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Moment-rotation estimation of steel rack connection using extreme learning machine

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Abstract. The estimation of moment and rotation in steel rack connections could be significantly helpful parameters for designers and constructors in the initial designing and construction phases. Accordingly, Extreme Learning Machine (ELM) has been optimized to estimate the moment and rotation in steel rack connection based on variable input characteristics as beam depth, column thickness, connector depth, moment and loading. The prediction and estimating of ELM has been juxtaposed with genetic programming (GP) and artificial neural networks (ANNs) methods. Test outcomes have indicated a surpass in accuracy predicting and the capability of generalization in ELM approach than GP or ANN. Therefore, the application of ELM has been basically promised as an alternative way to estimate the moment and rotation of steel rack connection. Further particulars are presented in details in results and discussion.

Keywords: steel racks; moment rotation behavior; upright column; beam-end connector; ELM

1. Introduction

Estimation for behavior of structural members is useful for design of structures. This phenomenon has been used in many recent researches including steel-concrete beams, reinforced concrete columns, etc. (Vo-Duy *et al*. 2017, 2018, Heydari and Shariati 2018, Ho-Huu *et al*. 2018, Hosseinpour *et al*. 2018, Ismail *et al*. 2018, Nasrollahi *et al*. 2018, Paknahad *et al*. 2018, Wei *et al*. 2018, Zandi *et al*. 2018, Abedini *et al*. 2019, Davoodnabi *et al*. 2019, Luo *et al*. 2019, Sajedi and Shariati 2019, Xie *et al*. 2019), and may be useful to give design perspectives for utilizing newly developed beams and columns made of materials with inherent tailored micro-structures (known as meta-materials). Knowing the way of estimation of structural member behavior could help for more optimized and affordable design of them. Steel rack has been taken as an applicable resolution to the situations by providing an adequate and accessible storage, if low space is provided and juxtaposed with the higher storage items' volume (Shariati *et al*. 2010, 2012, 2015, 2017, 2018, Shah *et al*. 2015, 2016a, b, c, Chen *et al*. 2019).

Three dimensional structures have provided a direct and availability to the whole stored items and have been easily demounted with a reassembling capability. The effectual application of racks has required a material flexibility to constitute the racks. Respectively, cold-formed steel has been regarded to the manufacture of these weird structures (Kheyroddin *et al*. 2008, Gilbert and Rasmussen 2009, Bazzaz *et al*. 2011, 2012, 2014, 2015a, b, Gilbert *et al*. 2012, Andalib *et al*. 2014, Shah *et al*. 2016b, Abedini *et al*. 2017, Anicic *et al*. 2017, Khorami *et al*. 2017b, Andalib *et al*. 2018, Bazzaz *et al*. 2018, Paknahad *et al*. 2018) to allow a hand-adjusting and rack parameters' resembling when needed and to its good strength to weight rate. In contrast, AS4084 has permitted the use of hot roll steel to be manufactured, if rack should support the severe loading.

The current research has evaluated the improvement in beam-column connection function under static load by changing the most effectual characteristics. 32 different tests by using a double cantilever testing method have been performed on the rack connection by changing beam depth, column thickness and beam end connector's depth. The moment-rotation and load-strain behavior of connections have been checked, also the effect of the elements on general connection function has been experimented. On the other hand, a comparative research to gain the joint stiffness by using three various models as (1) the primary stiffness

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model; (2) slope to half ultimate model; and (3) the equal area model is performed.

