss term (training data point's approximate accuracy) and l is the element number in training data sets.
A generic function might be gained by Lagrange multiplier presentation and optimal constraints (Eq. (4)).

$$f(x, a_i a_i^*) = \sum_{i=1}^{n} (a_i - a_i^*) K(x, x_i) + b \quad (4)$$

$K(x_i, x_j)$ as the kernel unit in feature space of $\varphi(x_i)$, and(x_j).

SVM has attempted to perform data correlation using a non-linear mapping, when the mean is to analyze the inner property of feature space as the main function of input variable. Considering non-linear learning machine as a kernel function (shown as K), flexible SVM is to obtain K to change data to a greater feature space dimension correlated to the main and lower input space dimension.
Considering the four kernels: 1) lineal, 2) sigmoid, 3) polynomial and 4) radial, the radial based function (rbf) is the best for efficient, simple, reliable and adapted computing for optimization and other adaptive techniques (Koza 1992, Govindaraju 2000); therefore, it has been applied in a set of linear equation's solution instead of long and quadratic demanding problem (Guven and Gunal 2008). In this study, rbf with the parameter (σ) has been used, when the non-linear radial based kernel is as follow

$$K(x_i, x_j) = exp\left(-\gamma\|x_i - x_j\|^2\right) \quad (5)$$

(x_i - x_j) as the input space vectors.
rbf depends on three parameters (γ, ε , c).

In the current study, the parameters' optimized variables have been used by Firefly optimization algorithm.

3.1.1 Firefly optimization algorithm

Metaheuristic optimized algorithms have been applied in major human endeavors (Assareh *et al.* 2010)and mostly in ant colony optimization (ACO), genetic algorithm (GA), particle swarm optimization (PSO), and cuckoo search (CS) developed according to the best selection mechanism through the firefly algorithm (FA) (Yang 2009). FA has been developed according to the fireflies' flashing characteristic (behavioral pattern) based on the bioluminescence to catch mates or prey. Firefly has produced luminance enabling the fireflies to follow the prey path to develop the algorithms and solve the optimized problems. Comparing other biological inspired optimization algorithms, FA is more effective algorithm in finding all optimum (Fister *et al.* 2013). Recently there are more heuristic approaches for tuning of SVM parameters. Also there are different approached for prediction and estimation of different parameters. Firefly algorithm was applied in this study since nobody used it before for this topic.

3.1.2 Fundamental rules in FA development

Unisex: All fireflies have used unisex to attract one another regardless of their sex.
Luminous intensity: firefly attractiveness has proportionally related to the number of the produced luminance and has been decreased in distance growing.
Cost function: the firefly's brightness has been affected by the encoded cost function; therefore, the objective function formula (attractiveness) and the light intensity variation have been regarded as the major issues in firefly algorithm development.
Fitness function: the Fitness function has proportionally related to the number of produced brightness. Hence, any distance growing has reduced the light intensity and created intensity variations in the Eq. (6).

$$I(r) = I_o \exp(-\gamma r^2) \quad (6)$$

I(Light intensity), r (distance between firefly), I_o(initial light intensity), and γ (light absorption coefficient as constant variable (0.1-10) have shown the equation.

When the attractiveness β is correspondent to the light amount cared by other fireflies, β in r has been shown the Eq. (7).

$$\beta(r) = \beta_o \exp(-\gamma r^2) \quad (7)$$

Here, $\beta_o$is the attractiveness at a distance r ($r = 0$), so the Eq. (7) has shown a vast change from β_o to $\beta_o e^{-1}$.
The Cartesian distance between two fireflies (i and$j$) has been shown in Eq. (8).

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}\left(x_{i,k} - x_{j,k}\right)} \quad (8)$$

The firefly movements (i attracts j) have been presented in Eq. (9)

$$\Delta x_i = \beta_o e^{-\gamma r^2}\left(x_j - x_i\right) + \alpha\varepsilon_i \quad (9)$$