The steel rack connection analysis has required a precise on line determination of moment and rotation, accordingly, the estimation model of steel rack connection moment and rotation through the Extreme Learning Machine (ELM) are used. Nowadays, computational models' applications to solve real shortcomings and determining the optimum variables and performances have enormously been considered in various scientific realms (Hamidian *et al*. 2012, Toghroli *et al*. 2014, Aghakhani *et al*. 2015, Mohammadhassani *et al*. 2015, Toghroli 2015, Mansouri *et al*. 2016, 2017, Safa *et al*. 2016, Toghroli *et al*. 2016, Khorami *et al*. 2017a, Sadeghi Chahnasir *et al*. 2018, Sedghi *et al*. 2018, Shariat *et al*. 2018, Toghroli *et al*. 2018, Zandi *et al*. 2018). Neural network (NN) would be recently nominated in various engineering era to solve the complicated non-linear shortcomings by using classic parametric methods. On the other hand, back propagation (BP), support vector machine (SVM), and hidden Markov model (HMM) are taken as training NN algorithms. The neural network's problem is in its learning time requirement (Singh *et al*. 2008, 2012, Mansouri *et al*. 2016, Safa *et al*. 2016, Toghroli *et al*. 2016). an algorithm for single layer feed forward NN as ELM specified to solve shortcomings occurred by gradient descent algorithm(s) like BP used in ANNs has been nominated by Huang *et al*. (2004). ELM has also the capability of reducing the required training time for one NN, in other word, using ELM has tremendously raised the speed of learning process and generated a robust performance (Huang *et al*. 2006c). Thus, likewise other algorithms, ELM is also used in diverse scientific problem-solving fields (Mohammadhassani *et al*. 2013, 2014, Wang and Han 2014, Yu *et al*. 2014, Anicic *et al*. 2017), but a powerful algorithm with fast learning speed and well function compared to the classic ones as BP. ELM has focused to gain the lowest train error and weights' norm. In the current study, a predictive method of steel rack connection moment and rotation has been created by ELM. The results have indicated the capability of proposed model in the prediction of energy usage in buildings. Also, the results of ELM have been juxtaposed with the results of GP and ANN. There is an attempt to retrieve the correlation among the column-thickness, beam-depth, connector-depth, load and steel rack connection moment and rotation. The system is for predicting the moment and rotation of the steel rack connection in terms of four input parameters.

2. Methodology

2.1 Testing

To study the behavior of beam-end connector, a comprehensive research has been conducted recently (Shariati *et al*. 2018). In this research design standards for storage rack design including Rack Manufacturers Institute (RMI 1997), Australian Standard (AS 4084) (2012), Storage Equipment Manufacturing Association (SEMA 1985) and F´ed´eration Europ´eenne de la Manutention are the recommend alternative testing methods as cantilever testing model and portal frame testing model. Later, cantilever testing has been extended by the attachment of one extra beam to other side of column, mightily named as double cantilever testing model. Although, it is difficult to equally load the connections on both right and left side of the column and the consequent deflection may not be the same, the related literature has proved that double cantilever test is more beneficial with better results than cantilever test. The beam-end connector adjusted to moment, axial pull, and shear, like to real frame, has mightily provided a satisfactory estimating of shear and moment rate. The shear to moment ratio in a real rack frame might be better reproduced by double cantilever test. Consequently, in this study, the results of double cantilever test method have been used as testing arrangement. A brief report of this research is brought below.

2.2 Specimen and material

Two types of beam-to-upright connections have been supplied; however, only one type has been experimented. Schematic diagrams of selected connection for beam-end connector are depicted in Fig. 1.

2.3 Material properties

Cold-formed steel section(s) have been applied for column and beam. Also, the beam-end connectors are built of hot roll steel. The material features of members and beam-end connectors are given in Table 1.

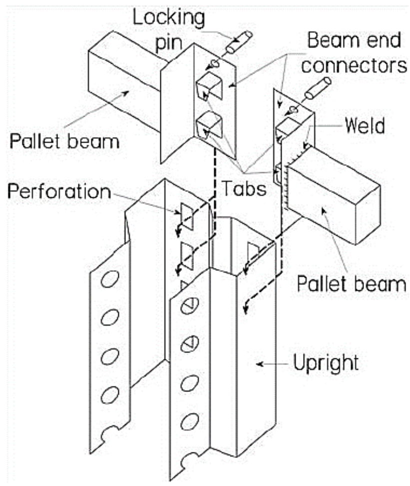


Fig.1 Detail of the beam end connector (Shariati *et al*. 2018)

Table 1 Specimens' material property (Shariati *et al*. 2018)

Member	Young's modulus (E)	Poisson's ratio (v)	Yield strength (f_y)	Ultimate strength (f_u)
Column	205	0.3	280	382
Beam			327	435
Beam-end-Connector			304	353

Table 2 Beam dimensions

Type of beam	Width 'b' (mm)	Depth 'h' (mm)	Thickness 't' (mm)
B1	40	92	1.5
B2	40	110	1.5
B3	50	125	1.5
B4	50	150	1.5

2.4 Specimen details

Totally, 32 experiments have been conducted composed of 4 trials of each specimen's set defined by 2 various column-thickness, 4 various beam-depth and 2 different umbers of tabs in beam-end connector. The column specimens have been spotted by their thicknesses. Column A is 2.0 mm thickness and column B is 2.6 mm thickness.

Welding of beam in compression zone has resulted to a weak point in the exposed portion of beam-end connector with tabs to make the connector susceptible to tensile failure and to reduce the final moment carrying the capacity of connection (Abedini *et al*. 2019). Failure assessments in design have drawn many attentions (Bobaru *et al*. 2018, Mehrmashhadi *et al*. 2019a, b). Down welding of the beam has minimized the tensile failure of beam-end connector. The cross section of the box beam and upright are represented in Figs. 2(a) and (b). The beam sections' details have been provided in Table 2.

2.5 Test setting up

Double cantilever testing has been followed for predicting the moment-rotation behavior of the connection(s). Therefore, test has restrained the shear displacement in the column(s) to be treated as a rigid body. The column has been initially correlated and vertically levelled below the load tool. Later, two beams are attached to the right-left side of the column at its center. Small amount of pre-loading has been primarily used and the displacement measuring tools are adjusted. The schematic representation of test setting up is illustrated in Fig. 3.

2.6 Instrumentation

Within the tests besides loading, three various measurements have been performed to gain a data-set on connection behavior throughout the whole ranges of used loading including: (1) performing of strain reading to steel-yielding monitoring; (2) displacement measurement to gain the load deflection behavior; and (3) rotation measurement to gain moment rotation properties.

Deflection measurements are performed at the selected zone by linear variable differential transformer (LVDT) in a measurement range (50-200 mm). Two digital inclinometers are installed on both sides of the beam to directly gain the beam-rotation (degree) by taking them on the beam sides.

2.7 Input and output variables

Four input parameters have been obtained from the experimental test results to analyze the steel rack connections moment as: column-thickness, beam-depth, connector depth and loading (Table 3). On the other hand, 5 input parameters have been obtained to analyze the steel rack connection rotation as column-thickness, beam- depth, connector depth, load and 5) moment (Table 4).

2.8 ELM

ELM has been nominated for the single layer feed forward NN (SLFN) architecture (Annema *et al*. 1994, Huang *et al*. 2006b), randomly choosing the input weights and analytically determining the output weights of SLFN. ELMS with its fast learn speed has no required many human interventions compared to conventional algorithm(s).

ELM has also the capability of analytically defining all network elements to prevent the trivial human interventions known as an influential algorithm with more merits like smooth use, fast learning, and high function, suitable for more non-linear activation and kernel performances.

2.8.1 SLFN

SLFN performance with L hidden nodes has been offered as mathematical explanation of SLFN, interlocking the additive and RBF hidden-nodes (Huang *et al*. 2006a, Liang *et al*. 2006)

$$f_L(x) = \sum_{i=1}^{L} \beta_i G(a_i, b_i, x), \quad x \in R^n, \quad a_i \in R^n \tag{1}$$