Here, $\beta_o e^{-\gamma r^2}\left(x_j - x_i\right)$ shows the attraction, α is the randomization coefficient (ranges: 0 - 1) and ε_i is the random number vector (Gaussian distribution). Firefly's next movement has been shown in Eq. (10)

$$x_i^{i+1} = x_i + \Delta x_i \quad (10)$$

\Firefly Algorithm

```
start
    Define the objective function, f(x), x = (x_i,,,,,,,,,,x_d)T
    Generate initial population of fireflies x_i (i = 1,2, … … n)
    Determine light intensity l_i at x_i from f(x_i)
    Define light absorption coefficient γ
        while t < Max Generation
                Make a copy of population for movement function
            for i = 1: n all n fireflies
                for j = 1: i all n fireflies
                        if (I_j > I_i)
                        Move fireflies i and j in d-dimension;
                        end if
                        Attractiveness varies with distance r via exp [−γr]
                        Evaluate new solution and update light intensity
                end
            end
           Rank the fireflies and find the current best
        end
        Post process results and visualization
end
```

Fig. 4 The basic steps in Firefly Algorithm using Pseudo-code

3.2 ANN (artificial neural networks)

The neural network ANN is a multi-layer feeding forward network with a back spreading learning algorithm comprising input, output and intermediate or hidden layers, when input layer has been shown as $D \in R^n$ and $D = (X_1, X_2, \dots, X_n)^T$. The outcomes of the q neurons in the hidden layer are $Z = (Z_1, Z_2, \dots, Z_n)^T$; and the outcomes of the output layer are $Y \in R^m$ and $Y = (Y_1, Y_2, \dots, Y_n)^T$. If the weight (wij and wjk) and the threshold (yj and yk) have represented the values (input & hidden) and (hidden & output), the outputs of each neuron (hidden & output) are as follows

$$Z_j = f\left(\sum_{i=1}^{n} w_{ij} X_i - \theta_j\right) \tag{11}$$

$$Y_k = f\left(\sum_{j=1}^{q} w_{kj} Z_j - \theta_k\right) \tag{12}$$

f as transfer unit (mapping the summed input of neuro n to the output)

Transfer function (f) is an appropriate selection to present a non-linearity into the network design. The common Sigmoid transfer function is based on the monotonic increasing with the ranges of 0 to 1 (Yang 2013, Olatomiwa *et al.* 2015).

3.3 Genetic Programming (GP)

The Genetic Programming (GP) or evolutionary algorithm has been provided according to the natural selection and survival of the fittest equation theories by Darwin. GP has focused on the primary population of randomly generated equations obtained from 1) random input- variable combining 2) random numbers and 3) functions. Initial population equation has been presented by $(+, -, \times, \div)$, sine, cosine, exp, logarithms, and logical comparing units. The initial population related to the evolutional processing and the evolved fitness program has been analyzed to choose the greatest programs offering the fitted data, and lately, the obtained programs have been used to exchange a part of the information among them. The exchanging part of the aforementioned programs has been named *cross over* and arbitrarily changing programs for creating new programs has been named *mutation*, which is to produce the proper programs to mimic the reproduction process of natural world. The evolution procedure has been repeated on the successful generations but not on less fitted programs to find the symbolic data expressions. GP has also designated to gain the related evolutionary processing knowledge with a scientific interpretation (Olatomiwa *et al*. 2015).

4. Results and discussion

4.1 Experimental results

Generally, the behavior of both shorter channel and longer channel is different. When the channel fracture has been occurred, the slabs of the longer channels have experienced the concrete cracking on the slabs sides but not with the shorter channels. Likely, more concrete cracking might occur in specimens with longer channel comparing to the shorter one.

Likewise the connector fracture, the crushing and splitting of the concrete element are the shear connectors' most common failing. For designing the shear connector, static strength and ductility measurement are two necessary