a_i and b_i = learning characteristics of hidden-nodes

β_i = the weight connecting i^{th} hidden node to the output node

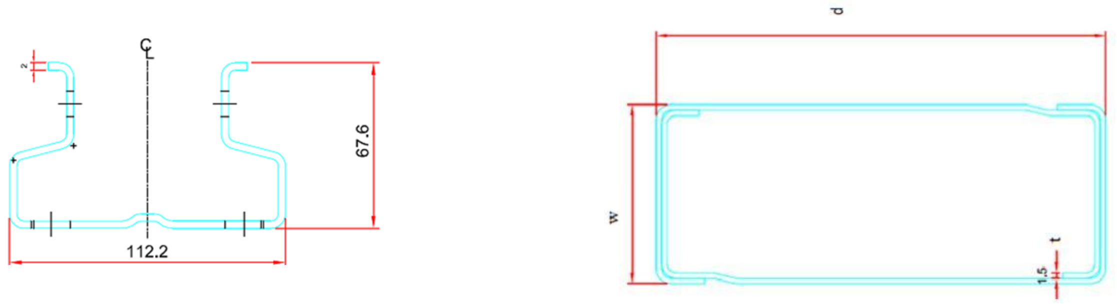
G (a_i, b_i, x) = output value of i^{th} hidden node regarded to input x

Table 3 Input parameters for steel rack connection moment prediction

Inputs	Parameters description	Parameters characterization
Input 1	Thickness of column (mm)	Min: 2 Max: 2.6
Input 2	Depth of beam (mm)	Min: 92 Max: 150
Input 3	Depth of connector (mm)	Min: 205 Max: 250
Input 4	Loading (kN)	Min: -23.184 Max: 4.218

Table 4 Input parameters for steel rack connection rotation prediction

Inputs	Parameters description	Parameters characterization
Input 1	Thickness of column (mm)	Min: 2 Max: 2.6
Input 2	Depth of beam (mm)	Min: 92 Max: 150
Input 3	Depth of connector (mm)	Min: 205 Max: 250
Input 4	Load (kN)	Min: -23.184 Max: 4.218
Input 5	Moment (kNmm)	Min: -0.0075 Max: 5.224372



(a) Upright cross section (b) Beam cross section

Fig. 2 Beam and column section details (Shariati *et al*. 2018)

The additive hidden node with the activating performance of $g(x)$: $R \rightarrow R$ (say, sigmoid and threshold), G (a_i, b_i, x) is

$$G(a_i,b_i,x) = g(a_i.x + b_i), \qquad b_i \in R \tag{2}$$

a_i = vector- weight connecting the input layer to i^{th} hidden node
b_i = bias of i^{th} hidden node a_i
x = inner product of vector a_i and x in R_n

G (a_i, b_i, x) has been obtained for RBF hidden node with activating function $g(x)$: $R \rightarrow R$ (say, Gaussian), G (a_i, b_i, x) as

$$G(a_i,b_i,x) = g(b_i\|x - a_i\|), \qquad b_i \in R^+ \tag{3}$$

a_i and b_i = center and impact factor of i^{th} RBF node
$R+$ = set of all positive actual variables

RBF network is a specific SLFN with RBF nodes in its hidden layer. For N arbitrary distinct samples $(x_i,t_i) \in R^n \times R^m$, x_i is $n\times1$ input vector and t_i is $m\times1$ target vector. If one SLFN with L hidden nodes could approximate the N samples with zero error, then it means that there is β_i, a_i and b_i like

$$f_L(x_j) = \sum_{i=1}^{L} \beta_i G(a_i, b_i, x_j), \quad j = 1, \ldots, N. \tag{4}$$

Eq. (4) could be

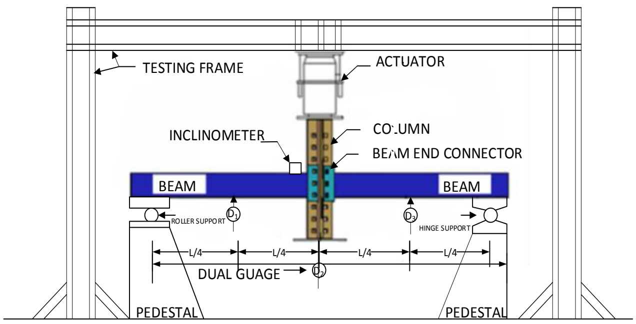


Fig. 3 Double cantilever test set-up diagram (Shariati *et al*. 2018)

$$H\beta = T \tag{5}$$

Where

$$H(\tilde{a},\tilde{b},\tilde{x}) = \begin{bmatrix} G(a_1,b_1,x_1) & \cdots & G(a_L,b_L,x_1) \\ & \cdots & \\ (a_1,b_1,x_N) & \cdots & G(a_L,b_L,x_N) \end{bmatrix}_{N\times L} \tag{6}$$

With

$$\tilde{a} = a_1,\ldots,a_L; \quad \tilde{b} = b_1,\ldots,b_L; \quad \tilde{x} = x_1,\ldots,x_L \tag{7}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times m} \quad and \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_L^T \end{bmatrix}_{N\times m} \tag{8}$$

Table 5 Comparative performance statistics of ELM, ANN and GP in moment prediction

ELM			ANN			GP		
RMSE	R^2	r	RMSE	R^2	r	RMSE	R^2	r
0.326023	0.9013	0.949345	0.8672	0.931215	0.376358	0.931347	0.326023	0.9013

Table 6 Comparative performance statistics of ELM, ANN and GP in rotation prediction

ELM			ANN			GP		
RMSE	R^2	r	RMSE	R^2	r	RMSE	R^2	r
0.0183	0.9157	0.956927	0.023317	0.8607	0.927737	0.023314	0.8623	0.928585

H is the hidden layer output matrix of SLFN with i^{th} column of H being the i^{th} hidden node's output regarding to the inputs $x_1,..., x_N$.

2.8.2 ELM principle

ELM has been defined as a SLFN with L hidden neurons to learn L distinct samples with 0 error. When a number of hidden neurons L < the number of distinct samples N, ELM has randomly assigned the characteristics of hidden nodes and computed the output weights by pseudo instead of H offering one small error $\varepsilon > 0$. The hidden node characteristics of ELM as a_i and b_i couldn't be tuned in train and is applied with random variables as the thesis below:

Theorem 1: Let an SLFN with L additive or RBF hidden nodes and an activation function $g(x)$ which is infinitely different in any interval of R be given (Liang *et al*. 2006). Arbitrary L distinct input vectors $\{x_i \mid x_i \in R^n,\ i = 1,..., L\}$ and $\{(a_i,\ b_i)\}_{i=1}^{L}$ have been randomly developed by any continuous probability distribution, the hidden layer outcome matrix is invertible with probability one, the hidden layer output matrix H of the SLFN is invertible and $||H\beta - T|| = 0$.

Theorem 2: Given any small positive variable $\varepsilon > 0$ and activating performance $g(x)$: $R \rightarrow R$, unlimited discrepancies in any interval, there would be $L \leq N$, then for N arbitrary distinct input vectors $\{x_i \mid x_i \in R^n,\ i = 1,..., L\}$, for any $\{(a_i,\ b_i)\}_{i=1}^{L}$ that are randomly developed according to any continuous probable distributing $||H_{N\times L}\beta_{L\times m} - T_{N\times m}|| < \varepsilon$ with probability one (Liang *et al*. 2006). Since the hidden node characteristics of ELM couldn't be tuned across the train or easily assigned with random variables, Eq. (5) has become a linear system and the output weights could be computed as (Khu *et al*. 2001)

$$\beta = H^{+}T \tag{9}$$

H^+ is the Moore Penrose generalized inverse of hidden layer output matrix H calculated by few models comprising orthogonal projection, orthogonalization, repeating, and Singular Value Decomposition (SVD). The orthogonal projection has been applied if HTT is non-singular and H+ = (HTT) – 1 HT. Because of the seeking and repeating, orthogonalization and iterative approach are including few curbs. The use of ELM has applied SVD to analyze the Moore Penrose generalized inverse of H, due to its general usage in all cases proving ELM as a batch learning approach.