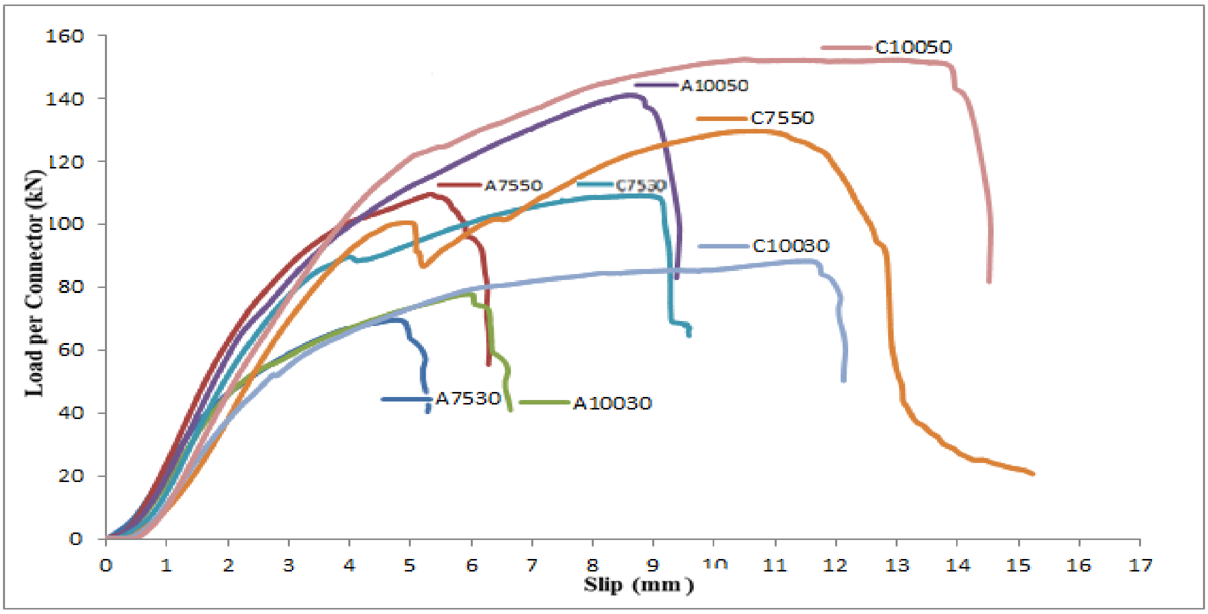
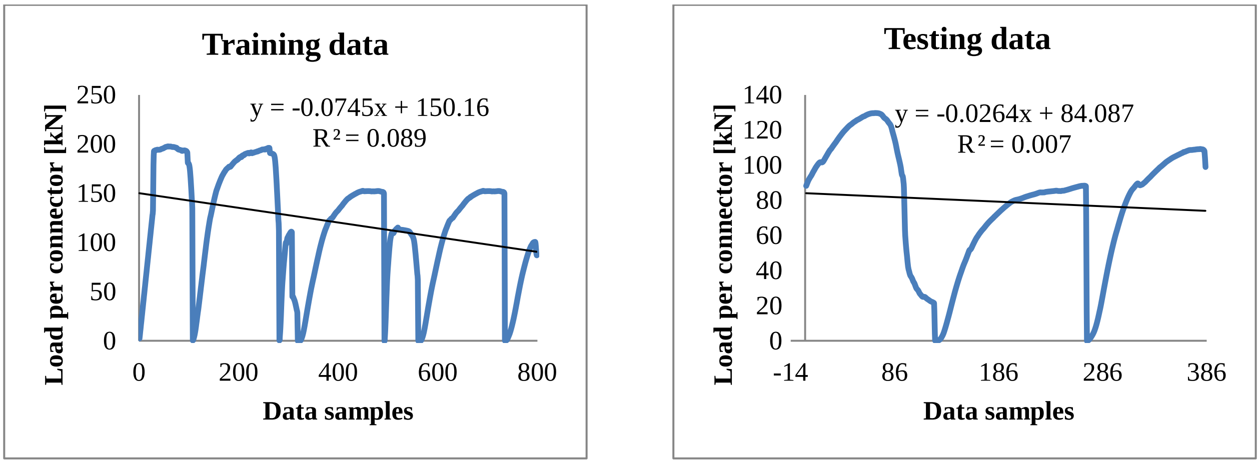


Fig. 5 Specimens' load slip curves in monotonic load



(a) (b)

Fig. 6 Time series of heat loading (a) Training data set and (b) test data set

assumptions confirmed through the final slip. Figure5 has showed the load slip measurement of monotonic loads in all specimens, moreover, the load slip curve of one channel has been applied to extract the mechanic- properties of channel connector. Across the monotonic and cyclic, load slips have been presented in I-beam and the concrete block. In High Strength Concrete (HSC), when the slip is bigger than 4 mm, there would be adequate ductility for all channel connectors. The relative slip for all specimens is 4 - 9 mm at the peak load in monotonic load. As a result, in HSC push out testing, the various phases statistically are not significant for the connector ductility. In all specimens, the sudden changing of the peak load and the load slip curve has reduced the loading capacity. Hence, all specimens have shown a yield plateau by an increased slip at the peak load.