2.8 ANN

The multilayer feedforward network with BP is a very common NN, precisely investigated and commonly applied in more realms. Generally, one NN has consisted of three layers: (1) one input layer; (2) one output layer; and (3) one intermediate or hidden layer. The input vectors are $D \in R^n$ and $D = (X_1, X_2, \dots, X_n)^T$; the outputs of q neurons in the hidden layer are $Z = (Z_1, Z_2, \dots, Z_n)^T$; and the results of the output layer are

$$\mathrm{Y} \in \mathrm{R}^{\mathrm{m}},\ \mathrm{Y} = (\mathrm{Y}_1, \mathrm{Y}_2, \dots, \mathrm{Y}_\mathrm{n})^{\mathrm{T}}$$

w_{ij} and y_j = weight and threshold between the input layer and hidden layer
w_{jk} and y_k = weight and threshold between the hidden layer and output layer

The outcomes of any neuron in one hidden layer and output layer are

$$Z_j = f\left(\sum_{i=1}^{n} w_{ij} X_i - \theta_j\right) \tag{10}$$

$$Y_k = f\left(\sum_{j=1}^{q} w_{kj} Z_j - \theta_k\right) \tag{11}$$

f is transferring performance or mapping rule to sum up the neuron's input to its output, and applies a proper option of an instrument to nominate a nonlinearity into the network designing. Another typically applied function is sigmoid function as a monotonic increment ranging from zero to one.

2.10 GP

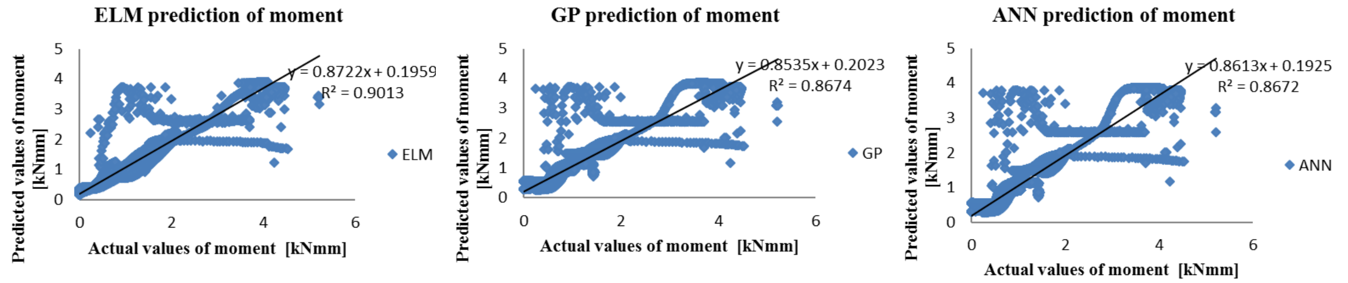
GP as an evolutionary algorithm is according to the natural choice and survival to approximate the equation (Darwinian theories), ironically describing how the output has related to input values, so it is about the primitive population of randomly generated equations, obtained from randomly input values combinations, random functions and numbers, including arithmetic operators $(+, -, \times, \div)$, mathematic parameters as (sin, cos, exp, log), and logical comparison performances properly derived from appropriate process conception. Therefore, the population of potential solution(s) has been adjusted to the evolutionary procedure and fitness (measuring the quality of problem solving) of the evaluated evolved programs. In the following, separate programs (best fitted to the data) have been obtained from the primitive population, and then these best fitted programs have been chosen to change the part of information between the programs to make the best ones by 'crossover' and 'mutation', imitating the real reproduction procedure of nature. Accordingly, the process of changing parts within the (best) programs is crossover, and randomly changing programs to create the new ones is mutation. Thereafter, those programs with a less fitting - data have been discarded. This evolution process has been iterated on the sequential generations to find the symbolic explanations about data that scientifically has been described to gain the knowledge about the process.

3. Results and discussion

3.1 Accuracy evaluation of the proposed approaches

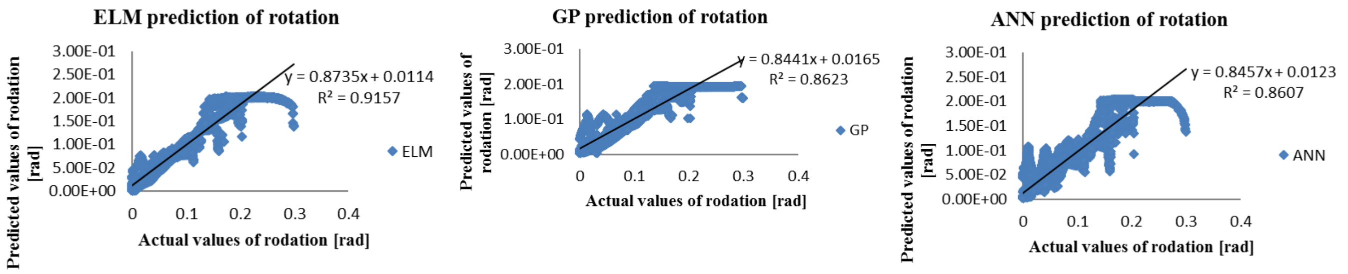
The predictive function of the methods has been provided as RMSE, R^2 and r

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{12}$$



(a) (b) (c)

Fig. 4 the scatter plots of real and predicted variables in moment through: (a) ELM; (b) GP; (c) ANN



(a) (b) (c)

Fig. 5 the scatter plots of actual and predicted variables in rotation through: (a) ELM; (b) GP; (c) ANN

$$r = \frac{n\left(\sum_{i=1}^{n} O_i \cdot P_i\right) - \left(\sum_{i=1}^{n} O_i\right)\cdot\left(\sum_{i=1}^{n} P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - \left(\sum_{i=1}^{n} O_i\right)^2\right)\cdot\left(n\sum_{i=1}^{n} P_i^2 - \left(\sum_{i=1}^{n} P_i\right)^2\right)}} \quad (13)$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)} \quad (14)$$

P_i and O_i = test and predict variables of steel rack connection moment and rotation
n = total test data number root means square error (RMSE),
Coefficient of determination (R^2)
Pearson coefficient (r)

3.2 Performance evaluation of ELM

This section has focused on the outcomes of ELM steel rack connection moment and rotation predictive models of building as follows:

The accuracy of developed ELM in moment and rotation predictive methods is illustrated in Fig. 4(a). The accuracy of developed GP and ANN in moment predicting methods is illustrated in Figs. 4(b)-(c). The accuracy of developed ELM, GP and ANN in rotation predictive methods is illustrated in Figs. 5(a)-(c).

Therefore, the majority of points have fallen along the diagonal line for ELM predicting models. So, the prediction outcomes have been aligned with the measured variables in ELM, confirmed by higher R^2 variable. The number of overestimated and underestimated maintained variables is confined. Then, the predicted variables have obviously enjoyed from high level precision.

4. ELM, ANN and GP performance comparing

To define the positive features of ELM in an obvious basis, the prediction accuracy of ELM has been juxtaposed by the prediction accuracy of GP and ANN applied as a benchmark by using RMSE, r and R^2. Tables 5-6 have summarized the predicting accuracy for test data-set, because the training error is not a reliable index to predict the potential of particular method. According to the outcomes, ELM has drastically outperformed than GP and ANN, in other word, based on RMSE analysis, ELM has significantly provided better results than benchmark models (ANN and GP).

5. Conclusions

The current research has performed a systematic model to create ELM steel rack connection moment and rotation predictive model. The comparison of ELM with GP and ANN has been used to verify the prediction accuracy, thereafter, by using RMSE, r and R^2, the results has confirmed the superiority of ELM to GP and ANN. On the other hand, ELM has few more demanding properties distinguishing it from the classic (ordinary) gradient based learning algorithms for feed forward NN. ELM is fast in learning than the classic feed forward network learning algorithms like BP, also, ELM has the efficiency of achieving the lowest train error and also weights' norm. The current study has shed light on the computer science applications in steel rack connections. Consequently, the estimating procedure in moment and rotation has assisted the construction section having a broad view in structure behavior across the design, constructing and operations resulting to more realistic and accurate design and construction.

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