4.2 Input variables for model building

The rational estimates of SVM-FFA is based on its parameter selection, therefore, a precise attention over the involved system factors is essential to produce a reliable network. The current study has precisely gathered and spotted the input parameter (slip) to the learning techniques, on the other word, around 70% of data is for training samples and 30% is to test samples (Table 2). All 1186 observations have been divided in training set (70%) and test set (30%) for potential predictor. The series of heat loading time for training data set and test data set with a linear trend are shown in Fig. 6.

Table 2 Input statistics in shear connectors

	Input parameters	Mean value	Maximum value	Minimum value
		$\bar{x}$	(x_{max})	(x_{min})
Load & Slip	*Tf (Flange thickness)*	8.07	8.50	7.50
	Tw (Web thickness)	5.57	6.00	5.00
	Fc (Concrete Compression strength)	49.09	82.00	38.20
	LC (Connector length)	43.09	50.00	30.00

4.3 Accuracy of the proposed models

RMSE *, R^2, and r have been applied to the training data set and testing data set to measure the proposed model's predictive performance as follow:

* Root means square error (RMSE)
* Determined coefficient (R^2)
* Coefficient of Pearson (r)

1) RMSE

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}} \tag{13}$$

2) r

$$r=\frac{n\left(\sum_{i=1}^{n}O_i\cdot P_i\right)-\left(\sum_{i=1}^{n}O_i\right)\cdot\left(\sum_{i=1}^{n}P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n}O_i^2-\left(\sum_{i=1}^{n}O_i\right)^2\right)\cdot\left(n\sum_{i=1}^{n}P_i^2-\left(\sum_{i=1}^{n}P_i\right)^2\right)}} \tag{14}$$

3) R^2

$$R^2=\frac{\left[\sum_{i=1}^{n}\left(O_i-\overline{O}_i\right)\cdot\left(P_i-\overline{P}_i\right)\right]^2}{\sum_{i=1}^{n}\left(O_i-\overline{O}_i\right)\cdot\sum_{i=1}^{n}\left(P_i-\overline{P}_i\right)} \tag{15}$$

P_i and O_i (the test and forecast variables of heat loading data)
n (the total number of test data)

Despite of few contradictions on the validity of error metrics in forecast methods, its values are not considered to this test.

4.4 Performance of SVM-FFA

SVM-FFA performances (load predictive models) for shear connectors have been represented in Fig. 7 as follows: (a) the accuracy of SVM-FFA, (b) GP method, (c) ANN method for the shear load predictions. In the current study, GP and ANN have been more effective in training phase for shear load prediction compare to SVM-FFA confirmed by the high value of coefficient of determination. Albeit the prediction accuracy has destroyed the prediction view, the training error is not a reliable tool to predict the potential of a particular model. The potentiality of SVM-FFA has been assessed to test the shear load prediction with the connectors. The scatter plot of the shear load variables against testing phase by using SVM-FFA has been depicted in Fig. 8: a) SVM-FFA b) GP c) ANN. During the test, the coefficient of determination (R^2=0.6641) has proved SVM-FFA highly well-performed than GP and ANN. The confined amount of over-estimated or under-estimated variables has proved the predicted values as proper for high level precision.

4.5 SVM-FFA, ANN and GP Comparison

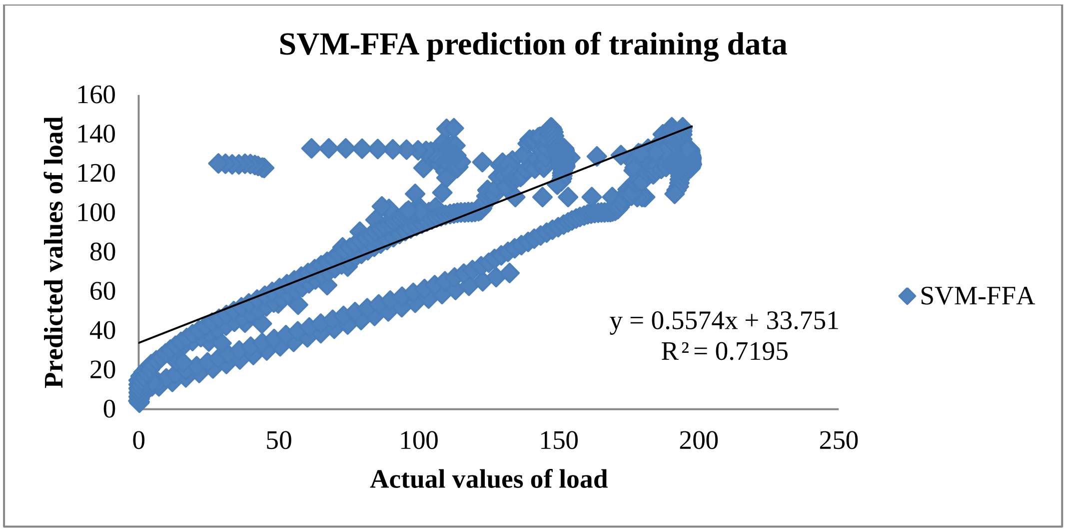
Considering SVM-FFA's merits in a benchmark study, the accurate prediction of SVM-FFA, GP and ANN have been compared by RMSE, r, and R^2 *(see 4.3) (Table 3).

Regarding the mentioned methods, similar outcomes have been achieved for training data set but significantly different outcomes for testing data set. SVM-FFA has significantly performed better than GP and ANN according to RMSE analysis due to its high narrow value range of RMSE fluctuation. Table 4 shows the user defined parameters (optimal parameters) which are used for the three methods.

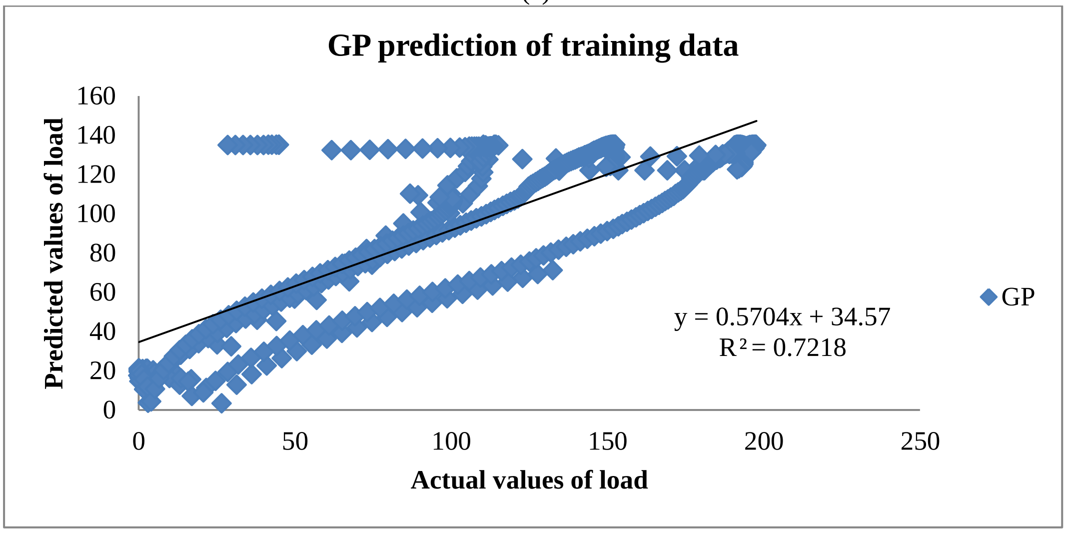
5. Conclusions

Though, shear studs of shear connectors have been widely used, the channel connectors are more preferable. Due to the complex behavior and lack of valid approaches of shear capacity, its prediction is very difficult. The current study has investigated SVM-FFA (SVM and FFA*) as a non-linear tool to predict the relationship of load slip in the channel shear connectors proposing adequately accurate prediction of the load slip relationship of the channel shear connectors. In comparison of SVM-FFA prediction to GP and ANN by using RMSE, r, and R^2, the robustness of SVM-FFA has proved a superior performance than GP and ANN.

*SVM for structural minimization
FFA for determining optimal SVM parameters



(a)



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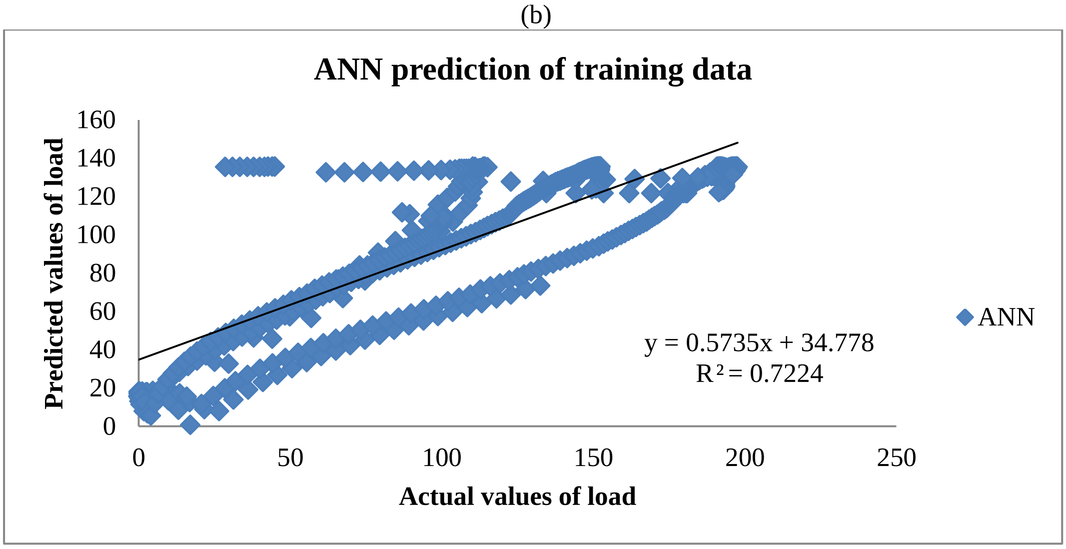
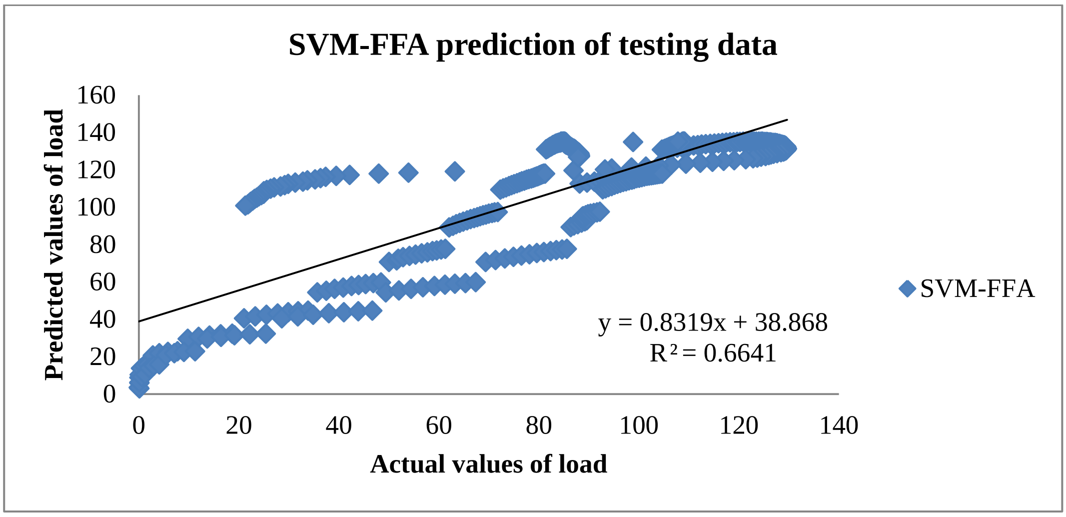
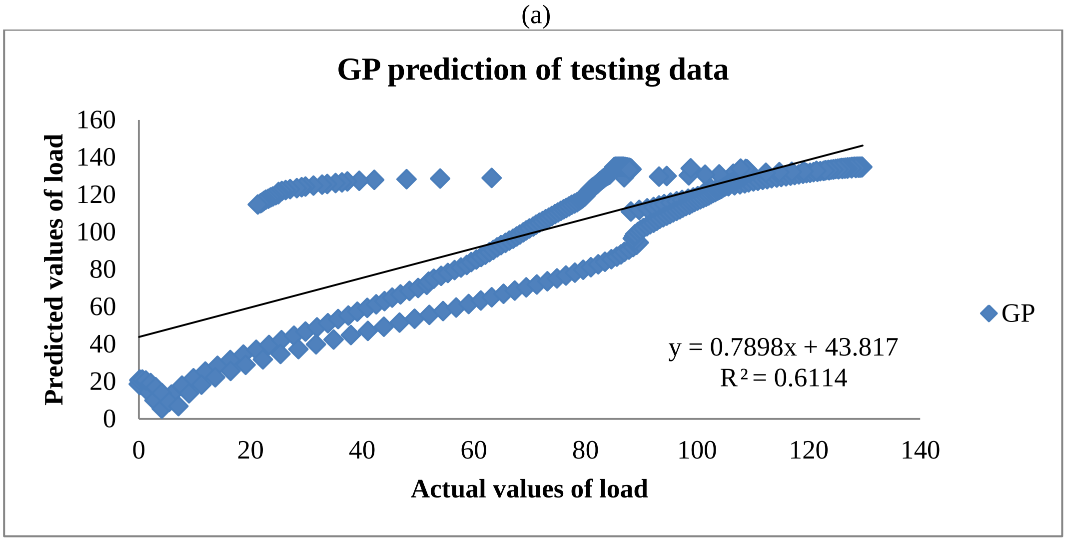


(c)

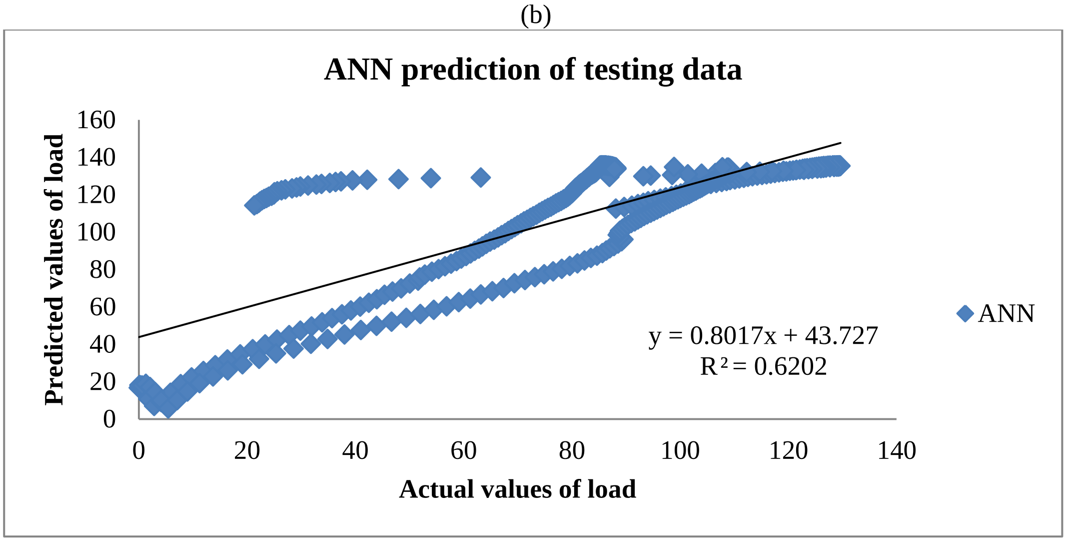
Fig. 7 Scatter-plots of shear load (training data set's actual-predicted variables) SVM- FFA (b) GP (c) ANN



(a)



(b)



(c)

Fig. 8 Scatter plots of shear load (actual and predicted values of testing data set) (a) SVM-FFA (b) GP (c) ANN

Table 3 Statistical comparison of SVM-FFA, ANN and GP

Prediction horizon	SVM-FFA			ANN			GP		
	RMSE	R^2	r	RMSE	R^2	r	RMSE	R^2	r
Training data set	37.84531	0.7195	0.848205	36.00263	0.7224	0.84994	36.34904	0.7218	0.849616
Testing data set	110.502	0.6641	0.814926	112.8201	0.6202	0.78752	111.9259	0.6114	0.781896

Table 4 The main parameters of SVM-FFA, ANN and GP (user defined)

SVM-FFA	GP	ANN
C=1.72 γ = 0.49 ε = 0.29	Population size: 1024 Head size: 5-9 Chromosomes: 25-35 Mutation rate: 91.55 Crossover rate: 30.77 Inversion rate: 108.99	Activation function: Continuous Log-Sigmoid Function Number of iteration: 1000 First layer: 9 nodes Hidden layers: 3, 6, 10 Output layer: 1 node

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